Cellular Network Based Real-Time Road Traffic State Estimation Framework for Urban Road Networks

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A Dissertation Submitted to

IT-PhD Program (Software Engineering Track)

Presented in Fulfillment of the Requirements for the Degree of

Doctor of Philosophy in Information Technology (Software Engineering)

Addis Ababa University

Addis Ababa, Ethiopia

January 2017

Addis Ababa University

School of Graduate Studies

This is to certify that the dissertation prepared by Ayalew Belay, entitled: *Cellular Network based Real-Time Road Traffic State Estimation Framework for Urban Road Networks*and submitted in fulfillment of the requirements for the Degree of Doctor of Philosophy in Information Technology (Software Engineering) compiles with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ABSTRACT

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Addis Ababa University, 2016

With the rapid increase of urban development and the surge in vehicle ownership, urban road transport problems like traffic accident and congestion caused huge waste of time, property damage and environmental pollution in recent years. To address these problems, use of Information Communication Technology–based transport systems that can support maximum utilization of the existing road transport infrastructure has been proposed by different researchers. Road monitoring systems are one of these solutions which support road users to make informed decisions. However, the current road traffic monitoring systems use road side infrastructures for road traffic data collection and these technologies lack accurate and up-to-date traffic data covering the whole road network. By comparison, cellular networks are already widely deployed and can provide large road network coverage. Besides, 3G and 4G cellular networks provide mobile phone positioning facility with better performance accuracy and this opportunity can help to obtain accurate traffic flow information in cost effective manner on the entire road networks. Mobile positioning technologies which aim to collect road traffic data in cellular networks can be either Handset-based or Network-based. Each of these technologies differ in their positioning accuracy as well as area coverage. But, there is no single cellular network positioning technology that can support wide area coverage with high accuracy simultaneously. To improve positioning accuracy, coverage and communication latency of

positioning technologies, combination (hybrid) of Handset-based and Network-based positioning techniques has been proposed. The objective of this research is, therefore, to develop a real-time road traffic estimation framework, which utilizes a hybrid cellular network positioning technology as a source of road traffic data.

To achieve this objective, the study uses a design science research approach. Detail literature review on past and current research studies was conducted to identify the need for better road traffic flow estimation accuracy together with improved performance of the procedures. With the help of systematic literature review better understanding on road traffic flow estimation procedures and tools was identified.

The results of literature review on the different positioning principles and state estimation models formed a base to design a hybrid mobile phone positioning and tracking algorithm and real-time road traffic state estimation framework. An experimental research method is employed in evaluating the accuracy of the proposed hybridized positioning technology and validating the performance of road traffic state estimation framework. To evaluate the operational effectiveness of the framework sample road networks of Addis Ababa city are used. Data is gathered based on simulation experiment and also from field test conducted using J2ME location API (JSR-179) software installed on A-GPS enabled mobile phone moving in all journey of a moving vehicle. The evaluation of the framework using both simulation data and real-world data indicated that the developed estimation model could help to generate reliable traffic state information on urban roads.

To validate the research process and evaluate practical utility of the research result, a theoretical literature support and expert survey were employed respectively. Accordingly, both the process and result are found to be valid, reliable and practical.

Key Words: cellular Network, Positioning Technology, Framework, Artificial Neural Network, State Estimation

ACKNOWLEDGMENTS

Conducting research in doctoral level involves a great deal of collaboration with different people in various ways. For that reason there are certain persons that I would like to thank, for contributing to this dissertation; each of them with his/her own unique way.

First of all, I would like to thank my two supervisors Professor (Dr.) Ajith Abraham and Dr. Dida Midekso for their guidance and conscientiously reading the draft of the dissertation. I do realize that I have absorbed a great deal of knowledge and experience. The most valuable gift I obtained during these years is not only this dissertation but also the way to do the "real" scientific research. It also helped me to learn how to work independently and formulate my own research approach.

I would like to thank all the committee members for their time and effort, useful comments and suggestions and their approval of my draft dissertation.

I also thank Dr. Workshet Lamenew and Dr. Yekoyealem Dessie for their useful comments and time in reviewing my draft dissertation. I thank Dr. Abraraw Chane who helped me to get access to journal papers and articles. I am particularly grateful to my SE and IS track colleagues.

To my doting parents Ato Belay Habtie and W/o Tihunie Kumelachew for their love, to my Sisters Asnakech, Gete and my brother Ayalu who made scarifies in taking care of my children during my study.

Finally, my special thanks to my wife Kuribachew and wonderful children Feker Ayalew and SahelSelassie Ayalew for their love and enormous sacrifices made to allow me time to study.

ክብርና ምስጋና ለሀያሉ እግዚያብሄር ! "To the Greatest Glory of GOD!"

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Abbreviations and Acronyms

2G	2^{nd} Generation Cellular Radio System
3G	3^{rd} Generation Cellular Radio System
3GPP	3^{rd} Generation Partnership Project
4G	4^{th} Generation Cellular Radio System
A-GPS	Assisted Global Positioning System
A-GNSS	Assisted Global Navigation Satellite System
ANN	Artificial Neural Network
API	Application Program Interface
AOA	Angle Of Arrival
ATIS	Advanced Traveler Information System
ATMS	Advanced Traffic Management System
BTS	Base Transceiver Station
BS	Base Station
CELL-ID	Cell Identification
CN	Core Network
CRLB	Cram-Rao Lower Bound
FCC	Federal Communication Commission
E-CID	Enhanced CELL-ID
EDGE	Enhanced Data rate for Global Evolution
eNodeB	Evolved UMTS Terminology for Base Station
E-OTD	Enhanced Observed Time Difference
E-SMLC	Enhanced Service Mobile Location Center
E-UTRAN	Evolved UMTS Terrestrial RAN
FCD	Floating Car Data
GDOP	Geometric Dilution of precision
GDP	Growth Domestic Product

GERAN	GSM EDGE RAN
GHG	Green House Gasses
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GSM	Global System for Mobile Communication
IPDL	Idle Period Downlink
ITS	Intelligent Transport system
J2ME	Java 2 Platform Micro Edition
JSR	Java Specification Request
KF	Kalman Filter
KPS	Kel Perian State
LCS	LoCation Service
LBS	Location-Based Service
LMU	Location Measurement Unit
LS	Least Square
LTE	Long Term Evolution
MAE	Measurement Absolute Error
MAPS	Matching Analysis Projection Synthesis
MF	Measurement Fusion
MS	Mobile Station
MSE	Mean Square Error
NodeB	UMTS Terminology for Base Station
OBU	On-Board Unit
OTD	Observed Time Difference
OTDOA	Observed Time Difference Of Arrival
RAN	Radio Access Network
RMS	Root Mean Square
RMSE	Root Mean Square Error
RSE	Root Square Error
RTT	Round Trip Time
SF	State Vector Fusion

TA	Timing Advance
TDOA	Time Difference Of Arrival
TOA	Time Of Arrival
UE	User Equipment
UMTS	Universal Mobile Communications System
U-TDOA	Uplink Time Difference Of Arrival
WCDMA	Wideband Code Division Multiple Access
WNA	White Noise Acceleration
WPA	Wiener Process Acceleration

Chapter One: Introduction

With the rise of urban development and increasing number of vehicle ownership, road transportation problems like traffic accident, congestion and environmental pollution are affecting day-to-day activities of people. Although additional road infrastructure development can minimize traffic congestion problem, due to cost and environmental factors, identification of techniques for maximum utilization of the existing road transport infrastructure is proposed by many researchers.

Road monitoring systems are one of those solutions which support road users to make informed decisions. The current road traffic monitoring systems use road side infrastructures for road traffic data collection and these technologies lack accurate and up-to-date traffic data covering the whole road network. By comparison, cellular networks are already widely deployed and can provide large road network coverage. Besides, 3G and 4G cellular networks provide mobile phone positioning facility with better performance accuracy and this opportunity can help to obtain accurate traffic flow information in cost effective manner on the entire road networks. This research, therefore, focuses on the utilization of the existing cellular network as a source of traffic data to monitor urban road traffic flow and disseminating road traffic information to road users at real-time.

Hence, in this chapter the background of the study presents an overview about the importance of road transport, problems related to it and issues the research has dealt with. Following the background, description of the research problem is made in statement of the problem sub-section. The general and specific objectives are presented followed by scope and limitations of the study. Then, Significance and methodology of the research are discussed. Finally the organization of the dissertation is outlined.

Portion of this chapter entitled "Cellular-cloud integration framework in support of real-time monitoring and management of traffic on the road: the case of Ethiopia" is published as proceedings of the International Conference on Management of Emergent Digital Ecosystems, ACM, 2012.

1.1 Background

An automobile is one of the inventions that changed the way people work and live. Automobiles improve mobility of people and goods, allowing better accessibility to markets and promoting employment [1]. Proper utilization of natural resources, distribution of food and other finished goods, integration of the manufacturing and agricultural sectors, and provision of education, medical and other socially important services such as security, for example, are all supported by transport system.

In the last century, road transport has emerged as the dominant type of terrestrial transport system and is vital for economic development and social integration[2]. Because of its easy accessibility, flexibility of operations, door-to-door service and reliability, road transport has the highest share of both passenger and freight traffic compared to other transport modes [3].

Road transport is a major sector in the economy of different countries of the world. In the U.S. for example, road transport accounts for 63% of all commercial activities [4], in Europe it represents 73% [5], in Africa it accounts for 80% in the transportation of goods and 90% for passengers' traffic [6], in Ethiopia it represents 95% [7], in India it reaches 87% [3] and in China road transport accounts for 75% of the total freight volume [8]. Due to this, the need for road transport has increased from time to time in different parts of the world.

To satisfy the increasing demand of road transport, the length of road networks is also growing in different countries of the world. For example in the U.S.A, the growth of road network length in the past twenty years was about 0.2 % a year [9] where as in low- and middle-income countries, road networks are increasing in length, on average, by about 2 % a year [9]. In low-income countries like East Asia and Pacific countries, the average ratio of road network length to population is 1.6 Km/1000 people and in Africa, it is 2.8 Km/1000 people while in high income countries like the U.S.A. it is 15 Km/1000 people [9]. In Ethiopia, the total road network length has grown to 33279km [10] with a road density of 0.5 km per 1000 people [7].

In contrast to limited road infrastructure, the number of motor vehicles is also increasing in different countries of the world. According to World Bank report[9], in low- and middle-income countries the average increasing rate is 7 % per year. In Ethiopia, for example, the average growth of registered vehicles within the past fifteen years was 5% per year [7]. In high-income countries, the rate of motor car ownership increases by about 1% per year. By 2050,the world's light-duty vehicle fleet will be tripled and almost two-thirds of the global vehicle fleet is expected to be found in low-and middle-income countries [11].

However, this increasing number of vehicles within a limited size of road infrastructure causes serious economic and social problems across the world [12]. Among others, road traffic accidents, traffic congestion, and environmental pollution are the major ones.

Road accident potentially occurs due to vehicle-vehicle conflicts or vehicle-pedestrian conflicts. As it is indicated in World Bank report [9], 1.2 million people die in the world each year by road accident and most of the road deaths and injuries, which are about 90 %, take place in Africa and Asia. In Ethiopia, for example, car accidents claim the lives of 1,700 and injure 7,500 each year

[13].A study conducted on road traffic injuries by Murray and Lopez [14] indicated that by 2020 road traffic accident is predicted to become a leading contributor to the global burden of disease and injury.

The second socio-economic problem resulted from increased number of vehicles and scarce road infrastructure is traffic congestion. The work from Remi etal.[15] indicated that traffic congestion is a condition on road networks that occurs as its use is increased and it is characterized by slower vehicle speeds, longer trip times, and increased vehicular queuing. Delays of passengers and motorists from social and personal activities, wasting of time and fuel with an increase of pollution and carbon dioxide emission are some of the negative impacts of traffic congestion.

The cost of traffic congestion has been considered as a serious problem in different countries of the world. In America, for example, in 2010 congestion caused Americans to travel 4.8 billion hours more and to purchase an extra 1.9 billion gallons (7.2×10^9 liters) of fuel [16].In Europe traffic congestion costs 1% of the GDP [17]. In African countries, taking lost worker productivity into account, road traffic congestion costs the local economy 6,500 jobs and 844 million dollars a year [18].In Asia, road congestion costs the countries' economies from 2% to 5% of its gross domestic product every year due to lost time and higher transport cost [19].

Environmental pollution is another problem of the road transport sector. For example, it contributes to greenhouse gases (GHG) emission which is the cause for climate change. Globally, the road transport sector uses 26% of the world energy and it is responsible for about 23% of world energy-related greenhouse gases (GHG) emissions [20]. When we compare greenhouse gases emission rate in different countries of the world, the emission rate is high in low-and middle-income countries (3-5 % each year) but in high-income countries1 to 2 % each year [9].

To solve or at least minimize these road transportation related problems, two approaches can be applied. The first and most straightforward solution is to build more infrastructures, such as bridges and roads, in order to increase road capacity and connectivity. This solution is useful, especially for decreasing congestion [21, 22], but it is not sufficient. Moreover, constructing new road infrastructure is limited due to environmental, social and financial constraints.

Due to the difficulties of building more infrastructure to solve the aforementioned road transportation related problems, the optimized utilization of the existing road capacity is preferable. In relation to this, governments and scholars at different parts of the world make great effort to develop road traffic monitoring and management systems which enable them to gather road traffic information, monitor and schedule the traffic flow, support travelers to take fast and informed decision through real-time traffic information, as well as guide and control the vehicles. Such road traffic systems apply intelligence to the existing infrastructure and contribute to improve the efficiency and safety of traffic flow and also to reduce pollution effect on the environment [23].

The advancement of information and communication technology offers powerful options to solve problems of any city in the world involved with traffic accident, congestion and environmental pollution of road transportation. An Intelligent Transport System (ITS), for example, provides safety and comfort to road users and also increases maximum utilization of the existing transportation infrastructure [24]. The ITS improves driving experience, safety and capacity of road systems, reduces risks in transportation, relieves traffic congestion, improves transportation efficiency and reduces pollution [25].

There are a wide range of Intelligent Transport Systems and the most prominent and highly recognized ITS applications include Advanced Traffic Management System (ATMS) and Advanced Traveler Information Systems (ATIS).ATMS is useful to detect road traffic state, transmit the information to the central control center using the communication network and generate an optimal traffic control strategy utilizing the available traffic data [26]. While ATIS provides real-time travel and traffic information to road users, it empowers road users with optimal route selection and navigation direction and make road traffic information accessible on different platforms [25]. Hence, ATIS enables various road users to be better informed about the state of transportation networks at real-time and the existing road traffic networks can be utilized in more coordinated and safer way [26].

ATIS includes technological infrastructures that collect road traffic data, process the data to generate road traffic flow information and disseminates the information to road users. Different types of technologies are used to monitor traffic flow and collect traffic data. These traffic flow monitoring and data collection technologies can be grouped as fixed sensor technologies or mobile probe-based surveillance technologies [27].

Fixed sensor technologies like inductive loop detectors, Video Image Processing (VIP), etc. are the current state-of-the-practice of road traffic data collection tools to gather information about traffic flow in most part of the world [28]. But, these technologies don't cover a wide scale of urban road network due to high deployment and maintenance cost. Moreover, with fixed sensors, it is possible to gather spot road traffic data which can't reflect road traffic flow of the entire road network.

Mobile probe-based road traffic surveillance technologies are alternatives to these luxury fixed road side infrastructures. These surveillance systems support to collect and process road traffic data locating the vehicle via GPS or mobile phones over the entire road network [27].

Floating vehicle technologies or dedicated vehicle probes are one category in mobile probe-based traffic monitoring systems which totally depend on GPS to localize the vehicle and its trajectory. To have sufficient sensing capability utilizing floating vehicle technologies, significant percentage of vehicles should be equipped with GPS device and this mass deployment of GPS is expensive. Besides, automobile owners should also agree to share their location information to the traffic system. Furthermore, due to signal multipath and urban canyon obstruction, GPS do not work well in urban areas. Therefore, these traffic data collection technologies provide limited sample size [29] and the data collected cannot be representative for all vehicles on the entire road network [30].

Contrary to fixed sensor technologies and floating vehicle technologies, using the existing cellular network infrastructure to gather road traffic data offers large coverage capability, traffic data can be obtained continuously and also it is faster to set up, easier to install and needs less maintenance cost [31]. Besides, 3G and 4G cellular network generations provide key facilities in localizing subscribers' mobile phones. As a result of this, the interest of utilizing location based services by network operators and mobile subscribers is highly increasing.

These user equipment localizing technologies of the cellular network generations could be either handset-based or network-based positioning technologies [32]. In the handset-based positioning methods, the mobile itself computes the position of the subscriber mobile phone and it is highly secured, can support to gather more measurements. But, it demands high power consumption and also may need to incorporate special software and hardware in the handset as well as on the network [33]. The Network-based positioning methods determine the location of mobile phones using the mobile network and services utilizing these positioning technology can support legacy mobile phones without upgrading, reduces power consumption, can initiate mobile phone positioning without any intervention but may require software and hardware change on the infrastructure [33].

Individually, each of these positioning technologies cannot provide wider area coverage and improved positioning accuracy simultaneously [34]. Hence, exploring the use of supplementary and complementary positioning technologies can help to address deficiencies of individual positioning technologies. According to Clarkson et al.[35], hybrid of these positioning technologies provides better positioning accuracy and area coverage than the individuals. In relation to this, researchers like Tao et al.[36], Chew [34] and Broumandan et al.[37] proposed and evaluated hybrid positioning technologies for different applications. But there is no universally accepted standard on hybrid positioning components i.e., the hybrid can be the combination of two or more handset-based positioning technologies [36], handset-based and network-based positioning methods [38] or even multiple network-based positioning technologies.

According to 3rd Generation Partnership Project (3GPP) [38], the hybrid positioning technologies including handset- and network-based positioning technologies can enable to optimize accuracy, coverage, availability and decrease location delivery latency. In addition, in hybrid positioning method cellular network operators emphasize the implementation of at least one network-based positioning method [33, 39] due to the fact that legacy handset can be used in the positioning activity and in the cellular network, the infrastructure migration could be smooth.

Previous researches conducted on hybrid positioning technology were based on 2G cellular networks and most tried to address the problem of the old GPS positioning method and they hardly focused on vehicle location applications. Hence, the type of handset- and network-based positioning technology of the hybrid method on 3G cellular networks that can provide better accuracy and coverage needs to be researched.

Once hybrid positioning technologies are employed in tracking locations of moving vehicle on the road together with their trajectory, measurements gathered through the individual positioning technologies can be combined using multi-sensor data fusion algorithms. Generally, there are two approaches for multi-sensor data fusion: measurement fusion and state vector fusion [40]. These fusion algorithms provide different performance accuracy. Hybrid measurements obtained from realistic applications like moving vehicle tracking require high positioning accuracy [41]. Hence, to apply the appropriate data fusion algorithm in integrating moving vehicles tracking measurements obtained from hybrid positioning technologies, proper investigation on these data fusion algorithms is required. So, an experiment to compare performance of these multi sensor data fusion algorithms using road traffic data should be conducted and the one with better performance needs to be employed in the hybridization process.

Fused measurements of moving vehicles on the urban road can be used to perform different road traffic management activities including road traffic flow state estimation for every road link of the entire road networks. Particularly ATIS and ATMS of ITS applications need accurate current road traffic state estimation and short term prediction of the future for smooth road traffic flow [42].

Real-time traffic state estimation is a fundamental task for urban traffic management centers and is often a critical element of Intelligent Transportation Systems (ITS).Traffic state estimation for an urban network refers to estimating the traffic flow status of the network at the current time based on available real-time traffic-aware data [43].

Existing road traffic state estimation techniques can be model-based or data-driven approach. Model-based approaches can explicitly represent physical traffic flow. But, it is computationally complex, require intensive model calibration and high degree of expertise [44]. Data-driven approaches are easy to use, data intensive and can hardly enable to represent the physical traffic flow process [44].This approach, with the ability to learn from data/experience, is very important to many practical problems like road traffic flow estimation because it is often easy to get data than to have good theory governing the system from which the behavior is measured [45].

For traffic state estimation, a limited number of research works were produced and proposed corresponding estimation algorithms that were almost exclusively based on the seminal methodology of Kalman filtering (data driven method) [46]. However, to overcome limitation of a road traffic estimation approach by the advantage of another, hybrid based road traffic state estimation approach is appropriate. This is because, road traffic state estimation is complex and it cannot be addressed using single fore casting method. Besides, application of hybrid model-based and data- driven approach for state estimation reduces computational delay and increases forecasting accuracy [47]. Hence, literature investigation on the different types of model-based road traffic state estimation techniques as well as data-driven methods should be conducted and hybrid of better performing techniques of model-based and data-driven approach would be combined in the development of real time road traffic state estimation framework.

1.2 Motivation

Number of vehicles in urban road networks is increasing with the advancement of urbanization. This increasing number of vehicles resulted in the rise of traffic congestion, traffic accident and environmental pollution. Substantial amount of research has been conducted to address road traffic problems and recommended to use traffic monitoring technologies which can support for maximum utilization of road infrastructures. However, the data collection technologies used in the current traffic flow monitoring systems are situated at road intersections due to deployment and maintenance cost. Thus, traffic management activities like traffic flow information gathering, analysis and dissemination covering the whole road networks become challenging.

The motivation behind this research is, therefore, to develop real-time road traffic state estimation framework which utilize the already deployed cellular network infrastructure as source of traffic data. The framework will support to develop road traffic monitoring system which can support road users as well as other stake holders to acquire a continuous traffic flow information at real-time.

1.3 Statement of the Problem

Given that real-time road traffic flow information has extensive advantages to road users and other stakeholders, the current state-of-the-art data gathering technologies for traffic state information do not cover the whole road network and also do not provide acceptable accuracy. In relation to this, the utilization of the existing cellular network infrastructure for road traffic data gathering enable to cover large area and also has minimum maintenance cost. Particularly 3G and 4G cellular network generations provide mobile phone positioning facilities. These positioning technologies could be either handset-based or network-based. These positioning technologies have some advantages as well as limitations.

From the literature, for example [34], it is indicated that no single positioning technology can provide both wider coverage and required accuracy at the same time. Besides, as there is a great connection between a location based service and required location accuracy, moving vehicle positioning require high resolution and accuracy for proper navigation. To get an improved positioning accuracy as well as entire road network coverage, hybrid positioning technology is proposed.

As learned from the literature, there are research works on hybrid positioning methods most focused on the evaluation of the positioning accuracy of 2G cellular networks and tried to address limitations of the old GPS positioning method. Besides, none of these researches addressed vehicle location applications. Hence, to the researcher's knowledge, apart from fragmented researches on hybrid positioning technology performance evaluation of 2G, there is no comprehensive research work on the use of hybrid (combining handset based and network based) positioning technologies of 3G or 4G for road traffic application. This is supported by

Abo-Zahhad et al.[48] argument stating that further investigation is required to identify hybrid positioning technology with acceptable accuracy and coverage suitable for road traffic applications. According to 3GPP [38], to optimize accuracy, coverage, availability and decrease communication latency, the hybrid is expected to incorporate handset and network based positioning technology. Besides, in the hybrid the inclusion of at least one network based positioning technology is preferred by network operators [33, 39] as it enables smooth infrastructure migration and also does not require to change the legacy handset to get access to the service.

Hence, systematic investigation on each of the handset-based and network-based positioning technologies on the UMTS network and their possible combination to provide an optimized positioning accuracy of moving vehicles on a wide road network coverage is performed.

Measurements about moving vehicles location on road network from the hybrid positioning technologies needs to be combined for further use in traffic state estimation process. This fusion of gathered measurements from components of the hybrid positioning technology is important to improve accuracy and availability of data. The two commonly used multi-sensor data fusion algorithms are measurement fusion and state vector fusion algorithms. As learned from the literature, for example [36], employed state vector fusion algorithms as it is simple to compute and satisfies real time requirement. On the other hand, Mosallaei et al. [49] recommended measurement fusion algorithm as the overall estimation performance is better than state estimation algorithm. Because the type of fusion algorithm employed in combining measurements from multi-data sources for road traffic application affects positioning accuracy, the performance of these multi-sensor data fusion algorithms is evaluated using road traffic data.

Then, a hybrid data fusion scheme combining location estimates from the individual positioning technologies is developed and its performance in localizing a moving vehicle on the road is evaluated.

The challenge of providing road users with accurate and real-time road traffic flow information to make route selection decision and traffic management activity require faster and more accurate method of estimation and prediction of road traffic flow. There are different methods available to estimate road traffic flow from fused measurements of hybrid positioning technologies. These estimation techniques can be categorized into two approaches, model-based and data-driven approaches. Each of these approaches has some benefits as well as drawbacks.

Previous research works on road traffic state estimation employed loop detectors as source of traffic data and proposed an estimation algorithm which is exclusively based on (extended) Kalman filter (which is data driven) [50]. However, According to You et al. [51], road traffic state estimation is a complex activity which can't be done using a single forecasting method. To use the data-driven approach, for example neural network, deployment of data collection infrastructure on road segments needs high investment [44]. To train the neural network, model based traffic state estimation methods like microscopic or macroscopic simulators can be used [47]. Besides, application of hybrid of model-based and data-driven road traffic state estimation approach reduces computational delay and also increases forecasting accuracy [12].Therefore, to complement limitation of one approach with the advantage of another, hybrid of model- based and data-driven estimation method is proposed.

Hence, investigation on the different model-based as well as data-driven road traffic estimation methods is conducted. Based on the process of data collection activities and traffic state estimation procedures real-time road traffic state estimation framework is proposed and the efficacy of the framework is evaluated using simulation as well as real world data.

Generally, this research tried to answer the following research questions:

- Which of the handset based and network based positioning technologies of 3G (UMTS) network should be combined to get an improved positioning accuracy?
- Which of the existing multisensory data fusion algorithms has better fusion performance and is suitable in combining measurements from the proposed hybrid 3G positioning technologies?
- What is the performance of the hybrid positioning technology in localizing a mobile phone moving in all journey of the vehicle with respect to the E-911 positioning accuracy standard?
- What are the components of real-time road traffic state estimation framework provided that source of estimation data is gathered using the existing cellular network?
- How is the framework performing in terms of estimation coverage and accuracy?

1.4 Objectives of the Research

General Objective

The general objective of this research is to design and develop real-time road traffic state estimation framework that utilizes the existing cellular network infrastructure as source traffic data, support for traffic data processing, analysis, generation and dissemination of road traffic flow information to road users across all road networks.

Specific Objectives

Specifically, this study aims to accomplish the following objectives.

i. Analyze the handset based and network based positioning technologies of 3G (UMTS) cellular network and propose a hybrid positioning technology that can met requirements of operators, subscribers and E-911 standard ;
ii. Evaluate a better data fusion algorithm experimentally and develop multi-sensor data fusion scheme using the proposed hybrid positioning technology data sources;
iii. Implement the proposed vehicle positioning technology solution and examine if the proposed approach enables to locate moving vehicles and trajectory through laboratory experiment as well as real world data;
iv. Analyze road traffic state estimation procedures, techniques and propose and implement real-time road traffic state estimation framework; and
v. Evaluate the estimation accuracy of the framework using simulation as well as real-world data.

1.5 Scope and Limitations of the Study

In this research investigation on the current road traffic monitoring technologies, positioning methods on the different generations of cellular network, data fusion algorithms and road traffic state estimation procedures will be made. To conduct the research a design science research approach will be employed. As evaluation is one major activity of the research approach, simulation as well as real world data using sample road network of Addis Ababa will be gathered and evaluation on the performance of data fusion algorithms, hybrid positioning algorithm and real time road traffic state estimation framework will be performed. To evaluate the practicality of the framework an E-mail interview on ITS researchers and practitioners will be carried out.

The following limitations were considered to be significantly important to be mentioned as limitation of this study.

- This dissertation doesn't attempt to move beyond the design and efficacy evaluation of road traffic state estimation framework.
- Although there is one governmental company which focuses on providing location identification services, the fact is that all of its operations embrace complex issues privacy, security and market values. It is, therefore, difficult to get access to mobile network infrastructure or get anonymised positioning data. The researcher used simulation and field test data during the evaluation and validation process.
- In-depth investigation into issues associated to security, privacy and ethical issue when conducted the research will not be discussed.

1.6 Significance

Real-time road traffic flow information is utilized for various purposes including vehicle route guidance, incident detection, vehicle emission monitoring and also for successful development of road traffic control and management systems. Road traffic data collection technologies play important role in the acquisition and transmission of traffic flow information.

Although fixed sensor technologies are the current state-of-the art data collection technologies, due to deployment and maintenance cost higher emphasis is given to utilize the cellular network as a source of road traffic data. In this regard, this research made a thorough investigation with the focus on the positioning standards of the different cellular network generations. This helped the researcher to understand and conduct performance comparison survey among the positioning standards of the cellular network generations. Accordingly, hybrid positioning method of the UMTS cellular network with an improved positioning accuracy and coverage is proposed.

Multi-sensor data fusion algorithms including state vector fusion and measurement fusion were researched and used to combine measurements from multiple data sources for several years. However, performance of these algorithms were not compared through experimentation using road transport data and no research, as long as the knowledge of the researcher is concerned, recommended which algorithm is suitable to combine data from multiple sensors for transport applications. In this research, comparison on these algorithms were made using simulation and field based data gathered on sample road networks of Addis Ababa. The result helped the researcher to develop hybrid mobile phone positioning algorithm. The result of the comparison is also expected to be useful to other researchers as well as practitioners who are interested in applying data fusion algorithms in their activities.

The aim of this research is to develop and evaluate real-time road traffic state estimation framework which uses cellular network as source of traffic flow data. State estimation has been a research agenda for transportation researchers for decades. Nevertheless, the studies were not comprehensive. This study reviewed the different procedures (data collection, preprocessing, analysis, estimation model selection and estimation) and methods (model based and data-driven estimation) of traffic state estimation activity and identified sub problems to be addressed.

Though the output of the research is an estimation framework which can be used as guide line for practitioners to develop traffic control and management information system, it can also be used as source of methodological approach for studies or/and ITS projects dealing with the application of traffic flow estimation framework.

1.7 Methodology

This research follows a design science research approach. The study starts with literature review. An in-depth investigation on the different procedures of real-time road traffic state estimation procedures like data collection, mobility classification, map matching, multi-sensor data fusion and traffic state estimation will be conducted. The research also involves the study on the past and current road traffic data collection technologies, which result in the identification of handset- and network-based mobile positioning technologies in UMTS network with an improved positioning accuracy and area coverage. The key attributes that will be investigated include positioning standards of 2G, 3G and 4G cellular network generations , positioning accuracy of handset-based, Network-based and hybrid positioning technologies and road traffic state estimation procedures.

Due to the nature of this dissertation, a design science research approach sustained by experimental data gathering methods will be adopted to address the research gap, problem statement and objectives. This approach is chosen after exploring the nature, objectives and data need of the research problem [52]. To identify the different UMTS positioning technologies, understand the procedures of road traffic state estimation and describe state estimation techniques, the qualitative data gathering method- systematic literature review will be applied.

The data gathered from systematic literature review in conjunction with performance comparison survey on the different mobile phone positioning technologies of the UMTS cellular network will help to establish possibility of combining selected positioning technologies and estimation approaches to form an integrated environment that can be used to provide accurate moving vehicle location identification as well as road traffic flow information.

For the evaluation of vehicle position integration scheme and road traffic state estimation framework, simulation as well as field based data will be gathered using sample road networks of Addis Ababa city. This is because, in Ethiopia64% of the total registered vehicles is located in Addis Ababa and from all road traffic accidents reported in the country, 65% occurred in this city [53]. Moreover, the road network complexity is high in Addis Ababa compared to other regional state as well as city administration road networks and the total road length of the city reached 2,150km as of June 2014. The overall research process, which is further described in Chapter Two , follows the Peffers et al. [54] design science research process guide. Depending on the design science evaluation guidelines and methods both the research process and result will be validated.

1.8 Definitions of concepts used in the study

The following terms/concepts need to be understood as they are defined underneath.

- Urban road is a small scale low speed connector. It provides frontage for buildings such as offices, shops, apartment buildings, and row houses. It is also with raised curbs, closed drainage, wide sidewalks, parallel parking, trees in individual planting areas, and buildings aligned on short setbacks.
- A road link is a section of urban street between two consecutive intersections.

- Traffic flow/state estimation is inferring the amount of vehicles going through a road link based on the information at hand.
- Traffic flow/state assessment is a process used to identify road links with traffic congestion or not.
- Traffic Demand: Set of all Vehicles together with their associated routes.
- Real time: response to stimuli within some small upper limit of response time (typically millisecond or microseconds)
- Mobile phone and User Equipment (UE) are used interchangeably in this dissertation and both refer to a device end-user use to get access to cellular network services.
- Framework is a real or conceptual structure intended to serve as a support or guide for the building of something that expands the structure into something useful [55].

1.9 Organization of the Dissertation

This study is organized in to Eight Chapters including the current one.

Chapter Two discusses the research methodology which comprises research approach, research method and research design. Design science research approach with its detail principles is explained and justified.

Chapter Three presents literature review on the different traffic management systems which utilize different traffic data collection technologies. Thorough investigation is made on the different cellular network generations, positioning standards and techniques and with comparative analysis, UMTS (3G) positioning technologies are proposed. Besides, different steps of traffic state estimation activity including mobility classifications, map matching and state estimation methods are reviewed.

Chapter Four discusses related works on handset-based, network-based and hybrid positioning technologies, state estimation approaches and their specifics and further suggestions that are done in the next chapters of the study.

Chapter Five is devoted to the implementation of hybrid moving vehicle positioning and tracking solution which was proposed in Chapter Three. Hybrid scheme of A-GPS and U-TDOA based measurements is implemented. The statistical as well as field test based evaluation of the hybrid scheme on the localization of moving vehicle on the road network is presented in this chapter.

Chapter Six presents real-time road traffic sate estimation framework, explanation about each of the components, the application of the framework using a three layer Artificial Neural Network (ANN) model estimator and the evaluation of the ANN model using both simulation and real world data.

Evaluation of the research process and the research result is discussed in Chapter Seven and the conclusion and future work and concluding remarks of the study is presented in Chapter Eight.

Chapter Two: Research Methodology

2.1 Introduction

Research methodology is a way to systematically solve a research problem [56]. It defines what methods to apply, how to measure progress, what constitute success and also specifies how to communicate the research findings [57]. The research methodology is a structure containing approaches, strategies and techniques needed for the conduct of a complete research[58].The selection of suitable research methodology is therefore crucial for proficient research activity and result. This chapter describes methodology selection process and justifies the selection of the research approach and method in addressing the research objectives which are identified in Chapter One and presented the research design.

Hence, this chapter starts with the discussion of the general research approach of the study. The research methods and techniques which are going to be employed are explained next. Finally, following the research design, summary of the chapter is presented.

Portion of this chapter entitled "Applying Design Science Research to Design and Evaluate Real-Time Road Traffic State Estimation Framework" is published on Advances in Nature and Biologically Inspired Computing, Springer International Publishing, 2016. Pp. 223-233.

2.2 Research Approach

> *"Research approach is a plan and the procedure for research that span the steps from broad assumptions to detailed methods of data collection, analysis, and interpretation."[59]*

The plan involves decisions about the research approach, methods and analysis techniques which will be used to study the research problem. Selection of a research approach depends on the nature of the research problem and the research objectives [58].

As it is presented in Chapter One, the central theme of this research work is to develop and evaluate a real-time road traffic state estimation framework. In relation to this, the research approach appropriate to guide this research work is a design science approach.

> *"Design Science approach is problem-solving paradigm seeking to create innovative artifact, ideas and products through analysis, design and implementation process"*[60].

The aim of a design science approach is develop and evaluate artifacts which offer value and utility as opposed to behavioral research approach which attempts to validate theory to explain the world [61].

Additional reasons motivated to adapt design science research approach in this study include:

- The main activity in design science research approach is to design and build the artifact to solve the problem in practice based on contextual information, theoretical knowledge and organizational needs [62]. In this study also, the design and development of the real-time road traffic state estimation framework has been drawn based on the principles/standards of mobile phone positioning technologies, measurement hybridization schemes, traffic state estimation models and positioning and estimation performance requirements.
- The other research activity given higher emphasis in design science research approach is evaluation. According to Hevner et al [61], evaluation is a crucial component in design

science research and the value, utility and efficiency of the designed artifact should rigorously be demonstrated using appropriate evaluation method.

The artifact itself and the identified evaluation matrices are bases for the selection of suitable evaluation method. Evaluation methods can be artificial (based on simulations or laboratory experiments) or naturalistic (on realistic settings like case study and action research) [63]. In this study also, the utility (efficacy/effectiveness) evaluation of the proposed hybrid positioning algorithm and the developed frame work is conducted through simulation and filed based data(see Chapter Five and Six for further explanation). Besides, expert evaluation will be employed to test feasibility and completeness of the framework. Hence, evaluation is considered as vital in this research work due to the following reasons.

- ❖ The evaluation can help to justify the feasibility of the developed framework and offers an improvement on the current road traffic state estimation activity.
- ❖ The evaluation will support to get feedback to the researcher to identify if the problem is well understood, if the hybrid positioning technology proposed is appropriate, if the quality of the design process is appropriate, and if there are needed refinements for the framework.

To conduct a design science research, application of commonly accepted research framework and a template for its presentation is crucial [54]. This framework is expected to incorporate principles, practices and procedures required to carry out the design science research. In relation to this, different process models, descriptions, diagrams of design science research process are given by different researchers including Hevner et al [61], Purao and Sandeep [64], Peffers et al. [54] and Vaishnavi and Kuechler [65]. The difference in the process models is due to the fact that the activities to be carried out at similar phases of the design science research are different depending on the design science research setting [66].

In this research work, the design science research process model developed by Peffers et al. [54] is adopted due to the following reasons.

- The model has a problem identification and motivation phase that can support for the synthesis of selected prior literature to the topic of study.
- The model helps to adapt different theories depending on the framework to be designed and developed.
- The multiple entry points to the research process of the model can easily be mapped to the design and development of artifacts with different entry points.
- Although all design science research models focus on the contribution of new knowledge, the design process model given by Peffers et al. [54] has a separate phase, communication phase, used to communicate the problem and its importance, the artifact, its utility and novelty, the rigor of its design, and its effectiveness to researchers, domain experts and other audiences. The experts' comments while reviewing of the manuscripts are useful in improving the artifact design and usefulness.
- For research publications, the structure of this design process model can be used to structure the paper [54], just as the nominal structure of an empirical research process (problem definition, literature review, data collection, analysis, results, discussion, and conclusion).
- The design process model fits with the research setting of this study. For example, the artifact design and development is presented together and during demonstration, a light-weight evaluation on the artifact feasibility in solving one or more instances of the

problem will be demonstrated. During evaluation a formal and extensive activity to see how well the artifact supports the solution of the problem will be done. The demonstration and evaluation will be conducted through simulation as well as filed experiment.

Peffers et al. [54] prescribe six processes for design science research steps: identify problem, define objectives of a solution, design and development, demonstration, evaluation, and communication. But detail guideline on the design steps is not properly presented. Offermann et al. [67] based on the work in Peffers et al. [54] presented a three-process framework entailing problem identification, solution design and evaluation and considered Matching Analysis Projection Synthesis (MAPS) [68] as a design steps. Hence, in this research to design and evaluate the hybrid positioning algorithm and real-time road traffic state estimation framework, the design science research process model offered by Peffers et al. [54] will be used. As a design guide for the design steps in the design science research process Matching Analysis-Projection-Synthesis (MAPS) tool will be applied. The integration of the design guide and the selected design science research model is depicted in Figure 2.1.

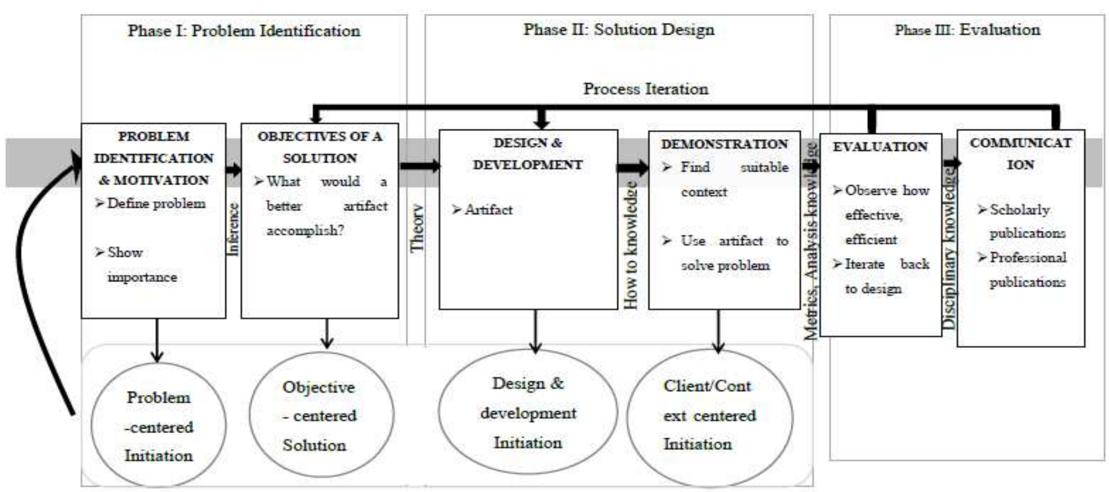


Figure 2.1 Integrated design science research model with the design guide.

2.3 Research Methods

This study will be guided by the proposed design science research process model and different research methods will be employed at different phases of the research activity. It will begin with detail literature review on mobile phone positioning standards of the different generation of cellular network, fusion algorithms, traffic flow estimation procedures and estimation models which will help to realize the gap within the literature and address the objectives of the research project. Although the review of literature is the initial activity in the research, the literature in the topic will be continuously reviewed along the rest of the work in order to keep up to date with related works.

Experimental research method is the second which will be used in this research. According to Goddard et al [56], the purpose of experimental research method is to collect data that can be used to validate theories, models used in the process of the research. In this study an experimental research method will be employed to demonstrate the performance of fusion algorithms, the hybrid positioning technology and estimation framework.

According to Peffers et al. [54] , the initiation of a design science research could be at one of the six steps of the research process. In this study, three iterations using the selected design science research process model will be conducted. The first iteration in the design science research process is to compare performance of state vector and measurement fusion algorithms. The need for a multi-sensor data fusion algorithm that can improve positioning accuracy of the fused measurements and will be suitable for road traffic application is the initiation of the research process. The problem identification and formulation of the research process is done based on detail literature review on past and current research studies of the different fusion algorithms.

The data fusion principles of each of these data fusion method are used to develop the algorithms.

For evaluation, simulation as well as field based positioning measurements will be used. The performance of the algorithms will be compared based on position and velocity estimates of moving mobile (Further detail is found in Chapter Five Section 5.2).The selected design science research process model is tailored to the context of this iteration and the activities to be done at each phase are filled as it is depicted in Figure 2.2.

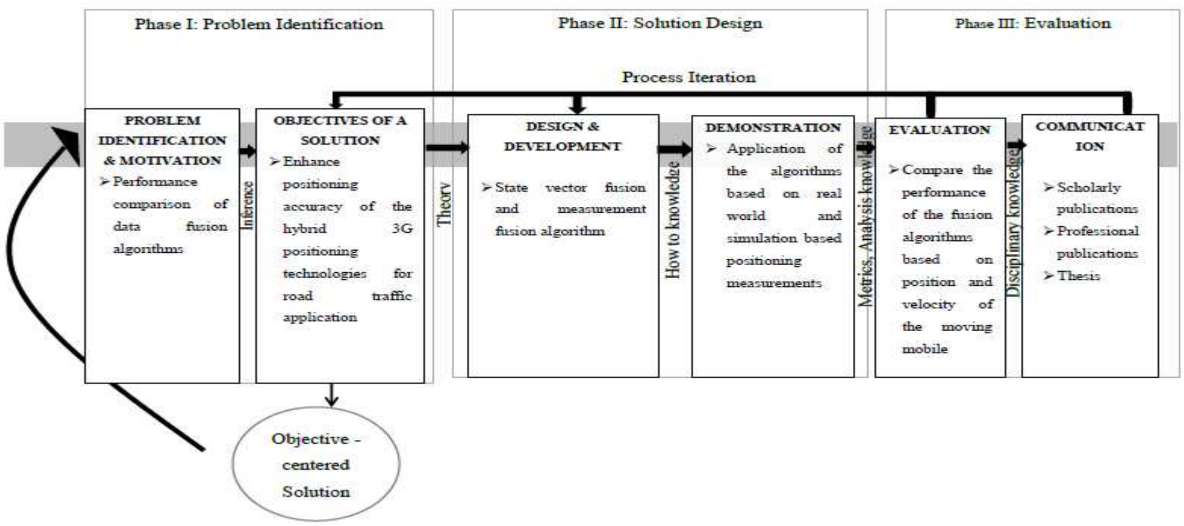


Figure 2.2 Design Science Research Process model for data fusion algorithm comparison

The result of the first iteration of the research process will be used in the research process of the second iteration. The triggering step of this research iteration is an enhanced positioning accuracy of hybrid (Combination of handset and network based) positioning technologies of the 3G cellular network. To formulate the problem systematic literature review on standards of 3G cellular network will be conducted. Literature on the principles and concepts of mobile phone positioning standards of the UMTS network together with the fusion algorithm of first iteration result will be used in the design and development of a hybrid mobile phone positioning scheme.

To evaluate the positioning accuracy of the hybrid positioning algorithm, data based on simulation and laboratory experiment will be gathered. The utility/accuracy of the hybrid positioning algorithm will be evaluated with respect to E-911 positioning standard (detail is found in Chapter Five Section 5.3). The activities in this iteration of the research process are presented on Figure 2.3.

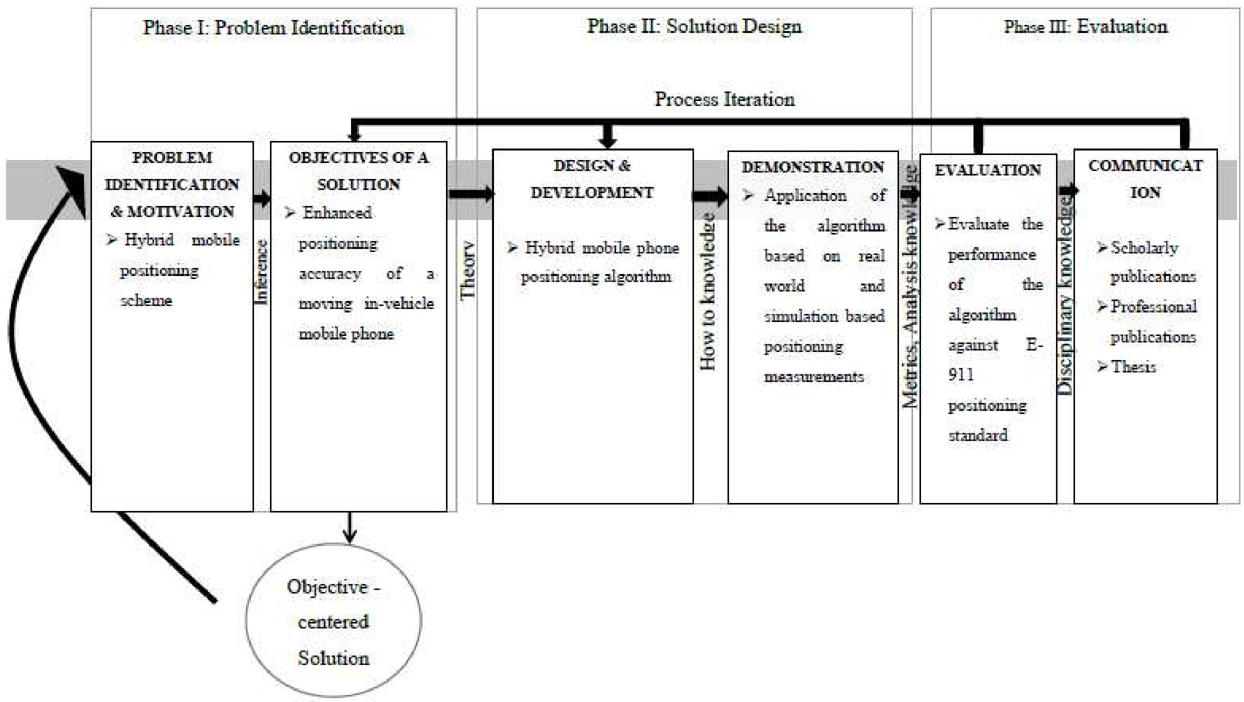


Figure 2.3 Design Science Research Process model for hybrid positioning scheme

The development of road traffic state estimation framework with an improved estimation performance utilizing road traffic data collection technology covering all road networks is the triggering step of the third iteration of this research. The problem identification and formulation of this iteration of the research process is done based on detail literature review on past and current research studies. Systematic literature review on the different road traffic state estimation methodsallowto better understand on the needs for better performance on road traffic flow estimation procedures. Literature on road traffic estimation procedures, technique, models and result of the 2nd iteration on hybrid position scheme are important in the design of the framework.

To evaluate the framework, sample road networks of Addis Ababa will be used. To represent the traffic flow on the road network a simulator will be employed. Based on laboratory experiment, the framework efficacy will be evaluated. The evaluation on the estimator will also be conducted using filed based data gathered on the same road network (the detail is presented in Chapter Six). Activities of this iteration on the research are filled on the design science research process model and depicted on Figure 2.4.

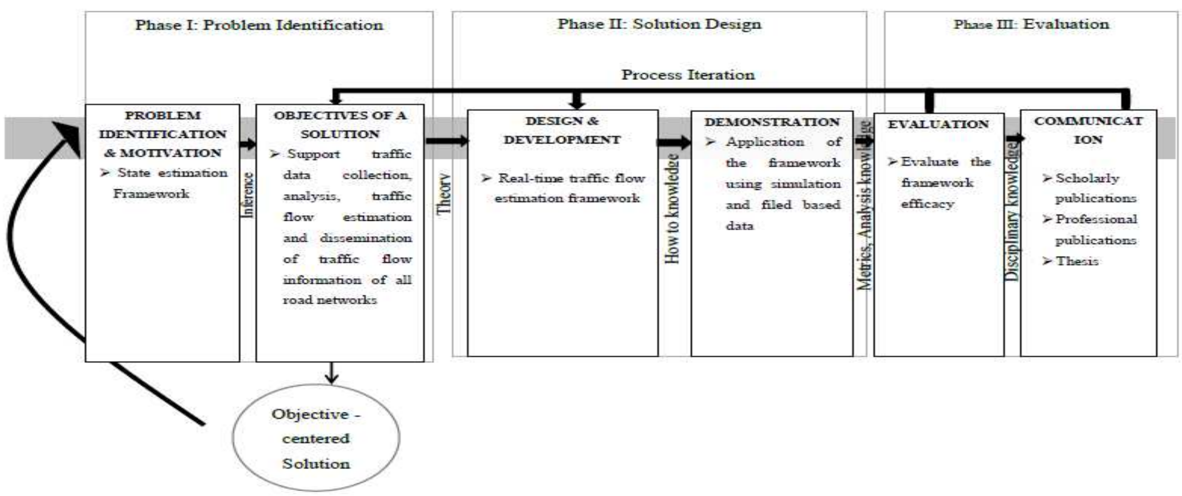


Figure 2.4 Design Science Research Process model for State estimation framework

2.4 Research Design

"Research design refers to the overall strategy that is chosen to integrate the different components of a study in a coherent and logical way, thereby, ensuring to effectively address the research problem; it constitutes the blueprint for the collection, measurement, and analysis of data "[69].

The overall research design follows the design science research guidelines and the design science research process as defined by Peffers et al.[54]. The research design integrating the research methods with the design science research process model is depicted in Figure 2.2.

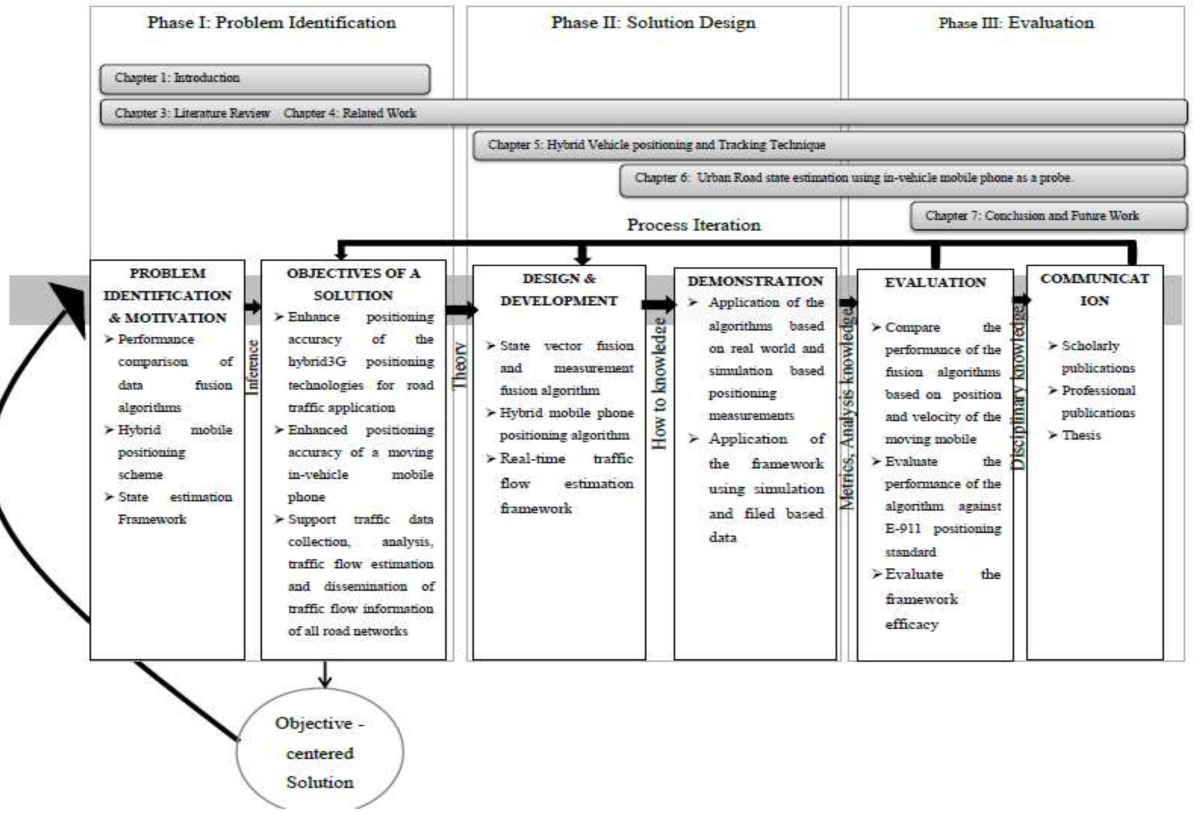


Figure 2.5 Research design of the study

2.5 Data Collection and Analysis

To address the research problem explained in Chapter One Section 1.2, qualitative and quantitative (experiment based) data about the different UMTS user equipment positioning standards, their positioning accuracy, U-TDOA and A-GPS based user equipment measurements, multi-sensor data fusion algorithms, road traffic state estimation procedures and tools will collected.

Data using simulation experiment will be gathered for the U-TDOA based location estimate. A cellular network topology with seven adjacent cells will be created on MATLAB and a noisy location measurement of a moving user equipment will collected. To gather the A-GPS based measurement, J2ME location API (JSR-179) software app will be developed and installed in A-GPS enabled mobile phone so that the location of the mobile moving in all journey of the vehicle will gathered on a serve.

To collect data sample road networks of Addis Ababa city will be used. The selection is made based on the following criteria.

- Road networks having more than three traffic lights, junctions and with at least ten road links so that different traffic demands can be experienced.
- Road networks which were not under railway construction.

To model the traffic flow on the selected sample roads the microscopic simulator Simulation of Urban Mobility (SUMO) will be used. The result of the simulation will generate files which will be used for further analysis (the detail is on Chapter Five and Six). To test feasibility of real-time road traffic state estimation framework and check component completeness expert evaluation will be used.

For analysis, the performance indicators Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and linear regression will be applied.

2.6 Evaluation Approaches

Evaluation is a basic component in design science research method. Effectiveness, utility of designed artifact must be rigorously demonstrated using an evaluation method [61]. The evaluation method is identified based on the evaluation criteria selected for the designed artifact. Evaluation approaches may include observational methods like field studies and experimental methods like controlled experiments and simulations. Designed artifact evaluation is not limited to the design cycle, evaluation of the model with respect to their fidelity with real world data is also appropriate [70]. According to Hevner at al. [61], designed and developed artifacts can be evaluated in terms of performance, accuracy, functionality, completeness, usability and other relevant quality attributes.

In this study an experimental evaluation method will be employed. The evaluation of fusion algorithms will be performed in terms of estimation accuracy, the hybrid positioning scheme based on positioning accuracy against E-911 standard and the real-time state estimation framework will be evaluated with respect to forecasting accuracy, efficacy and coverage. To incorporate the experts view as feedback information to improve the different artifacts design and performance, reviewers' comments on the submitted papers to conferences/journals as well as comments gathered during conference presentations will be applied. Interview results of experts will be used to perform practical and completeness utility evaluation.

Chapter Three: Literature Review

3.1 Introduction

This Chapter presents review of the literature to-date on the use of cellular network in estimating real-time road traffic flow on urban road networks. It focuses on studies done in two basic aspects of road traffic monitoring activity; namely road traffic management systems and road traffic state estimation procedures. More specifically in the first part, traffic management systems with respect to the surveillance technologies used for the purpose of road traffic information gathering, features of sensor as well as cellular network-based technologies, vehicle location techniques in different generations of cellular networks together with measurement requirements are properly reviewed. The second part discusses the review on road traffic information estimation methods based on cellular network data. Concepts like mobile device filtering/classification; map matching, road traffic state estimation approaches and frameworks are described.

Portion of this chapter entitled "In-Vehicle Mobile Phone-Based Road Traffic flow Estimation: A Review," is published on Journal of Network and Innovative Computing, ISSN 2160-2174 Volume 1 (2013) pp. 331-358

3.2 Road Traffic Management Systems

The number of vehicles on our streets is constantly growing. Today, there are more than 394 thousand cars on Ethiopian roads [71] responsible for an increasing number of traffic accidents and congestion causing economic and environmental problems. The number of motor vehicles is also increasing in different countries of the world. In general, the world vehicle population reached 1.015 billion in 2010 [72] which is 3.6 % rise from 2009 and the average registered vehicle increase is high in low- and middle-income countries with an increasing rate of 7 % per year when compared to developed countries with a rate of 1 % per year [73]. The fact that traffic density is continuing to grow with traffic accident, congestion and environmental pollution problems, efficient road traffic flow policy and system which performs real-time load balancing resulting in more suitable transport service is needed. In relation to this, road traffic management systems are widely acknowledged as a means to optimize the utilization of existing transport infrastructure [23]. These systems, which are developed using traffic surveillance technologies, enable to gather road traffic information, monitor and schedule the traffic flow, as well as guide and control the vehicles so as to improve the efficiency and safety of traffic flow and also to reduce pollution effect on the environment. The global architecture of such a system is depicted in Figure 3.1 and it comprises three main components.

1. *Road Traffic Data Gathering Instruments:* It consists of sensor technologies on roads or cars like inductive loop, micro-loop , moving probes, floating car data, mobile phones etc. that are used to gather traffic data and also information from traffic police, road and transport authority are involved and sent to traffic data management center.
2. *Traffic Management Center:* It consists of applications used to process collected data to provide current road traffic flow which can be distributed to customers for traffic control and guidance purpose.
3. *Communication System:* It is responsible to interconnect the control center with customers to disseminate current picture of traffic sate.

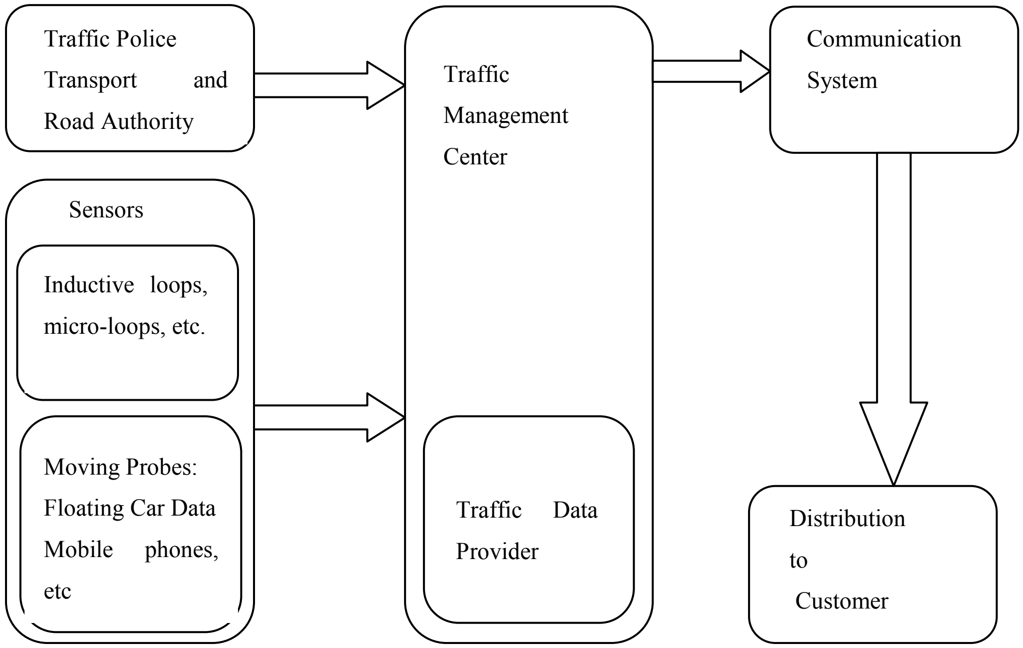


Figure 3.1 Road Traffic Management System Architecture [74]

3.2.1 Review of Current Road Traffic Management Systems

Existing road traffic management systems use fixed sensors, moving probes, mobiles and other location technologies for monitoring road traffic flow. The following sections discuss the most commonly used technologies to gather road traffic data for monitoring purpose.

Fixed Sensor-Based Road Traffic Management Systems

These systems refer to technologies where traffic data is gathered using detectors located along the roadside. Sensor-based traffic management systems are used for vehicle surveillance purpose. Indeed, such systems are able to collect and process vehicle count, speed, classification, occupancy and presence at real-time [75]. Sensor-based road traffic management systems could be either intrusive or non-intrusive [76]. Intrusive traffic sensor technologies refer to those that require installation directly onto the pavements, in saw-cut, holes or tunnels under the pavement surface. Most conventional traffic surveillance systems use intrusive sensors, which include inductive loop detectors, micro-loop probes, pneumatic road tubes, piezoelectric cables and other weigh-in-motion sensors. For maximizing the benefits from all these surveillance technologies, there must be a large scale deployment of traffic controls on all major freeways and local streets. Yet this may not be viable or scalable as its installation and maintenance costs are high.

Non-intrusive traffic sensor technologies do not need any installation on or under the pavement, so that the installation and repair of such a system can be done without disrupting the traffic. The detectors are usually setup on the roadside, or at an overhead position. Examples of this type of technology include microwave radar, infrared, video image processing (VIP), ultrasonic and passive acoustic array. These surveillance technologies have limitations. For example, microwave radar cannot detect motionless vehicle unless an auxiliary device is used, performance of infrared system is greatly affected by the environment, as infrared energy is absorbed or scattered by atmospheric particles, such as fog, rain or snow and temperature change affects performance of video image processing, ultrasonic and also acoustic array systems.

Both intrusive and non-intrusive traffic surveillance technologies, which have expensive costs of implementation and maintenance, are installed at strategic locations along the highway to support road traffic monitoring and management activities. These technologies, even though matured with high potential and quality, the accuracy for travel time and area coverage as well as urban area precision is low [75]. Because of their limited coverage, traffic data gathered using these technologies cannot produce reliable information about road traffic condition [77].

Mobile Probe-Based Road Traffic Management Systems

This road surveillance technology collects and processes road traffic data by locating the vehicle via GPS or mobile phones over the entire road network. This basically means that every vehicle is equipped with mobile phone or GPS which acts as a sensor for the road network. Data such as car location, speed and direction of travel are sent anonymously to the central processing center. After being collected and extracted, useful information (e.g. status of traffic, alternative routes) can be redistributed to the customers on the road.

Mobile probe-based traffic management system is an alternative or a complement to source of high quality data to existing technologies. These monitoring systems improve safety, efficiency and reliability of the transportation system [75]. They are becoming crucial in the development of new intelligent transportation systems (ITS).

Floating vehicle technologies are one category in mobile probe-based traffic monitoring systems that are based on either GPS or Cellular Network. GPS equipped vehicle can obtain its own accurate and detailed trajectory. The vehicle location precision is relatively high, typically less than 30m [75].A GPS-based traffic management system is vital for intelligent transport system that guarantees safety and improves traffic management as it provides high location accuracy for broad range of traffic data estimation. Currently, GPS probe data are widely used as a source of real-time information by many service providers but it suffers from a limited number of vehicles equipped with GPS and high equipment costs compared to cellular network-based traffic management system [31]. Hence, traffic data from GPS equipped vehicle has limited sample size and can't be representative for the entire population when compared with cellular-network based solution. Moreover, benefits of GPS could be limited and backup could be needed where location information is needed due to obscure view to satellites or degraded accuracy due to multipath [78].

Millions of mobile devices are held by vehicle drivers and it may be worth using mobile phones as anonymous traffic probes. Mobile phones are means to collect and process traffic data in cellular network-based traffic control systems and need to be turned on, but not necessarily in use. This approach is particularly well adapted to deliver relatively accurate information in urban areas where traffic data are most needed due to the lower distance between antennas [79].

Contrary to stationary traffic detectors and GPS-based systems, in cellular network-based traffic management system, no special device/hardware is necessary in cars and no specific infrastructure is to be built along the road. It is therefore less expensive than conventional detectors and offers larger coverage capabilities. Traffic data are obtained continuously instead of isolated point data. It is faster to set up, easier to install, and needs less maintenance. The following section discusses how moving vehicle localization could be done in cellular network-based traffic management systems together with mobile positioning principles.

3.2.2 Vehicle Localization Using the Cellular Network

Vehicle localization and navigation system is a driving assistant system which uses navigation digital map, vehicle location, route guidance and other technologies. Vehicle location and navigation system has a long history, though these systems have only recently started to reach the world market. Nowadays vehicle location and navigation systems are inertial navigation system (INS). Modern INS is normally equipped with (relatively) expensive On-board Unit. Considering the expansion and proper exploration of location based services, locating vehicles using the cellular network can be an alternative to the positioning module in INS [80]. Moreover, the communication functionality of mobile phones can replace the ITS specific communication module. Economically, it is desirable to develop vehicle positioning techniques that take advantage of the well-established cellular networks and the pervasive low cost mobile phones. In this sense, the problem of positioning a vehicle becomes the problem of accurately locating the mobile phone traveling on-board the vehicle.

3.2.3 Mobile Positioning and Performance Metrics

Mobile positioning has become a remarkable technology because of its commercial potential, increased subscriber safety and services envisaged under Intelligent Transport System. The driving force for mobile positioning was initiated by the U.S. FCC (Federal Communication Commission) in the case of emergency calls. The calling party of all emergency calls (911) in the United States should be located with a defined degree of accuracy [32, 81]. Other countries use similar system but define different numbers such as 110 for China, 999 for UK and 17 for France [81]. In Europe; the European Community defines positioning performance requirements for emergency location to their E-112 location systems [82], as specified in Table 3.2. In contrast, vehicle positioning requires greater accuracy. Location technologies are increasingly designed to meet the requirements for certain location-based services (LBS), rather than simply to meet the mandatory regulations (as per Tables 3.1 and 3.2). Table 3.3 lists some specific LBS and their expected accuracy ranges [41].

Table 3.1 Accuracy Requirements adapted from FCC[81]

Solution	67% of calls	95% of calls
Handset-Based	50 meters	150 meters
Network-Based	100 meters	300 meters

Table 3.2 E-112 Accuracy Guideline adapted from [82]

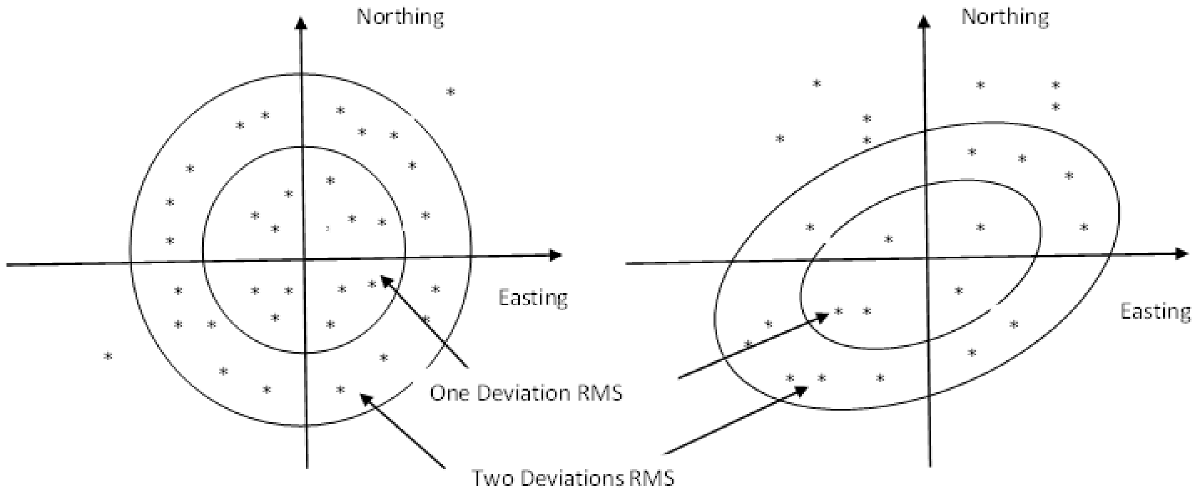
Urban	Suburban	Rural	Crossroads
50 meters	50 meters	100 meters	<100 meters

Table 3.3 LBS Position Accuracy adapted from [41]

Service Type	Accuracy Rage
Fleet Management	125m-Cell ID
Network Planning	10m-Cell ID
Asset Management	10m-125m
Person Tracking	10m-125m
Navigation and Route Guidance	10m-125m
Traffic Congestion Reporting	10m-40m

Requirements and Metrics for Vehicle Localization

Vehicle positioning requires high resolution and accuracy for proper navigation. The positioning technology used should have the ability to determine the vehicle location within 20 meters of the actual location for about 90% of the travel time [80]. This is in the accuracy range of 10m-40m for Traffic Congestion Reporting in Table 2.3 as Traffic Congestion Reporting is standardized location based service type in 3rd Generation Partnership Project(3GPP) within the category of traffic monitoring [41].Generally, accuracy, precision and coverage are the three important performance measures for positioning technologies but positioning accuracy is a critical factor when selecting a positioning technology for different services [34].To evaluate performance of position location methods, different standards were proposed. One of them is Root-Mean-Square (RMS) and it is specified for two dimensions which is composed of standard deviation of two one-dimension axes (σ_N for Northing axis and σ_E for Easting axis)spanning two-dimensional plane[39].Depending on the distribution of the error, the position samples may center in a confidence circle or ellipse around the true positions as illustrated in Figure 3.2a and Figure 3.2b.



a) Confidence Circles b) Confidence Ellipses

Figure 3.2 Confidence Circles and Ellipses adapted from [39]

When the error distribution is the same in both dimensions, the position samples center in a confidence circle (see Figure 2.2a) and $\sigma_N = \sigma_E$. The standard deviation is defined as:

$$\sigma D_2 = \sqrt{2(\delta_N)^2} = \sqrt{2(\delta_E)^2} \tag{3.1}$$

When the error distribution in the two-dimensions differ, the positing samples center around a true position of confidence ellipse and it is approximated as :

$$\sigma D_2 = ½ (\sigma_N + \sigma_E) \tag{3.2}$$

where, σ_N is standard deviation for Northing axis and σ_E for Easting axis

The Root Mean Square Error (**RMSE**) is also used to measure the aggregate error on position estimate [36] and defined as:

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{K=1}^{N}[x_{Measured}(K)-x_{True}]^2} \tag{3.3}$$

where, N is the total number of trials and X_{Measured} is the position estimates in the K^{th} trial.

The other measure of accuracy is the comparison of the Mean-Square-Error (MSE) or root-mean-square (rms) position error with the Cramer-Rao Lower Bound (CRLB) [83]. For a location in two-dimension, the MSE position estimate is given by:

$$\text{MSE} = \text{E}\ [\left(x - x'\right)^2 + \left(y - y'\right)^2] \tag{3.4}$$

Where (x, y) is coordinate of a target and (x', y') is the estimated position and E represents the expected value of the squared difference between an estimate and the actual observed value of the parameter.

Geometric Dilution of Precision (GDOP) is used to measure effects of base station configuration on location estimation. GDOP is defined as the ratio of root-mean-square (rms) position error to root-mean-square ranging error [83] and for unbiased error it is given by:

$$\text{GDOP} = \frac{\sqrt{E[(x - x')^2 + (y - y')^2}\,]}{\delta_r} \tag{3.5}$$

where, δ_r represents the fundamental ranging error of the positioning technique.

3.3 Basic Mobile Positioning Techniques

This subsection discusses the different mobile positioning methods. There are six different positioning methods but only two of them are important for mobile positioning in cellular network[39].These positioning methods are proximity sensing and lateration.

3.3.1 Proximity Sensing

It is the most widespread positioning method used to obtain location of mobile device based on limited coverage of radio signal. The location of a mobile device is derived from the coordinates of the base station that either receives the pilot signals from a terminal on the uplink or whose pilot signals are received by the terminal on the downlink channel. Locating the mobile device is done during ongoing connection or if the mobile device is idle. In the former case, the network simply adopts the coordinates (X_1, Y_1) of the base station that currently serves the terminal. If the terminal is idle, the mobile device listens to the broadcast transmissions of nearby base stations and derives a position fix by contacting a remote database that performs a mapping from cell identifiers to base station coordinates. The base station that sends or receives signal is assumed to be near the location of the mobile device and the expected deviation error is dependent on the radius of sensing area [39]. It is illustrated in Figure 3.3.

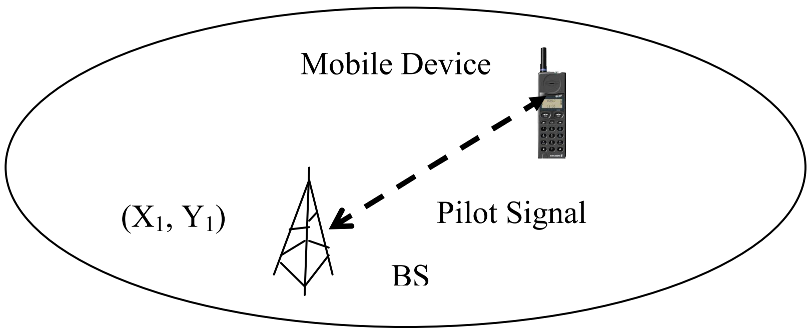


Figure 3.3 Proximity Sensing Illustration

3.3.2 Lateration

Lateration is a mobile positioning method that tries to determine location from multiple distance measurements [33]. In this method, mobile device position is determined either from absolute distance or distance differences from at least three base stations. If positioning is based on absolute distance measurements, the position fix is calculated by Circular Lateration, while distance differences form the basis for Hyperbolic Lateration.

Circular Lateration

Circular lateration uses the assumption that the distances r_i between the mobile device and number of base stations are known[39]. For unambiguous positioning of a mobile device at least three base stations with known coordinates (X_i, Y_i) are required. The unknown mobile device position (X, Y) is the intersection of the three circles as it is depicted in Figure 3.4 and using the Pythagoras theorem its location is given as:

$$r_i = \sqrt{(X_i - X)^2 + (Y_i - Y)^2} \quad (3.6)$$

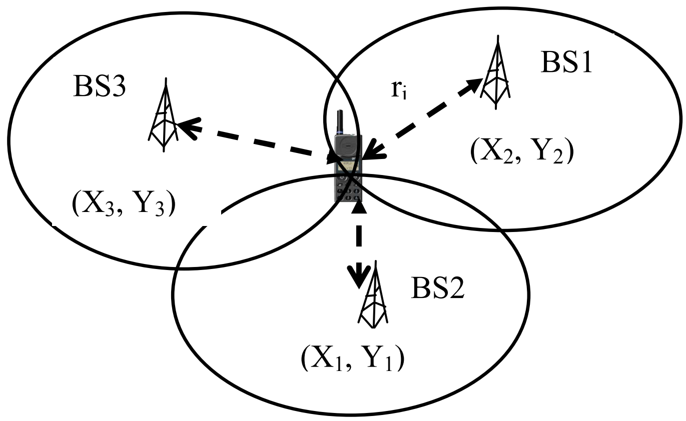


Figure 3.4 Circular Lateration Illustration

Due to refraction, inaccurate clock synchronization and multipath propagation, the measured distance d_i may have a deviation error ε_i from the actual distance r_i. Hence, the circles will not have intersection point (X, Y) rather becomes error margin as shown in Figure 3.5.

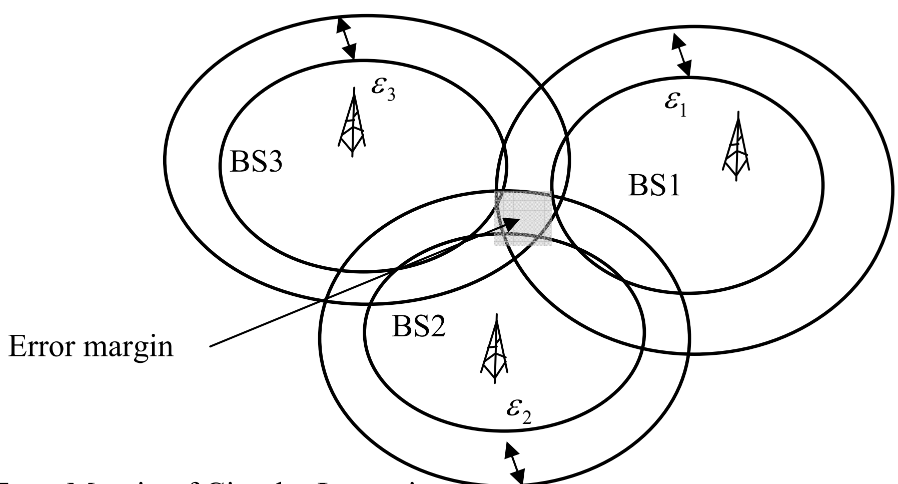


Figure 3.5 Error Margin of Circular Lateration

Hyperbolic Lateration

In a hyperbolic lateration method of mobile device positioning, the location of the mobile device is determine by the distance difference ($r_i - r_j$) instead of the absolute distance r_i. A hyperbola is a set of points where the distance from two fixed points is constant[39]. Considering two base stations with known coordinate forms hyperbolic curves and their intersection can help to determine a fixed point. To determine position of a mobile device, three base stations are required and its location is illustrated in Figure 3.6.

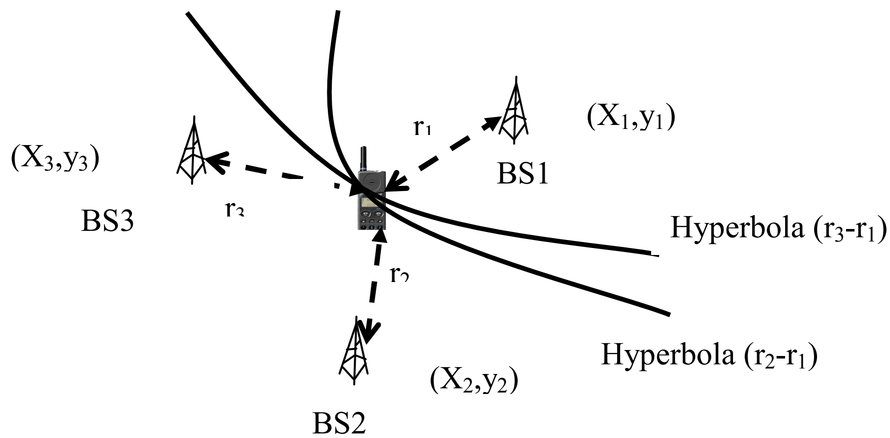


Figure 3.6 Hyperbolic Lateration

Like circular lateration, hyperbolic lateration has an error potential because of inaccuracies of range difference measurements. The error potential of two intersecting hyperbolas is depicted in Figure 3.7. Therefore, a least square fit can be used again to approximate a solution.

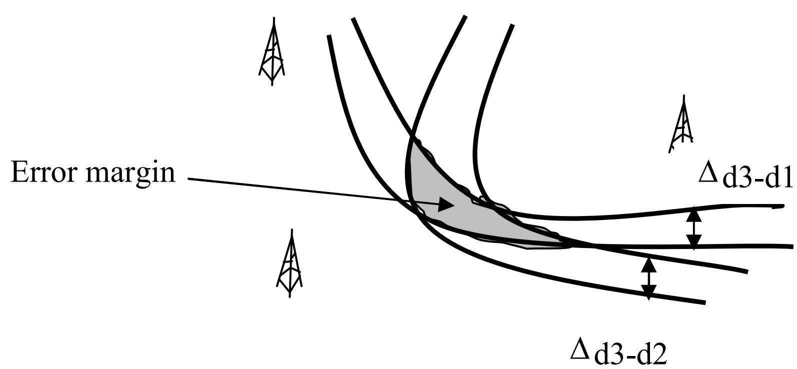


Figure 3.7 Error margin for Hyperbolic lateration

3.4 Standardization of Mobile Phone Positioning

The acceptance and success of services developed using position technologies is essentially based on the availability of appropriate standards. Standards guarantee a seamless interworking between equipment and software originating from different sources and in this way enable the use of services that are technically independent of a certain operator or provider.

The 3rd Generation Partnership Project (3GPP) is an international collaboration of several national standards bodies and focuses on the production of technical recommendations and reports for wideband code-division multiple access (W-CDMA) and Global System for Mobile Communication (GSM) systems while 3GPP2 is focusing on CDMA2000 and CDMA One system.

Location Service (LCS) is primarily concerned in delivery of location data and it is very important for building Location-Based Services[39]. According to 3GPP, LCS covers several generations of radio access networks (RAN) like GERAN (GSM, EDGE RAN), UTRAN (UMTS Terrestrial RAN) and E-UTRAN (Evolved Universal Terrestrial RAN). EDGE (Enhanced Data rate for Global Evolution) is an evolution with respect to the 2G system .i.e., GSM. UMTS (Universal Mobile Telecommunication System) is a 3G system commonly named WCDMA. E-UTRAN refers to the 4G system which is LTE (Long Term Evolution).

3GPP specifications are continuously enhanced with new features and these enhancements are structured and coordinated based on releases. For example, specification TS 22.071 [41] provides overall descriptions and requirements of LCS. Specification TS 23.271 [84] provides LCs architecture and message flow. This specification, unlike TS 22.071 which describes services with respect to the subscribers' point of view, presents the service realization and also defines the service with respect to the operators and providers point of view.

3.4.1 GSM and UMTS Location Service Standards

In the long run, GERAN and UTRAN access networks coexist under an integrated core network architecture that offers common infrastructure components, protocols, and management mechanisms. Accordingly, the components and architecture of LCS is shown in Figure 3.8.

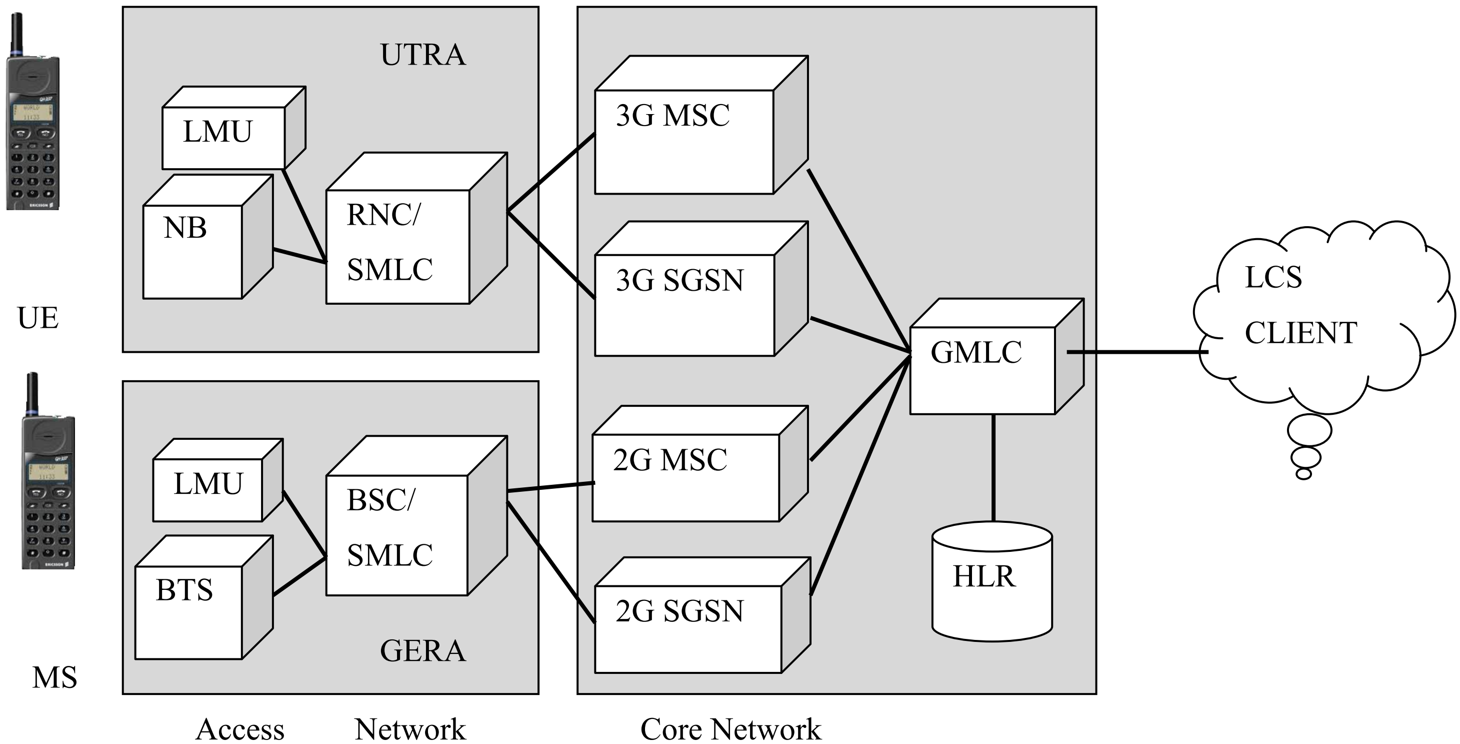


Figure 3.8 3GPP LCS Architecture adapted from [39]

Where GMLC = Gateway Mobile Location Center, SMLC= Serving Mobile Location Center, LMU = Location Measurement Unit, RNC= Radio Network Controller, SGSN= Serving GPRS Support Node, NB= Node B, MSC= Mobile Switching Center, BSC= Base Station Controller and HLR= Home Location Register, BTS= Base Station Transceiver, LM= Location Management.

During position location determination in GSM and UMTS network, three basic activates are performed. The first one is location preparation where determination of position method used and checking privacy policy is done and the second one is establishing position measurement. In this step, components like SLMC, LMU and UE/MS exchange measurement data. After successful measurement position location is calculated either at the terminal or in the network and resources involved during the process is released. The following subsection illustrates the standardized position methods in GSM and UMTS networks.

Standard Mobile Positioning in GSM Networks

For GERAN (GSM/EDGE Radio Access Network), different mobile positioning methods are developed and each differs in degree of accuracy and complexity of control mechanism in the network and in the MS/UE. 3GPP TS 43.059 [85] specifies four positioning methods which are supported in GSM/EDGE RAN.

Time Advance (Cell-ID in combination with Timing Advance): Cell-ID is based on proximity sensing, that is, the position of the target MS is derived from the coordinates of the serving base station. To achieve position fixes of higher accuracies, Cell-ID is combined with timing advance value. Timing Advance (TA) Value corresponds to the time a signal takes from MS to serving base station. In this method, the Cell ID of the corresponding serving base station together with the TA value is returned.

Enhanced Observed Time Difference (E-OTD) positioning mechanism: This method is based on hyperbolic lateration (trilateration) and is applied in the downlink channel. The E-OTD method is based on measurements in the MS of the Enhanced Observed Time Difference of arrival of nearby pairs of BTSs. For E-OTD to work properly additional software and hardware need to be added in the network [81].

Global Navigation Satellite System (GNSS) based positioning mechanism: Global Navigation Satellite Systems (GNSS) are satellite systems like Galileo that are set up for positioning purposes[85]. The MS must be equipped with a GPS receiver and are supplied by additional assistance data from the network, which allows to reduce the acquisition time and to increase the accuracy of position fixes. The MS with GNSS measurement capability may operate in an autonomous mode or in an assisted mode. In the autonomous mode, MS determines its position based on signals received from GNSS without assistance from network. In the assisted mode, MS receives assistance data from network.

Uplink Time Difference of Arrival (U-TDOA) positioning mechanism: This method is also based on hyperbolic lateration, but is applied in the uplink. It is based on network measurements of the Time Of Arrival (TOA) of a known signal sent from the mobile station and received at three or more BTSs. This method will work with existing mobile stations without any modification because the position calculation is done by the network not at the handset like E-OTD.

Standard Mobile Positioning in UMTS Networks

3GPP TS 25.305 (Technical Specification Stage 2 functional specification of User Equipment (UE) positioning in UTRAN)[86] provides methods to support the calculation of the user Equipment (UE) position. Four standard positioning methods are supported in UMTS Terrestrial RAN.

Cell-Based Method: In UMTS, the Cell-Based method estimates the position of a UE based on the nearby base station that is Node B. If required, position data can be refined by taking into account the distance between UE and base station, which can be derived from round-trip-time

(RTT), the Angle Of Arrival (AOA) of signals from the terminal at the base station, or both of them.

Observed Time Difference of Arrival with idle period downlink (OTDOA-IPDL): This method is basically the UTRAN counterpart of E-OTD in GSM and follows the same principles, that is, the UE's position is determined by hyperbolas lateration based on at least two pairs of Node Bs. However, UEs may have difficulty hearing a sufficient number of cells needed for TDOA calculations. One solution, specified by 3GPP for this problem, is an idle period downlink (IPDL) where the serving Node B introduces idle periods in the downlink to improve the hear ability of weaker neighboring Node Bs.

*Network-assisted GNSS (A-GNSS):*As in GSM, a network-assisted GNSS method is also standardized in UTRAN. In particular, 3GPP TS 25.305 specified network-assisted GPS (A-GPS) in detail as a separated clause in the standard. The two A-GPS methods specified in UTRAN are UE-based and UE-assisted. Computation of the position can either be performed in UTRAN for UE-assisted or in the UE for UE-based. In UE-based, the UE employs GPS receiver with reduced complexity, whereas in UE-assisted, a full GPS receiver is required in the UE.

Uplink-Time Difference of Arrival (U-TDOA): The U-TDOA positioning method in UMTS is network-based and it is basically the same as U-TDOA in GSM. The difference between U-TDOA and OTDOA lies whether the measurement is done by the network or by the UE. In UTRAN, the U-TDOA shows significant advantage over its handset-based counterpart [87].In this method no need to modify the neither UE nor Node B. Network management becomes easier, as it is less complex to upgrade the software in network entities than it is to upgrade millions of UE.

Standard Mobile Positioning in E-UTRAN

3GPP TS 36.305 (the functional description of UE positioning in E-UTRAN)[88] describes the E-UTRAN (Evolved UTRAN) UE positioning Architecture, functional entities, operations to support positioning methods and the position estimation is made by UE or the Enhanced Serving Mobile Location Centre (E-SMLC). In the latest (Release 11), four UE position standards are supported for E-UTRAN access.

Network-assisted GNSS Methods: These methods make use of UEs that are equipped with radio receivers capable of receiving GNSS signals. As it is specified in detail in a separate clause in the standard, there are two Network-assisted GNSS Methods: UE-Assisted and UE-Based. In UE-Assisted, the UE performs GNSS measurements and sends these measurements to the E-SMLC where the position calculation takes place and in UE-Based, the UE performs GNSS measurements and calculates its own location, possibly using additional measurements from other (non GNSS) sources.

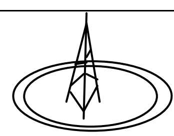
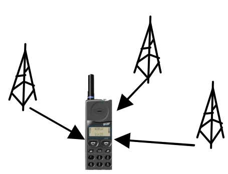
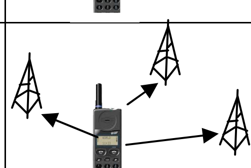
Downlink positioning: The downlink (OTDOA) positioning method makes use of the measured timing of downlink signals received from multiple eNode Bs at the UE. The UE measures the timing of the received signals using assistance data received from the positioning server, and the resulting measurements are used to locate the UE in relation to the neighboring eNode Bs. eNode B is a network element of E-UTRAN that may provide measurement results for position estimation and makes measurements of radio signals for a target UE and communicates these measurements to an E-SMLC.

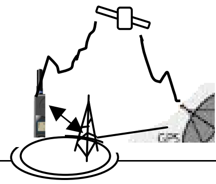
Enhanced Cell ID Methods: In E-UTRAN, Enhanced Cell ID method, the position of an UE is estimated with the knowledge of its serving eNode B and cell. To know the serving eNode B and the cell Paging, tracking area update, and other methods are used. Detail operation on Enhanced Cell ID is described in a separate clause in the standard.

Uplink positioning: The uplink (UTDOA) positioning method makes use of the measured timing at multiple LMUs of uplink signals transmitted from UE. The LMU measures the timing of the received signals using assistance data received from the positioning server, and the resulting measurements are used to estimate the location of the UE. Hybrid positioning using multiple methods from the above positioning methods is also described in 3GPP TS 36.305 specification standard.

In general, the standard mobile positioning methods in GSM, UMTS and LTE can fall into four classes: Cell area coverage based, downlink observed time difference, uplink time difference of arrival and network assisted GNSS. Table 3.4 gives summary of the different techniques with respect to each generation of networks.

Table 3.4 Summary of standard location methods in cellular network generations

<table>
<tr><th>Mobile Positioning Method</th><th>Diagram demonstrating the method</th><th>Standard Mobile Positioning technique</th><th>Generation of Cellular Network</th></tr>
<tr><td rowspan="3">Cell Area Coverage Based</td><td rowspan="3"></td><td>CID-TA</td><td>GSM</td></tr>
<tr><td>CID-RTT</td><td>UMTS</td></tr>
<tr><td>E-CID</td><td>LTE</td></tr>
<tr><td rowspan="3">Downlink Observed Time Difference</td><td rowspan="3"></td><td>E-OTD</td><td>GSM</td></tr>
<tr><td>OTDOA-IPDL</td><td>UMTS</td></tr>
<tr><td>Downlink</td><td>LTE</td></tr>
<tr><td rowspan="3">Uplink Time Difference of Arrival</td><td rowspan="3"></td><td rowspan="3">U-TDOA</td><td>GSM</td></tr>
<tr><td>UMTS</td></tr>
<tr><td>LTE</td></tr>
</table>

Network assisted GNSS		A-GPS	GSM UMTS LTE

3.5 Classification of Mobile Positioning Technologies

Different types of location based services require different position technologies based on position accuracy. Each positioning technology provides location information in its unique way. As highlighted in 3GPP specifications, each positioning technology has its own positioning logic. Despite their numerous variations, these standardized methods can be systematically classified. According to Zhao [81], positioning technologies are classified into two: network-based and handset-based (terminal-based) mobile positioning technology.

There is also another way to classify positioning technologies: self-positioning and remote positioning technology. But Self-positioning is generally synonymous with handset-based and remote positioning with network-based [33].

3.5.1 Network-Based Mobile Positioning Technologies

This category is referred as “Network-based” because the mobile network together with the Network-based positioning determination equipment is used to position the mobile device. Network-based positioning method has advantages that all legacy UEs can receive location service without upgrading. Because the network has more computing power, it can help for positioning when difficult using Handset-based method. It also reduces power consumption of the UE. The system can initiate target positioning and tracking without intervention or action by the target and the network operator could use the information for position based tariffs, generate and store statistics gross movement of the customers for network planning, feed into systems detecting traffic congestion and provide the mobile user with variety of position-based services (e.g. route guidance). However, Network-based positioning methods not only use network resources but also involve changes in the infrastructure as described in Table 3.5.

Table 3.5 Infrastructure change requirements in Network-based positioning standards

Generation of Cellular Network	Network-based mobile positioning method	Infrastructure change requirement	
		Network	Handset
GSM (2G)	CID-TA	Software	No
	U-TDOA	Hardware	No
UMTS (3G)	CID-RTT	Software	No
	U-TDOA	Hardware	No
LTE (4G)	E-CID	Software	No
	U-TDOA	Hardware	No

Performance Evaluation of Network-Based Mobile Positioning Technologies

There are so many performance metrics to evaluate different positioning technologies. Among those metrics accuracy, latency, availability, reliability and applicability are of major importance [89].Accuracy of a positioning technology refers to how close the location measurement is with respect to the UE be located. In network-based positioning accuracy must be 100 m for 67% of all calls and 300m for 95% of all calls [81]. Availability is related to environmental factors affecting positioning and it is represented based on classes like Remote, Rural, Suburban, Urban, Indoor and Underground [89]. The accuracy also is defined based on these classifications for E-112 guideline [82] and recommended to be applied for vehicle positioning [33, 90].Table 3.6 presents accuracy of Network-based positioning methods in Urban, Suburban and Rural areas.

Table 3.6 Comparison of Network-based positioning methods using Accuracy and Availability

Positioning Method	Accuracy vs. Availability		
	Urban	Suburban	Rural
CID-RTT	50m-550m	250m-2.5km	250m-35km
U-TDOA	40m-50m	40m-50m	50m-120m

As it can be seen from Table 3.6, U-TDOA is better to approach the Traffic monitoring accuracy range 10m-40m as indicated in table 3.3. Reliability is the ratio of successful positioning attempt out of all attempts performed. Latency measures the time that the position measurement takes from power-up until it is acquired. Applicability refers to physical limitations and requirements in relation to the use and implantation of the Network-based positioning method. Some of the issues affecting positioning include power consumption, hardware and software size, processing load, cost and standardization. Table 3.7 depicts these evaluation metrics in relation to Network-based positioning methods.

Table 3.7 Comparison of Network-based positioning methods with respect to reliability, latency and applicability

Positioning Method	Reliability	Latency	Applicability
CID-RTT	high	1-5sec	high
U-TDOA	medium	<10sec	low

From Table 3.7, one can see that CID-RTT Network-based positioning method provides very good reliability, minimum latency of measurement and easy to apply. But its position accuracy is not within the requirement.

3.5.2 Handset-Based Mobile Positioning Technologies

This category is referred as "Handset-Based" because the handset itself is the primary means of positioning the user. Sometimes the network is used to provide assistance for acquiring the UE or performing position estimation. In other words, in a handset-based location system any location measurement is made in the handset.

Handset-based positioning systems can be used with cellular networks that are not designed for location service and even with low capacity because handset-based positioning technologies don't use facilities and resources of the network. Moreover, roaming handsets can be used in position measurement activity. Since the handset is not limited on the number of measurements it can take, to improve position accuracy more measurements can be taken. For some situations this positioning method is more secured as the location information is not available in the network. But Handset-based positioning method demands the UE with high power consumption. To perform location estimation, special software, and often hardware is incorporated in the handset as well as in the network [33]. Table 3.8 shows the different Handset-based positioning methods together with the resource requirements across the different cellular network generations.

Table 3.8 Resource requirements in Handset-based positioning standard

Generation of Cellular Network	Handset-based mobile positioning method	Resource requirement	
		Network	Handset
GSM (2G)	E-OTD	Hardware	Software
	A-GNSS	Hardware	Hardware &Software
UMTS (3G)	OTDOA-IPDL	Hardware	Software
	A-GPS	Hardware	Hardware &Software
LTE (4G)	A-GNSS	Hardware	Hardware& Software
	Downlink	Hardware	Software

Performance Evaluation of Handset-Based Mobile positioning Technologies

The performance metrics used to evaluate Handset-based methods include accuracy, latency, availability, reliability and applicability are of major importance [89]. The position accuracy of Handset-based positioning methods as specified in FCC must be 50m for 67% of the measurements and 50m for 90% of the calls [81].Table 3.9 presents accuracy of Handset-based positioning methods in Urban, Suburban and Rural areas as classified in [82, 89].

Table 3.9 Comparison of Handset-based positioning methods using Accuracy and Availability

Positioning Method	Accuracy vs. Availability		
	Urban	Suburban	Rural
OTDOA-IPDL	50m-3000m	50m-250m	50m-150m
A-GPS	10m	10m-20m	10m

As it can be seen from the table, A-GPS has very good positioning accuracy. In relation to reliability, latency and applicability of Handset-based positioning methods, Table 3.10 shows that A-GPS has very low latency and moderately reliable as well as applicable.

Table 3.10 Comparison of Handset-based positioning methods with respect to reliability, latency and applicability

Positioning Method	Reliability	Latency	Applicability
OTDOA-IPDL	medium	<10sec	medium
A-GPS	medium	1-10sec	medium

3.5.3 Hybrid Mobile Positioning Technologies

In a hybrid positioning system, both the handset and the network are involved in the positioning function. In 3GPP, it is defined as the concurrent use of one network-based positioning method with a single handset-based positioning technology to provide a single location request service [38]. This combination enables to supplement and complement the limitations of one mobile positioning technology by capability of another. So, hybrid positioning methods optimize accuracy, coverage, and availability and also decrease latency of location delivery as it is shown inFigure 3.9.

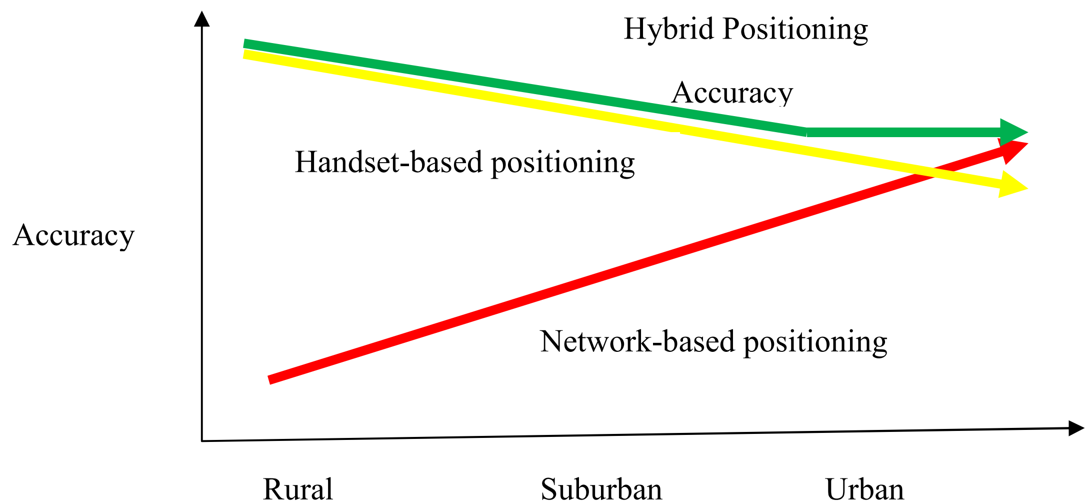


Figure 3.9 Position accuracy comparisons for different Mobile positioning Categories [35]

There is no literature that identifies positioning method that is perfectly suitable for vehicle positioning. But UTRAN supports a hybrid positioning solution from location technologies using separate resources. According to Chew[34], a framework of hierarchical integration of positioning technologies to support delivery of optimal position location is proposed. The interoperability of the integrated technologies is shown using dependency relationship as it is shown in Figure 3.10.

In a hybrid positioning method, cellular network operators emphasize the implementation of at least one network-based positioning method[33, 39]due to the fact that legacy handsets are used in the positioning activity and in the cellular network the infrastructure migration is smooth.

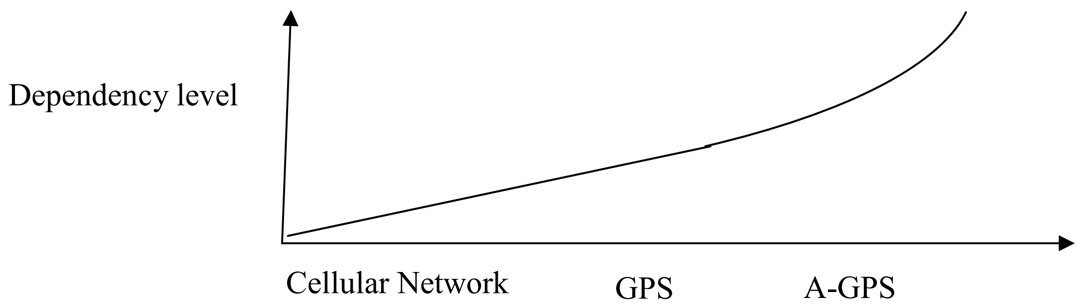


Figure 3.10.Dependecy Level of positioning technologies

As it can be seen from Figure 2.10, cellular network positioning methods (Handset-based and Network-based) are with the lowest level of dependency as the ability to locate position and area coverage is high. But A-GPS, because it needs resources like the network as well as server to compute position, its dependency level is high.

3.6 Road Traffic State Estimation Procedures

Real-time road traffic information is important for road traffic management activities like incident detection, traffic monitoring and so on. The traffic data can be gathered from several sources like loop detectors, microwave radars and more recently from mobile users [91]. Nowadays, road traffic information estimation from cellular networks has received much attention because of the widespread of the cellular network, its low cost, all-weather traffic information collection and with large number of mobiles to be used as location probes covering the whole road network. In order to estimate road traffic information from cellular network, the basic steps are location data collection, cell phone mobility classification, map matching, route determination and perform road traffic condition estimation using state estimation approach [92].

3.6.1 Location Data Collection

This phase involves how to gather location data from cellular network. As it is discussed in Section 3.5, location data can be collected from the cellular network using handset-based positioning method also named as active monitoring approach, network-based method in some literatures also called passive monitoring and hybrid-based positioning method. The hybrid-based positioning method, which is discussed in detail in section 2..1.4.3 and also the suggestion of recent commercial systems [93, 94] provides good positioning accuracy and coverage as the advantage of one positioning method improves the limitation of the other.

3.6.2 Cell Phone Mobility Classification

While moving vehicle location data is collected from cellular network using one of the positioning technology discussed in Section 3.5, the data could be from various types of mobile carriers like mobile phones in moving vehicles, carried by pedestrians, held by bicycle and motor cycle riders, stationary mobile phones etc. As the objective is to estimate travel times of road users, discrimination between mobile phones in moving vehicles and other phones is necessary.

In relation to this, mobility characteristic like speed, directivity, update interval and erraticity of mobile devices are also used for mobile device classification [95]. If the necessary information on active/switched on mobile phone like date, time, Cell Identification (Cell-ID) and its location coordinates is collected, fusion of speed, direction and location information enable to classify mobile phones in moving vehicles and others [96].

Speed

Speed is used to classify the type of mobility. In consecutive time interval, if a mobile phone traveled with a speed of *v* larger than some specified threshold repeatedly, the mobile phone is in a moving vehicle and it is defined as [95]:

$$v_i(t_n) = \frac{\sqrt{(y_i(t_n) - y_i(t_{n-1}))^2 + (x_i(t_n) - x_i(t_{n-1}))^2}}{t_n - t_{n-1}} \tag{3.7}$$

where $v_i(t_n)$ is the speed of the cell phone between t_n and t_{n-1} with location (x_i, y_i) at time t_{n-1} and t_n.

The work of Gundlegard and Karlsson [97], for example, discussed that speed can be used to filter stationary and pedestrians mobile phones. If a mobile phone has speed below 6km/hr it can be ignored as it will not be in a moving vehicle. But during congestion when vehicles are travelling at lower speed from the threshold, mobile devices that are registered recently for higher speed though the current speed is lower than the threshold are considered to be valid probes.

Directivity

This represents the amount of angular change in the direction of the movement of a mobile device compared to a previous measurement. Pedestrians compared to vehicular mobile device present large directional changes. Directivity is measured using a specified time scale T. The direction of movement θ_n at time (t, t + T) is defined as[95]:

$$\theta_n = \arctan\frac{y_{n+1} - y_n}{x_{n+1} - x_n} = \arctan\frac{dy_{n,n+1}}{dx_{n,n+!}} \tag{3.8}$$

And also at the time interval (t +T, t+2T) the direction of movement is given as:

$$\theta_{n+1} = \arctan\frac{y_{n+2} - y_{n+1}}{x_{n+2} - x_{n+1}} = \arctan\frac{dy_{n+1,n+2}}{dx_{n+!,n+2}} \tag{3.9}$$

Hence, a directivity element is equal to $\beta_n = \theta_{n+1} - \theta_n$ at time scale T.

Computation of θ_i depends on at which quadrant of the Cartesian coordinate system the location coordinates fall, and the movement is directed. The directive vector $\beta(T, N) = (..\beta_{n,}\beta_{n+1,}\beta_{n+2,}..)$ includes the last N directivity measurements (T,N) is expected to be stored by the network service provider. Fast moving vehicles are mostly with smaller directivity[96].

Update Interval

This is the time interval between two consecutive location updates of a particular mobile device. The location updates can be done centrally by the network requiring the mobile device to update its location. On the other hand, there are suggestions in the literature [98] that, to alleviate the signaling load on the network due to periodic updates, the mobile device updates its location whenever it crosses a boundary of a pre-determined area (e.g., circular, elliptic, etc.) centered at the coordinate of its last location update. Because the location of mobile devices is updated whenever the mobile devices cross the boundary of the cell, frequency of location update is a function of the radius of the cell. Hence, slow moving mobile devices like pedestrians or bicycle riders update their location less often than fast moving mobile devices like vehicles.

Erraticity

Assume that a circle of radius **r** defines the region for the location updates. When a mobile device traverses a distance **d** from the time of a location update (t_O) at position O to the next one (t_A) at position A, the corresponding erraticity within time frame [t_O, t_A] is denoted as E(t_O,t_A), and analytically represented as [95]:

$$E(t_O, t_A) = \left(1 - \frac{r}{d}\right) \quad (3.10)$$

Erraticity has no units, and takes values from [0,1] where 1 indicates the highest level of randomness and 0 the lowest level (e.g., movement with no directional change between two consecutive location updates). The comparison of the erraticity levels is made within each corresponding location updates interval and it is used in conjunction with the Update Interval.

Other approaches like location registration scheme [99] and Naïve Bayes model [100] are also used to discriminate mobile phones in moving vehicles from others.

3.6.3 Map Matching

The data collected from cellular network covers many roads and also most measurements suffer from non-line of sight error as well as sampling error which makes the vehicles position is unreliable. Hence, projection of position/velocity estimates on to road links is needed using map matching algorithms.

Map matching is the process of determining vehicle's location on the road segment, using the geographic coordinates obtained by mobile positioning technology and digital road map [101]. Map matching and route determination are often done together. Map matching algorithms are used to accurately locate a vehicle on a road map. The inputs to the algorithms come from mobile positioning technology and supplement this with data from a high resolution spatial road network map to provide an enhanced positioning output [102]. Map matching enables to identify physical location of a vehicle and also improves positioning accuracy depending on the quality of the spatial road network data [103]. Moreover, depending on the positioning technology used to collect vehicle location, the map matching approach differs [97].

There are different map matching algorithms produced and published in the literature. Most of these algorithms are designed for in-vehicle navigation systems equipped with GPS, Differential GPS and Dead Reckoning (DR). Based on the approaches, the algorithms can be categorized into four groups: geometric, topological, probabilistic and advanced map matching techniques.

Geometric Map Matching Algorithms

Geometric map matching algorithms use the geometric information of the digital road network considering the shape of the links but do not consider the way links are connected to each other [104]. The most commonly used geometric map matching approach is based on a simple search concept. In this approach, each positioning point matches to the closest 'node' or 'shape point' in the road network and it is named point-to-point matching [105]. In point-to-point matching, each measured vehicle location point is matched to the nearest node or shape point in the digital road network map.

To identify the closest node (or shape point) from a given point in the road network, Euclidian distance measurement is used. The measure of the Euclidean distance between two points x and y in $\mathbf{R}^2$is given by:

$$\|x-y\| = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \tag{3.11}$$

This method is easy to implement, although it is very sensitive to the way in which the network was digitized as it may lead to errors [106].

Point-to-Curve matching is another geometric map matching approach where the measured vehicle location is matched on to the closest road network curve [107, 108]. Each of the curves comprises line segments which are piecewise linear. Distance is calculated from the position fix to each of the line segments. The line segment which gives the minimum Euclidean distance is selected as the one on which the vehicle is apparently travelling. The minimum Euclidean distance from measured location c to line A containing points a and b which is denoted as

$\{\lambda a + (1-\lambda)b,\ \lambda \in R\}$ is given by:

$$d(c, A) = \sqrt{\frac{\{(a_2 - b_2)c_1 + (b_1 - a_1)c_2 + (a_1 b_2 - b_1 a_2)\}^2}{(a_2 - b_2)^2 + (b_1 - a_1)^2}} \tag{3.12}$$

Accordingly, if the minimum distance of point c is on a line segment between points a and b of the curve, it becomes the matched point, otherwise if the perpendicular distance between point c and line A intersect outside the lines segment, minimum distance from points c and a or from points c and b is selected as matched point.

Although this approach gives better results than point-to-point matching, it has several shortcomings that make it inappropriate in practice. For example, it gives very unstable results in urban networks due to the high road density. Moreover, the closest link may not always be the correct link [105].

The other geometric map matching approach is curve-to-Curve matching. In this approoach, more than one measured location is attributed to contineous road segments.Several location points are connected to form piecewise linear curve. Another piecewise linear curve is constructed using the vehicles trajectory and then the distance between the previous curve and the curve corresponding to the road network is determined. The road arc which is closest to the curve formed from positioning points is taken as the one on which the vehicle is apparently travelling. This approach is quite sensitive to outliers and depends on point-to-point matching, with the consequence of sometimes giving unexpected results [102, 105].

Topological Map Matching Algorithms

These map matching algorithms make use of the geometry of the links as well as the connectivity and contiguity of the links [104, 109]. Topological map matching algorithms utilize both geometrical and topological data to make matching decision. Topological map matching algorithms are simple, easy and quick and can be implemented in real-time [110].

Probabilistic Map Matching Algorithms

A topological map matching algorithm starts with nodal matching to identify the correct link among the links connected to the node closest to the estimated vehicle location. For complex urban road networks with high resolution digital maps, topological map matching algorithm is not helpful. Instead of using the links connected to the closest node, the map matching algorithm should take all links as candidate links that fall within an error ellipse around a position fix. The dimensions of the error ellipse are chosen based on the error variance-covariance matrix associated with the location estimation technology. The size of the error ellipse normally depends on the probability (95% or 99%) that the ellipse contains a true link [102].

Probabilistic map matching method is also discussed in[106]depending on GPS sensor for vehicle location and suggested that the error region can be derived from the error variances associated with the GPS position solution. This error region is superimposed on the road network to identify a road segment on which the vehicle is travelling. If an error region contains a number of segments, then the evaluation of candidate segments is carried out using heading, connectivity, and closeness criteria. For implementation purpose other parameters such as speed of the vehicle and distance to the downstream junction are used to improve the map matching process.

Advanced Map Matching Algorithms

Both geometrical and topological map matching algorithms are used as the basis for developing other advanced map matching algorithms [101]. These advanced algorithms employ additional techniques to improve performance. These algorithms use concepts such as Kalman Filter or an Extended Kalman Filter, Dempster-Shafer's mathematical theory of evidence, flexible state-space model and a particle filter, an interacting multiple model, fuzzy logic model or the application of Bayesian inference [101, 106].Some of these algorithms are discussed below.

Kalman Filter Approach

The Kalman filter is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance—when some presumed conditions are met. Kalman filter is the most effective method to filter signal with random noise [111]. Kalman filter operates in two distinctive stages: predictive (time update) stage and measurement update stage. It tries to estimate the state $x \in R^n$ of a discrete time controlled process governed by the transition and measurement equation defined as follows[111].

$$\begin{cases} X_k = \Phi X_{k-1} + W_{k-1} (3.13) \\ W_{k-1} \sim N(0,Q) \end{cases}$$

$$\begin{cases} Z_k = HX_k + V_k \ (3.14) \\ V_k \sim (0,R) \end{cases}$$

Where Φ is process state transition matrix, H is measurement design matrix, $Z \in R^m$ is measurement value at time t_k, Q and R are covariance matrices for the process error vector W_{k-1} and measurement error vector V_{k-1} respectively.

In the prediction stage, a new prediction of the error states (3.15) and error covariance states (2.19) are determined for the next step. The equation for the prediction stage is as follows.

$$\hat{X}_k^- = \Phi \hat{X}_{k-1}^+ \tag{3.15}$$

Where $\hat{X}^-$ is the error state vector, (−) indicates a priori estimate while posteriori estimate is indicated with (+). The predicted error covariance is defined as:.

$$P^- = \Phi P^+_{k-1} \Phi^T + Q \tag{3.16}$$

In the update stage, the Kalman Filter makes corrections to the predicted state estimate based on new information from the measurements. These corrections are appropriately weighed through Kalman gain (3.17) which determines if the prediction or the measurement should be trusted more. Then the Kalman gain is used to update the state estimate (3.18) and error covariance matrix (3.19) as the posteriori estimate for the next prediction stage.

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{3.17}$$

After processing the measurement Z_k, posterior state mean estimation $\hat{X}^+$ is obtained by updating $\hat{X}^-$ with correct version of measurement residual.

$$\hat{X}_k^+ = \hat{X}_k^- + K_k (Z_k - H_k \hat{X}_k^-) \tag{3.18}$$

Then the covariance matrix P_k^+ associated with $\hat{X}^+$ can be updated from the priori estimate as:

$$P_k^+ = (I - K_k H_k) P_k^- \tag{3.19}$$

Provided that matrices Φ, Q, H, R are defined beforehand, the calculation of $P_k^-, K_k\,and\,\,P_k^+$ is independent of any measurement.

Particle Filtering

Particle filtering, based on a stochastic process, is another approach to the map matching problem. Particle filters are recursive implementations of Monte Carlo-based statistical signal processing [112]. Particle filtering provides natural way of incorporating the digital road map information in to the vehicle position estimation while the uncertainty of the road link the vehicle is moving occurred. The basic principle in this model is to use random samples (particles) representing posterior density of the vehicle position.

Fuzzy Logic Map Matching

In dense urban areas, the vehicle trajectory taken from the positioning technology is often different from the actual vehicle route due to problems associated with the positioning technology used and the digital road map. For example, at a very high road density, many road patterns could be matched to the vehicle trajectory based on the data from positioning technology used but it will be difficult to precisely determine the road the vehicle is traveling. Hence map matching algorithm that suggests the link the vehicle more likely to be on one road and less likely to be on another is needed.

Fuzzy logic is a technique that deals with vague, imprecision and uncertain knowledge [113]. It is concerned with the use of fuzzy values that capture the meaning of words, human reasoning and decision making. Set of rules representing expert knowledge and experience is used to draw inference through approximate reasoning process. In map matching process, fuzzy logic can be used if the identification of the correct road link that the vehicle is moving becomes a qualitative decision making process with high degree of ambiguity. In this approach, the map matching algorithm is built with various expert knowledge and experience-based IF-THEN rules incorporating speed of vehicle, heading and historical trajectory of the vehicle, connectivity and orientation of the road link, the error contribution of the positioning technology and with the help of an optimal estimation technique, the physical location of the vehicle can be determined.

Hidden Markov Model

Error due to the positioning technology used affected the performance of map matching algorithms. Different methods are proposed to work with the sparseness and noises of GPS data. Recently, Hidden Markov Model (HMM) is shown to be effective in recovering the whole sequence of roads so long as the sequence of GPS measurements are used [114]. Hidden Markov Model is a statistical Markov Model in which the system being modeled is represented by a finite set of states, each of which is associated with a probability distribution [115]. Transitions among the states are governed by transition probabilities. Depending on the associated probability distribution, an outcome or observation can be generated at a particular state and it is only the outcome, not the state that is visible to an external observer. The general architecture of HMM is shown in Figure 3.11.

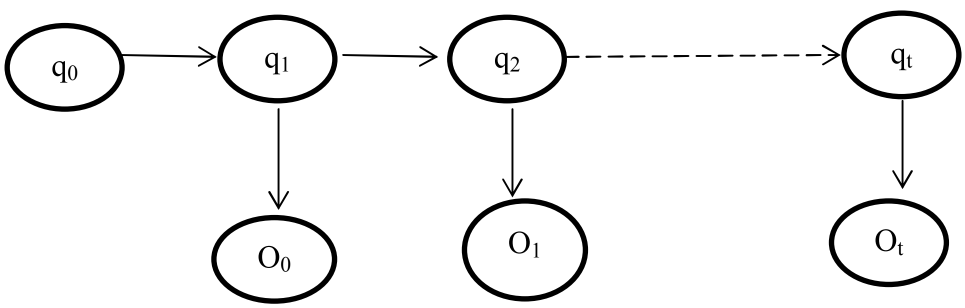


Figure 3.11 Hidden Markov Model Architecture

The architecture has two layers: $\{o_t\}$ represents the observable layer and ot corresponds to an observation value at time t. $\{q_t\}$ represents the hidden layer, and qt, at time t, comes from one state in a state space.As map matching algorithm, the states (hidden layer) of the HMM are the individual road segments, and the state measurements (observable layer) are the noisy vehicle location measurements. The goal is to match each location measurement with the proper road segment. This state representation naturally fits the HMM, because transitions between road segments are governed by the connectivity of the road network.

3.6.4 Road Traffic State Estimation Approaches

Road traffic state estimation is a fundamental work in Intelligent Transport System (ITS). It is applicable for dynamic vehicle navigation, intelligent transport management, traffic signal control, vehicle emission monitoring and so on. The two major components of ITS, Advanced Traveler Information System (ATIS) and Advanced Traffic Management System (ATMS) particularly need accurate current road traffic sate estimation and short term prediction of the future for smooth traffic flow [42].

Existing road traffic state estimation techniques can be grouped into model based approach which are used for offline traffic state estimation and data driven approach for online state estimation [116]. Model based traffic state estimation approaches use the analytical traffic model Lighthill-Whitham-Richards (LWR) model [117] or simulation based models which are more suitable to model complex road traffic flows [118].

Model-Based Road Traffic State Estimation Approaches

Traffic flow models can be categorized according to various criteria like level of detail, level of operationalization and level of representation of the processes. Depending on the level of details of the traffic system, traffic flow models can be microscopic, macroscopic or mesoscopic.

Microscopic Traffic Flow Models

Microscopic traffic flow models describe both the space-time behavior of vehicles and drivers and also their interaction at a high level detail. This model simulates vehicle-driver units and analyzes properties like position and velocity of each individual vehicle. In this model, road traffic is represented at each vehicle level and the interaction with each other and the road infrastructure. The interaction is captured as a set of rules that determines when a vehicle accelerates, decelerates, changes lane and also how and when the vehicle choose and change route to the destination.

Considering the vehicle's behavior, microscopic model can be decomposed into car-following model, lane-change model and route-choice model [119]. The car-following model describe the breaking and acceleration pattern resulted from the interaction of the driver and vehicle as well as other objects and the lane-changing model represents the driver decision to change lane based on preference and situation on the different lanes. The path drivers to take from origin to destination and the way they react to traffic and route information along the way is the route-choice model. The microscopic traffic flow model also enables to represent signs, traffic signals and also operation and location of traffic detectors. This model mostly is used to analyze traffic flow at each road network and number of vehicles travelling from origin to destination. Some of the microscopic traffic flow model simulators include INTEGRATION [120], HUTSIM [121], PARAMICS [122] and SUMO[123], VISSIM[124], MITSIMLab [125].

As a performance example, Tao et al. [126] used a microscopic simulation model to estimate road traffic sate using A-GPS traffic as probes. In the research, real-time location data is collected based on cellular network signaling and average link speed is calculated and aggregated to determine traffic state at each road link. The method is evaluated on a laboratory experiment using the microscopic simulation model SUMO (Simulation of Mobility). Liu et al.

[127] also used the microscopic simulator VISSIM to evaluate Neural Network based traffic flow model which is developed to address the problem of urban arterial travel time prediction.

Macroscopic Traffic Flow Models

Macroscopic traffic models describe traffic flow at high level of aggregation without distinguishing each of the vehicles. This model defines the relationship between traffic flow density, average velocity and road traffic flow or intensity [128]. The first macroscopic model was totally dependent on the fundamental diagram Lighthill-Whitham-Richards (LWR) model [117] referred as first order macroscopic model to determine traffic speed. To properly analyze traffic instability, delay responses and the anticipated behavior of drivers are important in macroscopic traffic flow model [129] which can explicitly be represented on speed dynamics under second order macroscopic model.

Compared to microscopic traffic flow models, macroscopic traffic models have minimum computational cost due to their few and directly measurable parameters. Moreover, due to high level of aggregate representation of traffic flow and road geometry, it is difficult to replicate and analyze traffic facilities. An example on its performance is the research work from Ziliaskopoulos et al. [130] where the researchers perform large scale dynamic traffic assignment applying cell transition model.

Mesoscopic Traffic Flow Models

This model is a link between microscopic and macroscopic traffic model. Mesoscopic model fill the gap between the aggregate level approach of macroscopic and the individual interaction of vehicles and road infrastructure of microscopic ones. Mesoscopic traffic flow model describes the distance-density relation based on the distance link between two sequenced vehicles in microscopic model and traffic flow density on macroscopic model. These models are applicable when microscopic activities are desirable but difficult due to large road network and also during shortage resources for coding and debugging the network [131].

Hybrid Traffic Flow Models

Each of the above traffic flow models are with some limitations. For example, microscopic simulation models are known in detecting, analyzing and understanding large range of traffic problems but problems related to calibrating and cost and time of computation during simulation are the identified drawbacks of the model [131]. Although the calibration in macroscopic and mesoscopic models is easier than microscopic model, their application is limited to situations where vehicle interaction and drivers' behavior is not crucial to the results of simulation.

Different researchers have proposed and implemented a hybrid traffic flow model to overcome limitation of one traffic flow model by the advantages of another. Hystra , for example, is hybrid model combining macroscopic and microscopic traffic flow models [132].According to the researchers, because Hystra is hybridized model it has minimized errors and also difficulty of calibration as it combines a flow and a vehicular representation of the classical Lighthill-Witham-Richards (LWR) model. MiMe [131] is also another micro-meso hybrid model. This model is a combination of the microscopic traffic flow model MITSIM Lab and the mesoscopic model Mezzo. Based on the evaluation conducted using laboratory test as well as field data on the hybrid model MiMe, the authors obtained a promising result.

Data Driven-Based Road Traffic State Estimation Approaches

Online traffic state estimation methods are data driven approaches that use real-time measurements for real-time traffic state estimation. To represent real-time traffic state, travel time of vehicles on a certain road link is used. Travel time, which is defined as the time required to travel along a route between any two points within a traffic network [133], is a fundamental measure in transportation. Engineers and planners have used travel time and delay studies since 1920s to evaluate transportation facilities and plan improvements [134].

In recent times with the increasing interest in Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS), providing travelers with accurate and timely travel time information has gained paramount importance. Operators, for example, can use travel time information (current and/or predicted) to improve control on their networks as part of ATMS. Drivers also can choose their optimal route, either pre-trip or en-route, provided that traffic information from an ATIS is available together with the drivers' individual preferences. For transport companies the knowledge of travel time can help to improve their service quality. Moreover, they can choose their routes dynamically according to the current and predicted state of traffic and thus increase their efficiency and reliability.

Because of this, a large number of research studies and literature reviews are concerned with the estimation, prediction and application of travel time in various areas of road traffic monitoring and management activities. One of the major issue in travel time estimation and prediction is the selection of appropriate methodological approach [135]. Current practice involves two separate modeling approaches: parametric and non-parametric techniques [136].

In the category of statistical parametric techniques, several forms of algorithms have been applied with greater weight to historical average algorithms and smoothing techniques. Autoregressive linear processes such as the auto-regressive integrated moving average (ARIMA) family of models also provided an alternative approach based on the stochastic nature of traffic

[137]. Other statistical-based algorithms are based on the applications of linear and nonlinear regression, Filtering techniques, Bayesian and time series models [138, 139] which are based on historical/real time data to forecast the travel time.

Some of the parametric algorithms also belong to multivariate time series model family. A good example for such kind of parametric technique is Kalman filter. The advantage of using Kalman filter algorithm in travel time estimation is that it enables the state variables to be updated continuously. The potential of the algorithm in travel time estimation is demonstrated in [139, 140]. Both Chien and Kuchipud [141] and Chen and chien [142] have used Kalman filtering for travel time estimation. The work of Tao et al.[126] also presented the use of Kalman filtering in urban traffic state estimation using A-GPS based vehicle location data. Moreover, the superiority of Kalman filtering over ARIMA is demonstrated in traffic state modeling during different period of the day [143].

The development of non-parametric techniques including non-parametric regression, neural network etc. has showed the potential to be an option against parametric methods. Some researchers demonstrate non-parametric techniques performing well due to the ability to capture nondeterministic and complex nonlinearity of travel time series [144]. Computational intelligence techniques like fuzzy logic, machine learning and evolutionary computation are also applied in travel time estimation.

Travel time prediction is a complex dynamic problem, it requires a data driven model capable of dealing with dynamic processes [44]. One of the most popular computational intelligence techniques applied in travel time estimation is Artificial Neural Network (ANN). State space neural network (SSNN) model (Figure 3.12) is a First Order Context Memory [145, 146]consisting of four layers, an input layer) receives the input data and distributes section specific input vectors to the hidden layer. The latter also receives signals from the context layer, which stores the hidden layer states (that is, the hidden layers output) of the previous time instant. The output layer finally processes the hidden layer outputs and produces a scalar output, which is the mean travel time on the route of interest. SSNN can be used to model travel time along a signalized urban route where it can be depicted by connecting several urban segments (links and intersections) and can be treated as basic element of urban route.

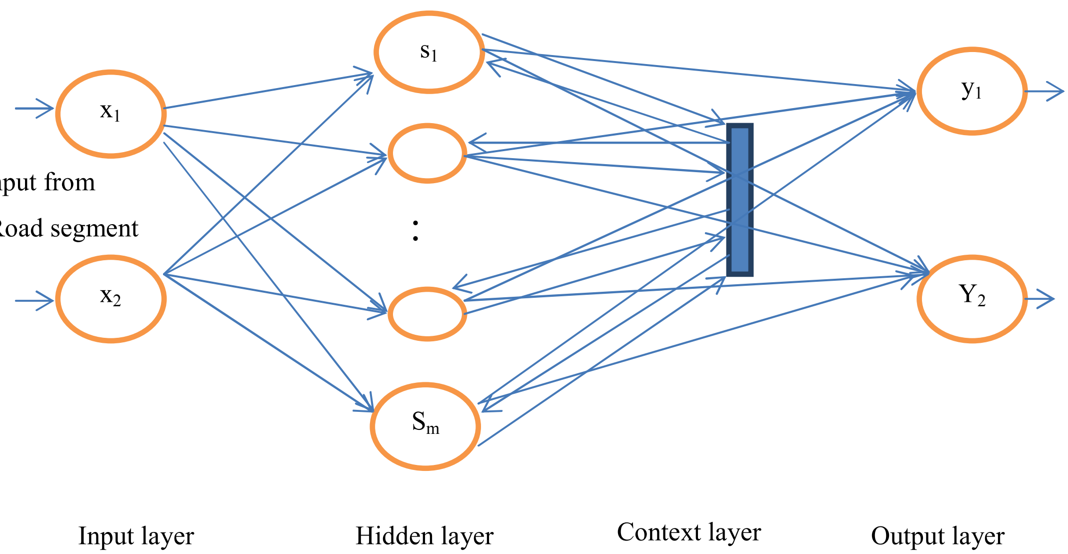


Figure 3.12State Space Neural Network (SSNN) model

Hybrid-Based Road Traffic Sate Estimation Approaches

Road traffic state estimation is a complex activity which can't be done using a single forecasting method [51]. To use the data-driven approach, for example neural network, deployment of data collection infrastructure on road segments need high investment [44]. To train the neural network model based traffic state estimation methods like microscopic or macroscopic simulators can be used [47]. Hence, application of hybrid model based and data-driven road traffic state estimation reduces computational delay and also increases forecasting accuracy [51].

Chapter Four: Related Work

4.1 Introduction

Real-time road traffic information is essential for the development of ITS applications like road traffic monitoring and so on. To provide road traffic information to users at real-time, activities like vehicle location data collection, identifying mobile carriers on moving vehicles, mapping the vehicle location to the digital road map and travel time estimation are basic steps to be done. Moving vehicle localization based on cellular network signaling using the mobile phone moving along all journey of the vehicle is a promising technology for delivery of wide area real-time road traffic information and has received much attention recently. As it is discussed in Section 3.5, in-vehicle mobile positioning technologies can be categorized into three: network-based, handset-based and hybrid positioning technology. Each of these positioning technologies have different positioning accuracy, coverage and suitable for different location based services. Accordingly, different investigations have been made on the performance of these mobile positioning technologies. Different mobility classification approaches, map matching algorithms and also road traffic condition estimation techniques have been investigated since the first day of proposing mobile probes as road traffic sensors.

Hence, this chapter presents review of the related work on the use of different cellular network based vehicle positioning techniques, moving vehicle tracking algorithms using the mobile moving along with all journey of the vehicle as a probe, algorithms applied to match vehicle location to digital road map, fuse measurements from multiple sensors, model and data driven-based road traffic state estimation approaches and state estimation frameworks. Finally, a chapter summary describes all road traffic condition estimation activities from the literature point of view and provides suggestion on what this research work has focused on.

Portion of this chapter entitled "In-Vehicle Mobile Phone-Based Road Traffic flow Estimation: A Review," is published on Journal of Network and Innovative Computing, ISSN 2160-2174 Volume 1 (2013) pp. 331-358

4.2 Cellular Network-Based Vehicle Localization

4.2.1 Network-Based Mobile Positioning Methods

Network-based positioning technologies do not require major changes in the network and terminal but support to utilize the existing network infrastructure to provide location of the UE. These technologies have been an active research area since the issue of FCC in 1996. A research conducted by Sayed et al. [147] used a simulator to compare the positioning accuracy of different network-based positioning methods; AOA, TOA and TDOA in GSM network. From these location estimation methods, AOA and TOA are found to meet the FCC requirement, a location error below 100m for 67% of the calls made. The work of Al-Jazzar, et al. [148] presented the joint TOA/AOA positioning method and a simulation experiment resulted minimum non-line-of-sight (NLOS) effect. To reduce the accuracy error in TOA/AOA hybrid positioning method, Kalman Filter is recommended and simulation based research conducted by Guangqian, et al. [149] showed that the theoretical position accuracy is further improved due to Kalman filtering applied in the hybrid network-based positioning method.

The other network-based mobile positioning technology is U-TDOA. The major challenge in this positioning method in cellular network application is noise and multipath effect resulted due to non-line of sight (NLOS) channel. The work of Mardeniet al. [150] focused on the improvement of UTDOA localization scheme using adaptive line enhancement (ALE) to pre-process signals heavily affected by noise and multipath before applying OTDOA. The authors used simulation test to validate as well as evaluate robustness of the proposed method.

Borkowski and Lempiäinen [151] and Jakub [152] conducted a research on Pilot correlation positioning method (PCM) for urban UMTS network. The researchers did their experiment on the method using UMTS network deployed in the urban environment. PCM is a finger print technique in UMTS which is based on Common Pilot Channel (CPICH) at the UE [153]. The CPICH power is measured for all Node Bs with the range and characterized throughout the area with the values modeled and stored in the database. The result of the experiment done on the position accuracy of PCM against Enhanced Cell-ID-RTT showed that the accuracy for 67% of the measurement was in the range of 70m-90m whereas for 90% of the measurement, the accuracy varies from 130m-195m.

A research conducted by Kunczier and Anegg [154] presented the use of network-based positioning method for location based applications in urban areas. Because GPS and Cell-ID are not providing the expected accuracy of positioning, utilization of Bayesian networks to improve localization accuracy of Cell-ID positioning method is proposed. To enhance the Cell-ID method, Network Measurement Report (NMR) based method which relies on received power level measurements is adopted. The achieved accuracy, based on measurements in the City of Vienna, is less than 20 meters in 67% of all estimates and about 50 meters in 90% of all estimates. Trevisani and Vitaletti [155] also showed how Cell-ID can be used for voice-based location services.

4.2.2 Handset-Based Mobile Positioning Methods

Handset-based mobile positioning methods are used when high position accuracy is needed. Different researches are conducted on the position accuracy evaluation and improvement of these position methods. One of the handset-based mobile positioning methods is Observed Time difference of Arrival (OTDOA). This positioning method suffers from near-far problem when the UE is close to NodeB. Duffett-Smith and Macnaughtan [156] proposed Cumulative Virtual Blanking (CVB),a technique used to take measurements of the downlink signal simultaneously at the handset and at NodeBs while position measurement is initiated [157], to overcome the hearability problem of the method and simulation based evaluation of OTDO supported with the new technique showed an accuracy of 20m in rural area.

In the same way, Ahonen and Eskelinen [158] conducted a research on the performance of standardized Observed Time Difference of Arrival (OTDOA) and a novel Database Correlation Method (DCM) for wide bandwidth systems. The evaluation of the proposed method through simulations in urban area confirmed that DCM provided a reasonable location error of 25 m for 67% of the calls. Ahonen and Laitinen [159] also conducted research to evaluate DCM against OTDOA and Cell-ID. Obtained results imply that DCM avoids most of the urban environment related problems and the simulation result showed a position accuracy of 25m in 67% of the estimates, which is adequate for most location applications and it is also within the range required by emergency service.

Singh and Ismail[160] conducted a research to use the handset-based positioning method OTDOA with the aim of generating 15% of location based traffic at peak hours in Malaysia. The simulation result showed a distance error of less than 12m but in average the error is more than

100m due to non-line of sight of Node Bs or additional time delay from multipath losses. The researchers recommended to use OTDOA in complement with Cell-ID if there are no proper alignments of 3 Node Bs. Handset-based mobile positioning using OTDOA-IPDL is detailed and implemented in [161] and the simulation result revealed that the location accuracy error in urban areas is 60m-115m for 67% of the cases.

Many authors highlighted A-GPS with high accuracy at reasonable cost and also fits the FCC positioning requirements [162, 163]. Most researchers used A-GPS to improve limitations of other mobile positioning methods as it is discussed in hybrid positioning method.

4.2.3 Hybrid Mobile Positioning Methods

Different authors conducted a research on hybrid mobile positioning methods aiming to complement downside of one method with the other method to provide better performance measure. Adusei et al. [89] discussed four possible hybrid positioning methods without conducting experiment to evaluate their performance. The methods include:

Cellular-Cellular Combination: A hybrid of AOA and TOA reduces signaling load because only one BS is required. But hybrid of E-OTD and Cell-ID-RTT greatly improves availability.

GPS-Cellular Combination: A hybrid of GPS and EOTD or GPS and Cell-ID-RTT gives good availability and good outdoor accuracy. Besides, the same cellular network elements can be used to support both technologies.

GPS-Inertial Sensors: Enhanced GPS (EGPS) is an example for this hybrid positioning method. The accuracy of this combination is within 1m and 30m in urban and suburban areas respectively.

GPS-Cellular- Inertial Sensors: A very high complexity, but superior availability and good accuracy could be hybrid of A-GPS, EOTD and low-cost low power inertia navigation system (INS). The author didn't evaluate any of the above hybrid positioning methods.

Hybrid mobile positioning methods combining network-based with handset-based and also fusion of two handset-based positioning methods for vehicle positioning are discussed in the work of Tao,S. et al.[80, 36]. Under the combination of two handset-based positioning methods, hybrid of A-GPS and OTDOA is described. The experiment result in [36] using a simulator showed that the hybrid positioning method has better accuracy compared with the individual positioning methods.

On the other hand, hybrid of Cell-ID and A-GPS, U-TDOA and A-GPS are discussed within the combination of network-based and handset-based positioning methods. A hybrid of Cell-ID and A-GPS is found to be the simplest and reliable UE positioning method and recommended to offer adequate positioning for vehicle location. A hybrid of U-TDOA and A-GPS is preferred for UE positioning as U-TDOA has better accuracy compared to Cell-ID and also doesn't require handset modification. In this hybrid positioning method, A-GPS provides positioning function when it is available; otherwise, the network-based U-TDOA would be used.

The work of Abo-Zahhad et al.[48] also described U-TDOA and A-GPS hybrid positioning method with respect to accuracy, latency, call state environment and system loading parameters and concluded that for mobile position based applications, the hybrid method provide high accuracy without time delay and preferred for outdoor applications with light system loading but U-TDOA is selected for indoor applications and with heavy system loading.

The work of Drakoulis et al [164] presented a hybrid positioning method based on the well-established positioning techniques GPS and the network-based positioning method TDOA in GSM network. The author evaluated the performance and the compliance of the method with respect to related standards. Son et al.[165] also introduced an integrated method for GPS pseudo ranges and wireless network TDOA measurements to solve the radiolocation problem when the number of visible satellites is not sufficient. They adopted the least squares method for evaluating user position and the Kalman filter (KF) for Non Line Of Sight (NLOS) error measurement. Broumandan et al.[37] analyzed the positioning performance using a TDOA/AOA hybrid system in CDMA network. Chen and Feng [166] presented a hybrid location scheme, which combines both the satellite-based (GPS) and the Network-based positioning methods.

In the hybrid positioning method GPS, TOA, TDOA and AOA positioning techniques are combined as UE-assisted and UE-based positioning methods. The authors used least square method to determine position of the UE, Kalman filtering to reduce error and track UE trajectory and Bayesian Inference model to merge TOA and TDOA/AOA estimations. Based on a simulation result, the hybrid positioning method provided consistent location estimation accuracy under different environments. Chen and Abedi [167] also experimented using a simulator on hybrid positioning methods based on Received Signal Strength (RSS), TOA, TDOA and AOA in W-CDMA network. The simulation result indicated, the hybrid estimation scheme combining RSS, TOA, TDOA and AOA data achieves higher positioning precision than that of the RSS-only, the TOA-only, and the TDOA-only or AOA-only methods.

To improve latency and enhance availability of A-GPS positioning method, Borkowski et al.[168]have proposed to combine network-based positioning method and handset-based positioning methods with A-GPS. The proposed assistance methods include PCM, which is entirely network-based method in UMTS [151], and signal strength measurement together with Cell-ID in GSM network. The simulation experiment conducted on the hybrid positioning method PCM and A-GPS in urban UMTS network provided accuracy below 70m for 67% of the location request and 130m-190m accuracy for 90% of the request. Whereas, the hybrid handset-based positioning methods based on A-GPS and Cell-ID + Signal Strength operated in rural GSM network provided accuracy below 300m for 90 % of the location request.

4.3 Mobility Classification

Vehicle location data collection using mobile phones needs to be separated as traffic probes consists of different mobile phone carriers. To discriminate mobile phones in moving vehicles from other mobile phones, different researchers used different approaches. For example, Choi and Tekinay [99]applied location registration mobile carriers are classified into two broad groups: predictable and unpredictable mobile. Using location update signal cost, predictability (when update signal cost is low) and unpredictability (update signal cost is high) is determined. However, practical implementation of the classification approach is not considered.

Puntumapon and Pattara-Atikom[100] proposed to use Naïve Bayes model to classify sky train and pedestrian mobility from mobile device information based on the number of unique Cell-ID and their average dwell time. Cell dwell time is the duration between two registration operations of a mobile device on the nearest base station while in motion.

Naive Bayes is a model for clustering and classification based on Bayes Theorem. This model estimates the per-class probability by assuming that the attributes are conditionally independent. Let C denote class variables used for classification, E_i denote conditional attribute i used for classification and P(C|E_1, ...,E_n) denote conditional probability of class C given that the evidence E_1,...,$E_n$have happened. The probability model for a Naive Bayes classifier can be defined as follows:

$$p(C / E_1,..., E_n) = \frac{p(C)xp(E_1,...E_n / C)}{p(E_1,..., E_n)} \tag{4.1}$$

Using joint probability model, Chain rule and repeated conditional probability equation (4.1) could be derived as:

$$p(C / E_1,..., E_n) = \frac{p(C)xp(E_1 / C)xp(E_2 / C)x....xp(E_n / C)}{p(E_1,..., E_n)} \tag{4.2}$$

The authors concluded that Naïve Bayes model based on the number of unique Cell-ID and the average Cell dwell time of unique Cell ID has a performance of sky train and pedestrian mobile device classification accuracy up to 93.1%. They recommended the model to be applied for large data sets and vehicle mobility classification.

4.4 Map Matching

Mapmatching algorithms integrate estimated locations from any kindof positioning sensorswith spatial network data on a digital map to identify the correct link on which avehicle is travelling and to determine the location of a vehicle on that link[169].Among the traditional map matching algorithms, the most common method is the geometric map matching approach which uses the geometric information of the road [105]. White et al.[107], Srinivasan et al.[170]and Bouju et al. [171] conducted comparison analysis on the geometric map matching algorithms, point-to-point, point-to-curve and curve-to-curve approaches and concluded that accuracy problem can't be solved only using geometric map matching.

A point-to-curve geometric map matching is also used to reconcile vehicle location determined using TOA/AOA mobile positioning technology [172] and A-GPS [126] on a digital road map.

In the conclusion, it is discussed that using Non-Line-of-Sight (NLOS) Least Square (LS) method together with map matching algorithm increases the position accuracy. The point-to-curve geometric map matching is simple to apply and effective in satisfying real-time requirement of a navigation system [105].

The work of Gundlegard and Karlsson [97] discussed the importance of map matching when using location data from cellular network. The authors based on the sampling measurement rate that results from location positioning technologies used recommended to apply Point-to-Curve geometric map matching algorithm for mobile-based/active monitoring and Curve-to-Curve geometrical map matching algorithm if network-based monitoring /passive monitoring is used to gather location of vehicles as the sampling rate of the former is low and for the latter is high.

Another map matching method is topological approach which uses link's geometry, connectivity and contiguity in the matching process. Different researchers have worked on the improvement and evaluation of topological map matching algorithms. GreenFeld et al. [104] for example proposed a weighted topological map matching algorithm which depends on topological analysis of road network using coordinate information for the position of the vehicle. The weighted scheme of the algorithm is based on the perpendicular distance of the position fix from the link, degree of parallelism between the line and the link and the intersecting angle.

Then, the authors have determined the vehicle location on the link using orthogonal projection. This method is very sensitive to outliers as these can lead to the determined vehicle heading to be inaccurate. The work of Quddus et al. [173] is another which has discussed topological map matching algorithm enhancement based on similarity criteria between the digital road network and navigation data. Vehicle speed, position of the vehicle with respect to the target link and heading information from the positioning technologies GPS/DR are used to improve the performance of the algorithm. Based on a field test evaluation of the algorithm, the authors concluded that the algorithm is very efficient at junctions and intersections. Moreover, the estimation of the vehicle location on the appropriate road link is found to be robust as errors due to bearing and positioning technologies were controlled. Wang and Yang [174] also proposed topological map matching algorithm to map moving vehicle on to vehicle road link using GPS vehicle location data. The algorithm is tested on a simulation in four road intersections and recommended that it provides high accuracy and solves spatial problems in complex vehicle road networks and also fulfills map matching in real time. The work of Blazquez [175] also discussed how spatial ambiguity can be resolved using decision-rule topological map-matching algorithm.

The work of Velaga et al [110] described an enhanced weight-based topological map-matching algorithm for intelligent transport system (ITS). The weight values are determined from real world field data. The weights for turn-restrictions at junctions and connectivity are used and checks are done to reduce mismatches. The authors tested the algorithm using a real data under different operational environment and concluded that the new features added have improved performance of topological map matching algorithm. But, according to the authors, the optimal algorithmic weights for different factors such as heading, proximity, connectivity, and turn-restriction still need to be estimated with a range of real-world field data from different road environments.

Meng et al.[109] have also used topological analysis based on the correlation of the trajectory of the vehicle and road features (road turn, road curvature and road connection) to develop a simple map matching algorithm. The algorithm is developed using data from GPS/DR and digital road map including information about road junctions. The authors conducted different tests to identify road segments which don't fulfill statistically determined threshold. The authors concluded that the algorithm can enable to correctly identify vehicle in the correct link even at real-time but the algorithm is sensitive to outliers and also doesn't work at junctions where the bearing of the connecting road is not similar.

Ochieng et al.[103] have proposed enhanced probabilistic map matching method that require definition of the error region of the ellipse when the vehicle travels in a junction. The algorithm is applied to determine the location of the vehicle and also in the identification of the road link that the vehicle is moving. The authors tested the algorithm off-line in a complex urban road with different traffic situation and provided a 100% correct matching and concluded that the algorithm has improved uncertainty of the vehicle position in addition to resolving problem of inaccurate road map data with the inaccurate vehicle location data.

Many researchers have also applied the Kalman filter theory to their map-matching models to solve spatial mismatch. For example, Kim et al. [176] have proposed a map-matching algorithm consisting of model of biased error and Kalman filter. The developed navigation system uses an integrated GPS, DR positioning technology. The authors first used Point-to-Curve matching algorithm to identify the correct road link of the vehicle. Then to get the initial location of the vehicle, orthogonal projection of the estimated positions on to the road link is done. Though orthogonal projection reduces cross-track error, along- track error is a big issue in the map matching process. So, the researchers applied Extended Kalman Filtering (EKF) to re-estimate the vehicle location with minimum along-track error. The authors, based on results of the real world experiment, concluded that the algorithm was effective in minimizing along-track error and need to be improved using heading, speed and topological feature of the road network as parameters in selecting correct road link.Xu et al.[177] have also proposed an improved Kalman filter algorithm with effective GPS error correction approach. The Kalman filter in the proposed map matching algorithm filters the white noise error and corrects the biased error in both the cross-track and the along-track directions. The algorithm is tested in real world situation and observed that the algorithm provided an improved accuracy and reliability. Similarly, an improved map-matching algorithm that employs Kalman filtering to filter unreasonable GPS data and the Dempster-Shafer (D-S) theory to correctly snap GPS vehicle coordinates to the digital road map is proposed in [178]. The D-S theory is used for the representation of ignorance and combination of evidence and it operates with a smaller set of uncertainties. Based on a real world experiment conducted, the authors concluded that the improved algorithm is effective and applicable though verifying the accurate performance of the algorithm is needed in further research.

Some new methods like particle filter, fuzzy logic (Fu and Wang [179], Zhang and Gao [180], Jagadeesh et al. [181], Yang et al.[182]) and Hidden Markov model were also proposed recently for map matching. Different literatures discussed the performance of particle filter to match the sensor based vehicle positions on to digital road map. Gustafsson et al. [112] for example, developed a framework for navigation, tracking and positioning problems using particle filtering. The general algorithm is evaluated in matching the aircraft's elevation on a digital elevation map and the vehicles horizontal driven path on to a digital street map. A real-time map matching implementation is done and the test result showed good accuracy. The authors also recommended particle filter to be used for cellular network based positioning measurements in tracking vehicles. But, determining nonlinear relations and non-Gaussian models that provide the most information about the position of a vehicle is still a challenge. Hence, the authors recommended for further research to seek a reliable way to detect divergence and restart the filter. The work of Toledo-Moreo et al. [183] is another one which has discussed multiple-hypothesis particle-filter based algorithm to solve the map matching problem with integrity provision at the lane level. The proposed model integrates measurements from a GPS receiver, an odometer, and a gyroscope along with road information in digital maps. Experiments were done on two different cities with two prototypes based on different sensors. A set of six experiments were conducted with real data for a period of 30 minutes proving positioning, map matching and integrity provision for lane-level applications and to achieve full integrity, the authors mention that outlier removal, multipath effect mitigation, and additional method validation need to be addressed. Davidson et al. [184] also developed and demonstrated numerical probabilistic approach for map matching problem based on particle filtering to improve positioning accuracy and vehicle navigation activity.

Particle filtering is preferable for nonlinear and non-Gaussian systems than Kalman filtering [185]. But, particle filtering diverges and causes degeneration with high measurement precision. Crisan and Doucet [186] presented a survey on the convergence results of particle filtering methods and concluded that most convergence results rely on strong assumptions which make the methods difficult to be applied in real world problem and recommended future research on the performance improvement of particle filtering. In relation to this, Xue et al. [187] have discussed filtering improvement method in reducing navigation error and increasing accuracy of performance. The authors used GPS/DR positioning systems and carry out a simulation for comparative analysis between the standard particle filtering and the improved algorithm named robust auxiliary particle filtering. Because one of the robust estimation method- maximum likelihood estimate with an equivalent weight is used in sampling and re-sampling of particles (vehicle positions), the latest measured values were considered and the particle degradation slows down. This has improved the precision of the map matching process with real time performance.

Fuzzy logic based map matching algorithms are developed by a number of researchers. The research conducted on adaptive fuzzy-based C-measure algorithm [188] is for example capable to identify the road way on which the vehicle is traveling by comparing C-measures associated with each candidate road links. The C-measures are membership functions representing the certainty of vehicle existence on a road link. Orthogonal projection is applied to determine the position of the vehicle based on the identified route. But, for proper use of the algorithm, there are some requirements like distance between vehicle position and its projected position need to be small and also the shape of the road way needs to be similar to the vehicle trajectory. The authors conducted a real road experiment based on GPS data and recommended real time applicability of the algorithm. Syed and Cannon [189] also discussed fuzzy logic based map matching algorithm using GPS/DR data. The algorithm identified the correct link of the vehicle and also the position of the vehicle on the identified link. The result based on a field experiment conducted for about 15 minutes considering low signal availability with variable speed of the vehicle showed that this algorithm is far better than geometric based map matching algorithms. But the process of determining the correct link of the vehicle is time taking and also error prone due to positioning technology and road map were not considered.

Quddus et al. [102] described high accuracy map matching algorithm based on fuzzy logic theory. The authors discussed limitations of the other map matching algorithms including previous studies on fuzzy logic and proposed an improved fuzzy logic approach that could solve the limitations identified. The input variables considered include vehicle speed, road link connectivity, quality of vehicle positioning technology, relative position of the identified vehicle position with respect to the candidate road link and three set of knowledge-based fuzzy rules. The authors tested the algorithm in different road networks in different environment and found that the performance in correct link identification is better than other map matching algorithms and also the along-track error and cross-road error of this algorithm is minimized. Because the position accuracy of the algorithm in urban areas was not evaluated in the experiment, the authors recommended it for future research.

Another map matching algorithm based on integrated fuzzy logic theory and look-ahead technique is proposed in [190]. The authors used vehicle position data collected from cellular network based on Time Of Arrival (TOA) positioning technology (i.e. position of phone in moving vehicle) and solved a map matching problem for road traffic information. The algorithm compares the similarity degree of phone in moving vehicle running road and the candidate roads to determine the road that the vehicle is travelling. Subsequently, fuzzy preference relations considering the similarity coefficients, projection distance, directional angle and run distance are adopted to perform a multi-criteria decision and a look-ahead technique is employed to improve the matching accuracy. The validity of the approach is tested using a simulator and the authors proposed to include other cellular network positioning techniques to improve the matching accuracy.

Because of the error on the positioning technology, the performance of the above map matching algorithms is affected. The map matching algorithm proposed to work with sparseness and noises positioning data is Hidden Markov Model [114]. Reymond et al. [191] also proposed a Hidden

Markov Model based map matching capable to cope with noise and sparse of GPS raw data. The algorithm used points sampled on the road map data as hidden states in the HMM framework and this enabled the state transitional probability to fit with Viterbi algorithm (i.e. an algorithm for finding the most likely sequence of hidden states). The algorithm is tested in a real world data using different sampling rate of points. The authors concluded that 46% of road data is needed for sufficient map matching using this algorithm when there are low rate GPS trajectories and proposed to identify best sampling rate of the road network map for map matching in the future. Similarly, Goh et al. [192] proposed to use HMM for an online map matching and tested the algorithm using real world data. The algorithm decides the sequence of roads incrementally based on the new position measurements obtained. But the method has a complexity problem when modeling the map matching in the HMM framework.

4.5 Multi-Sensor Data Fusion

Data fusion (DF) or multi-sensor data fusion (MSDF), according to Raol [193], is the process of combining or integrating measured or pre-processed data or information originating from different active or passive sensors or sources to produce a more specific, comprehensive, and unified dataset about an entity or event of interest that has been observed. MSDF enhances quality of the information output in a process in several ways like increasing robustness and reliability during sensor failure, extend parameter coverage, increase dimensionality of the measurement, improve resolution, reduce uncertainty and reduction of measurement time and possibly cost [40].

Data fusion is applicable in the estimation of target position or kinematic information from multiple measurements of single or multiple sensors[194]. It enables to combine different target localization techniques (named hybrid localization methods) and optimize accuracy, coverage, availability and decrease latency of location delivery. The widely applied and best known state estimator algorithm is Kalman Filter (KF)[195]. This recursive algorithm gives a linear, unbiased, and minimum error variance. KF optimally estimates the unknown state of a linear dynamic system from Gaussian distributed noisy observations. According to Qiang and Chris [196],the two KF-based data fusion algorithms are state vector fusion and measurement fusion.

State Vector Fusion

State Vector Fusion (SVF) is a KF based fusion. In this algorithm, a group of Kalman filters are used to obtain individual sensor based state estimates which are then fused to obtain an improved joint state estimate and the associated covariance. At the fusion center, track-to-track correlation is applied [193] as it is shown in Figure 4.1.

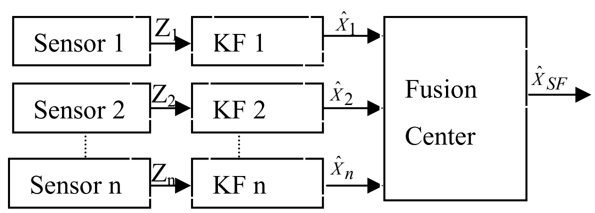


Figure4.1State vector fusion

Measurement Fusion

Measurement fusion (MF) algorithm directly fuses the sensor measurements in the fusion center and use a single Kalman filter [196] to obtain the final state estimate based upon the fused observation as it is shown in Figure 4. 2.

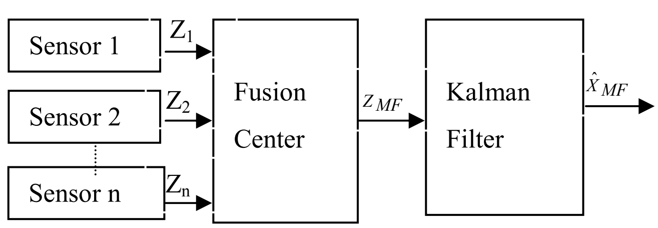


Figure 4. 2 Measurement fusion

In the past few decades, sensor-data fusion has been researched and has added developments for many fields such as science and technology. Most of these researches are based on Kalman filter algorithm that filters noise and recover signal. The work of Bahador Khaleghi et al.[197], for example, presented detail review of multi-sensor data fusion state of the art. The methods and the problems in using multi-sensor data fusion are described in [198]. The wide applications of MSDF in military, biomedical fields, engineering and its future research directions are described in [199]. Qiang and Chrisb [196] have compared Kalman filter based measurement and state vector data fusion algorithms and their theoretical proof showed the superior of measurement data fusion algorithms. Similarly, Mosallae and Salahshoor [49] have discussed measurement and state vector data fusion algorithms based on UKF algorithm for fault diagnosis and simulation result revealed that measurement fusion is better than state vector fusion algorithm. The work of Anitha et al. [200] discusses the different KF- based data fusion algorithms and experimentally compared the performance of the algorithms using IR and radar sensors data. The numerical result of the experimentation shows the superiority of state vector fusion over measurement fusion. Tao et al. [36] fused A-GPS and OTDOA based measurements using state vector fusion algorithm. The authors argue that state vector fusion is easy to implement and support real-time applications. Though this experiment was done for road transport application, there is not any experimental evidence stating the superiority of state vector fusion from measurement data fusion algorithm. However, for non-linear process sensors like road transport applications, KF performance during fusion process would be inconsistent and for such a case measurement fusion algorithm is recommended [196, 201].

4.6 Road Traffic State Estimation

Travel time estimation in urban road networks is very important for many intelligent transport system applications like ATIS and ATMS. These systems basically aim to provide information to drivers or control centers on current traffic flow condition which can help to handle unexpected incidents taking place on the road network. Road traffic state estimation techniques are model based, data driven or hybrid approaches. For real-time traffic state estimation data driven approaches are preferable [116]. Current practices on travel time estimation on urban roads applied parametric and non-parametric methods. Table 4.1 provides list of the current literatures on the implementation of short travel time prediction methods in urban networks.

Table 4.1 Literature review for travel time estimation methods in urban road networks.

	Data for travel time estimation			Methodological approach		Type of data used	
Authors	flow	speed	other	parametric	non-parametric	Real-time	simulation
Kamarianakis and prastacos[202]		x	x	x		x	
Stathopoulos and Karlaftis[143]	x			x		x	
Vlahogianni et al.[136]	x				x Non-parametric regression		
Clark [203]	x	x			x Non-parametric regression		
Yang [204]			x	x		x	

Vasudeva and Wunderlich[205]			x		x Neural Network	x	
Batool and Khan [206]	x				x Neural Network	x	
Guin [207]	x				x Non-parametric regression	x	
Liu et al.[208]	x			x		x	x
Liu et al.[127]	x				x Neural Network	x	x
Fabritiis et al.[209]		x			x Neural Network	x	
Zhu et al.[210]			x	x		x	
Liu et al.[146]	x				x Neural Network	x	
Dong et al.[211]	x			x		x	
Wei et al. [212]	x				x Neural Network	x	
Chen et al. [213]		x			x Neural Network	x	
van Hinsbergen et al.[214]			x		x Neural Network	x	
Wang et al.[215]		x			x p. regression	x	
Yang et al. [216]		x			x Neural Network	x	

As it can be seen from Table 4.1, both parametric and non-parametric methods are applied. But most studies used non-parametric methods in urban networks because it is more efficient as it cope with the fluctuating nature of traffic parameters like traffic flow, speed etc. Particularly, Artificial Neural Networks have been applied extensively in short term traffic forecasting field and acknowledged to be a promising approach because of its superiority in modeling complex nonlinear relationships [217-219]. Artificial Neural Networks have other advantages over other methods that make researchers choose them as road traffic modeling tool [136]. Strong adaptability of Artificial Neural Networks enabled them to learn from past data. Because they are data driven models, their transferability is strong and also need little experience when applied to different road traffic networks. Moreover, Artificial Neural Networks are very flexible in producing accurate multiple step-ahead forecast with less effort. Vlahogianni et al. [136] presented summary of various characteristics of neural networks together with other parametric and non-parametric methods as shown in Table 4.2.

Artificial Neural Networks have also some limitations like their "black box" nature, there are so many types of Artificial Neural Networks and as existing researches proved, appropriate network topologies and configurations can greatly affect performance of Artificial Neural Networks models [220]. But, still there is no standardized criterion to identify the most appropriate Artificial Neural Network model. Current researches follow a trial-and-error method to find the optimal scheme.

To overcome limitation of one data driven forecasting model by advantage of another, different researchers have been using hybrid models (combining parametric and non-parametric methods). For example, Yin et al. [221] developed fuzzy-neural model (FNM) to predict the traffic flows in an urban street network. Alescsandru and Ishak [222] also presented a model-based and memory-based hybrid system to improve performance of freeway speed forecasting systems. Zheng et al .[223] developed a Combined Neural Network Model (CNNM) for short-term freeway traffic flow prediction and Van Lint et al. [224] applied a Kalman filter neural network to forecast short-term travel time on freeways.

Table 4.2 Characteristics of parametric and non-parametric modeling techniques for travel time estimation [136].

Characteristics	Parametric methods			Non-parametric methods	
	Smoothing	ARIMA	KALMAN filtering	Non parametric regression	Neural Networks
Quantity of data	short series	Extensive	Extensive	Extensive	Extensive
Accuracy	Low	Low	Medium	High	High
Nature of Prediction	Static	Recursive	Static	Dynamic	Dynamic
Advantage	-Short series needed	Theoretical background	Multivariate nature	Simple model Structure	Wide mapping capability
Disadvantage	low accuracy	low accuracy slow data processing	Gaussian hypothesis	intensive data	intensive data Complex internal Structure

Because data driven approaches need intensive data, hybrid (combination of model based and data driven approach) urban road traffic state estimation method is applied in recent literatures. The research work of Anderson and Bell [47], for example, used the model based microscopic traffic flow VISSIM with Neural Network for traffic state estimation techniques and a queuing model for travel-time prediction in urban road networks. The work of Tao et al. [126] also presented the use of Kalman filtering integrated with a microscopic simulation model SUMO in urban traffic state estimation using A-GPS based vehicle location data.

4.7 Road Traffic State Estimation Framework

The successful wide scale deployment of ITS applications like ATIS and ATMS relies on the capability to perform accurate estimate of the current road traffic status and reliable prediction of its short term evolution on the entire road network. In this view the use of cellular network to gather road traffic data for wide-area road network is reliable and cost effective.

Different researchers have proposed road traffic state estimation models with different traffic data sources. For example, Tao et al. [126] proposed a simulation based road traffic state estimation framework that utilizes A-GPS as a traffic data source. In the framework, Kalman filter was used as traffic flow estimator. Ning et al. [225] also proposed a real-time road traffic state estimation using GPS and loop detector data. In this framework the traffic estimator was not considered. The emphasis was on the fusion of the measurements gathered by GPS-equipped taxis and loop detectors. The work of Minh et al. [226] discussed a three layer road traffic state estimation system. The first layer is real-time data collection layer. The data sources proposed include mobile phones and Personal Digital Assistant (PDA) devices. The estimation server is the second layer which is responsible for data preprocessing, data updating into database server, estimates traffic states and disseminates the traffic information to road users. The data base server is the third layer which stores digital map as well as location data. In this paper no experimentation on the application of the proposed model was conducted.

4.8 Summary

4.8.1 Mobile Positioning Technology

First and second generation cellular networks are not dedicated to location services (LCS)[80]. On the other hand, third and fourth generation cellular networks have protocol requirements for LCS. Third generation cellular network (UMTS) is with better inherent position accuracy when compared with GSM and CDMA [33] due to the increase signal bandwidth and shorter bit period, as these attributes improve the ability to distinguish the line-of-sight signal among multipath returns during reception. Moreover, third generation cellular network has been deployed pervasively worldwide and UMTS Forum confirmed that subscription to 3G/UMTS reached 500 million in January 2010 [227]. In Africa, the mobile subscription growth rate is easily outstripping the mature mobile markets elsewhere in the world. GSM (2G) mobile subscriptions now account for 62.7 % of mobile subscriptions in Africa, while 3G represents

11% of the overall market and it is expected to grow to 1.12 billion subscribers by 2017 contributing 13.9 % to take the global cellular market to 8.11 billion [228] . In relation to this, state-owned telecom monopoly (Ethio-telecom) announced to upgrade the current 3G network telecommunications infrastructure to 3G LTE (long-term evolution) networks [229]. While launching the current 3G cellular network in May 2012, Ethio-telecom announced that it was ready to deploy the service for 300,000 subscribers in Addis Ababa [230]. Hence, proposed solution and further discussions focused on UMTS (3G) network as it is standardized, well established and widely deployed.

In relation to this, the four standard LCSs in UMTS are presented and evaluated. None of them is perfectly suitable for vehicle location. The decision which class of mobile positioning method to use primarily depends on the characteristics of the location based service.

Network-based mobile positioning methods are preferable to system operators for two basic reasons. The first one is network operators' concern in relation to smooth migration of the network to support location functionality and the other is subscribers' concern where they refuse to exchange or to modify their devices solely in order to use the new network features that go along with the upgrade. Cellular network operators give higher emphasis for the implementation of at least one Network-based mobile positioning method in supporting location services.

Network-based mobile positioning methods in general have some limitations. Cellular networks using these methods may experience reduced capacity. The accuracy of network-based positioning depends on network-based factors including cell size and density, and in the case of TDOA based technologies, the location of the several base stations within hearing of the mobile unit. Besides, if the cellular network is not a 3G network, network-based mobile positioning methods may involve significant infrastructure change and investment.

Handset-based mobile positioning methods are preferable to secure location data and because the method doesn't use resources and facilities of the network, using these position methods don't affect the network capacity. More importantly, this method can help to improve location accuracy by taking more measurements as the handset is not limited by the network. In relation to this, Mohan et al [231] proposed handset-based mobile positioning method is a suitable traffic monitoring approach for low and middle income countries because of the following reasons. The road and traffic condition on these countries unlike the developed once is more varied due to various socio-economic reasons. For example, road quality is variable, bouncy roads are common even at the center of cities, the flow of traffic could be chaotic with no adherence to standards and vehicle types are also very variable. So, monitoring such varied traffic condition is difficult unless very rich sensing (location measurement) method like handset-based is used. Moreover, this approach avoids the need for expensive and specialized traffic monitoring infrastructure and can also take advantage of the booming growth of mobile telephones in the countries.

Handset-based mobile positioning methods have also a drawback of requiring special, more expensive and higher power consuming mobile phones. These methods have no potential to locate existing mobiles and may require synchronization.

Inspired by the above discussion of the standard location methods, it is straightforward to expect that hybrid mobile positioning methods can complement the limitations of one method with the advantages of another. In different literatures, attempts have been made to pursue hybrid mobile location and tracking [164, 165, 232, 233]. This is because hybrid mobile positioning methods like handset-based positioning methods can help to track many mobiles to improve accuracy, take advantage of transmissions originating from other networks, not to be affected by frequency hopping and because the methods are simpler to implement with no modification on the network, different researchers tried to demonstrate experimentally [234]. However, they still leave the doors open for further investigations. Most of these researches are based on 2G cellular network location techniques and only a few of them use the 3G standard location methods. In the hybrid positioning method, most aim to complement GPS performance not the more recently evolved

A-GPS and they hardly target vehicle location applications which will make difference in performance requirements.

Hence, one option of hybrid network-based and handset-based mobile positioning technique is the integration of Cell-ID based and A-GPS positioning methods. Cell-ID based positioning is the simplest and most reliable network-based UE positioning method. But its accuracy can't meet vehicle location requirement service. To improve accuracy of Cell-ID positioning method, different standards are implemented. In UMTS, Cell-ID+RTT can be an example. This enhanced Network-based positioning method is claimed to estimate the distance between UE and BS with accuracy of 36m [82]. Moreover, the great widespread of indoor and outdoor cellular network can enable better position location accuracy in the future.

In contrast, A-GPS UE positioning method provides excellent location accuracy, especially in open-space. Because it is network assisted, latency and positioning problem in dense urban environment is solved. Moreover, A-GPS phones gained significant market share in the mobile handset and personal computer markets, and this trend is expected to continue in the near future. According to Canalys [235], GPS-enabled Smartphone shipments were 43.7% of all handset shipments in 2012, and its share in the handset market is expected to grow to 65.1% , which is 2.6 billion units, in 2016 worldwide. Particularly in Africa and Middles East, GPS-enabled Smartphone sales volume rate rises to 56% in 2013 where the rate of growth in Africa is almost two times higher than the global average growth rate [236]. In Ethiopia also, Hong Kong-based mobile manufacturer TECNO Mobile released its first assembled Amharic language based Smartphone in 2012 [237].

The best positioning accuracy for A-GPS is achieved in rural environment but in urban areas it is affected by shadow of high buildings. Hence supplementing A-GPS with inexpensive positioning method is preferable. In relation to this, the Integration of improved Cell-ID and A-GPS can provide adequate positioning estimation for vehicle location [35, 80].

Another option for Network-based, handset-based integration UE positioning is to use U-TDOA instead of Cell-ID. U-TDOA has better accuracy compared to Cell-ID as well as OTDOA and doesn't require the handset modification. Hence, the combination of U-TDOA and A-GPS for UE positioning for vehicle location provides better accuracy. The integration can be done in two ways. Both U-TDOA and A-GPS can simultaneously be used in vehicle location activity or by default A-GPS can be used and when not available the robust positioning technique U-TDOA would take over.

Based on what we have discussed above, the hybrid positioning methods combining U-TDOA and A-GPS is proposed for the implementation and collection of vehicle location using the cellular network infrastructure and also to perform a real-time road traffic state estimation based on the location measurements.

4.8.2 Cell Phone Mobility Classification

As it is presented in Section 4.3, several studies explored methods to use the cellular network to estimate road traffic flow and detect congestions. Most of these studies didn't discuss the technique applied to filter out the irrelevant data before feeding to estimation and prediction algorithms. But the data collected using the cellular network consists of various types of mobile carriers, carried by pedestrians, stationary phones, etc. However, our interest is to track terminals that are found in-vehicles travelling on the road network. Therefore, it requires pre-processing to identify the irrelevant traffic data from relevant data set.

Different terminal classification approaches like Naïve Bayes model, location registration scheme, speed, direction, location update interval, erraticity, fusion of speed, direction and location of terminal as it is discussed in Section 3.6.2, are proposed in the literature. However, as it is discussed in Section 1.5, the researcher couldn't access and collect anonymized location data of vehicles from the cellular network infrastructure. For our experiment U-TDOA based location estimates are gathered through simulation and for A-GPS based measurements, A-GPS mobile phone which is installed with JSR 179 API application software (see Section 5.3) reports its location to a server while moving in all journeys of a vehicle

Hence, in this research mobile classification was not needed as the subscribers about whom location measurements are gathered are known.

4.8.3 Map Matching Algorithms

Map matching is the process of determining the correct road link of a moving vehicle and locating its position on the link. Different algorithms are developed and published in the literature. These algorithms used position data and digital road map in the course of matching. Positioning technologies, for example the most used are GPS/DR, are indispensible to vehicle location activities. These technologies as well as the digital road map used during matching can affect the performance and accuracy of the map matching algorithms.

The simplest map matching algorithm is the geometric Point-to-Point and Point-to-Curve map matching algorithm. These algorithms don't use historical information about the vehicle and may result in mismatch. In Point-to-Curve matching, matched position can oscillate between two closely situated parallel roads especially in dense urban street networks.

Some of the drawbacks of the Point-to-Curve method can be solved by another geometric method known as Curve-to-Curve map matching algorithm. The Curve-to-Curve method matches the piecewise linear curve formed by the sequence of estimated positions to a piecewise linear curve corresponding to a path in the network based on their closeness or similarity. The drawback of this algorithm is that the vehicle heading is not considered.

Map matching algorithms that make use of the Point-to-Point, Point-to-Curve or Curve-to-Curve mapping can be improved by incorporating topological information such that only those road segments that are directly connected to the current road of travel are considered.

Probabilistic map matching algorithm is another approach that makes use of statistical error models of the positioning sensor to define a confidence region within which the true vehicle position may lie. In this algorithm, only roads that lie within this region are considered for map matching. Although these algorithms can recover from wrong matches quickly, they require more computation time. In dense urban road networks, it is difficult to precisely identify the road on which the vehicle is travelling. Hence, advanced map matching algorithms using concepts like Kalman filtering, particle filtering, fuzzy logic etc. are proposed.The map matching algorithm that enables to determine whether a vehicle is more likely to be on some roads and less likely to be on other roads is fuzzy logic based map matching algorithm. This algorithm can deal with ambiguous situations and support for decision making based on degree of ambiguity.

Performance of geometric, topological, probabilistic and fuzzy logic map matching algorithms are evaluated with respect to correct link identification, horizontal accuracy and along-track and cross-track errors and fuzzy logic map matching algorithm gives best result from all map matching algorithms evaluated on the same test road network based on GPS data [169]. Performance comparison between fuzzy logic and Hidden Markov model in terms of accuracy, computational time and implementation complexity is done using a GPS data on the same test road network for pedestrian navigation [101] and Hidden Markov model based map matching performs better in accuracy and computational time than fuzzy logic based although its implementation is complex.

From the map matching algorithms reviewed above; we can say all used GPS or integration of GPS and DR positioning technologies to evaluate performance of the algorithms. As it is proposed in Section 4.8.1, cellular network signaling particularly hybrid-Positioning (U-TDOA and A-GPS) is going to be used in this research work. Besides, road traffic flow information about every road link needs to be delivered to road users at real-time. The map matching algorithm that is effective and satisfies real-time requirements of our state estimation activity is geometric map matching. Hence, in this research point-to-curve map matching is applied to correct location/velocity deviation of vehicle from real trajectory due to location error.

4.8.4 Multi-Sensor Data Fusion

Data fusion is the process of combining measurements from multiple sensors. It enhances coverage, resolution, reliability and accuracy. Currently, two KF based data fusion algorithms are commonly applied in Military, Engineering and Biomedical researches. These algorithms are state vector fusion and measurement fusion. According to the literature, there is no definite evidence showing that any of these data fusion algorithms are suitable for road transport applications. But, as it is discussed in Section 4.5 some studies have recommended measurement fusion to be used in applications that use non-linear process data. Besides, all the literatures reviewed in Section 3.5 used IR, Radar and other diagnosis sensors to collect measurements. Only a few works employed cellular network positioning technologies where state vector fusion is simply picked and used for fusing the measurements.

Hence, as it is proposed in Section 4.8.1, hybrid of A-GPS and U-TDOA is going to be used in this research work. Since error due to positioning technology affects the performance of the selected data fusion algorithms, we proposed to perform an experiment on state vector fusion and measurement fusion algorithm using Hybrid-based vehicle position data and employ the better performing algorithm to develop hybrid mobile phone positioning and tracking scheme as well as in the road traffic state estimation process.

4.8.5 Road Traffic State Estimation

Traffic state estimation has become more important to our daily life particularly with the rise of urban development. It is essential for intelligent transportation system, dynamic vehicle navigation, traffic signal control, transit scheduling systems, vehicle emission monitoring, emergency dispatching services etc.

Advanced traveler information system (ATIS) is one of the most principal subsystems of intelligent transportation systems (ITS) that offer users integrated traveler information. One form of user's information presented is the real time traffic state which is also used by network operators as an indicator of quality of service. This raises the interest of estimating road traffic state with an acceptable degree of accuracy and travel times and average velocities have always been of great interest to researchers in order to estimate traffic sate of a road network. Model based and data driven approaches are the two methods researchers applied in road traffic state estimation. Depending on the detail level of traffic state estimation system, models like microscopic, macroscopic, mesoscopic or a hybrid of them are used in different literatures as a tool to properly estimate urban traffic flow. These model based traffic flow predictors enable to predict traffic condition for a certain number of time period ahead and also deduce average travel time from these predicted traffic flow conditions.

Some of the advantages of model based traffic flow prediction is that they are generic in which application even on routes with no detection equipment is possible. Model based approaches allow to include different traffic control measures like traffic light, traffic information and also the models can provide full insight about the location and causes of delays on the road network of interest. Major disadvantages, however, include computational complexity, the degree of expertise required for design and maintenance, and influence of the inputs and boundary conditions on the quality of traffic flow prediction.

The other road traffic state estimation technique is data driven model. The basic difference between data driven and model based approach is that data driven approaches consider the road traffic process generating travel times as black box. These approaches include the parametric techniques ARIMA, Kalman filter, linear and support vector regression model, time series model etc. and non-parametric methods like neural networks and various hybrid approaches for example neuro-fuzzy approaches or combination of different Artificial Neural Network topologies.

The clear advantages of data driven approaches are that they do not require extensive expertise on traffic flow modeling, they are fast and easy to implement, and specifically neural network approaches have proven accurate and reliable traffic predictors [44]. The major drawback of the data driven approaches including neural networks is that they are location specific, which means a solution that works well at one location may not work at all on the next.

In general, an elaborated discussion of model based and data driven approaches have been given with their advantages and disadvantages. Moreover, a comprehensive overview of existing urban short term road traffic state estimation approaches was presented. With the investigation made on the existing approaches, this dissertation adopts a hybrid method of combining artificial neural network (data driven) and a microscopic model (SUMO) to estimate urban road traffic flow condition.

4.8.6 Real-time Road Traffic State Estimation Framework

Road traffic state estimation is important for different activities of road transportation sector. Accurate road traffic state estimation depends on the data gathering technology used as well as the estimation model employed. Previous researches as it is discussed in Section 3.6 presented state estimation models utilizing measurements of GPS device and loop detectors. The application of the proposed models was not experimentally shown.

In this dissertation, the real-time road traffic state estimation framework is designed using the cellular network as a traffic data source. The framework is designed in line with road traffic state estimation procedures. As it is proposed in Section 4.8.5, the application of the framework is evaluated using a neural network estimator and the evaluation is done using both simulation and real world data.

Chapter Five: Hybrid Vehicle Positioning and Tracking Technique

5.1 Introduction

Mobile positioning technologies have drawn a significant amount of attention over the past few years. Different types of location-based services utilizing mobile positioning technologies have been proposed and studied, including the emergency 911 subscriber safety services and application to intelligent transport system. Due to the current emergent interests in location-based services, 3G and 4G cellular networks provide a key facility to locate the mobile phone. Vehicle positioning and tracking using a mobile phone traveling on-board the vehicle is one of the value added location-based services enabled by this feature and has been studied by different researchers. However, there is no single standard on mobile positioning technique that can provide better accuracy and coverage. Hence, tracking the position and velocity of in-vehicle mobile phone along the journey with appropriate accuracy and coverage is a challenge. To address this problem, in this chapter, we conducted an experiment on the hybrid mobile-phone based vehicle location solution proposed at the end of Chapter Two, i.e. hybrid scheme combining location estimates from UTDOA and A-GPS positioning methods in UMTS network. This chapter discusses the comparison of data fusion algorithms, proposed hybrid scheme utilizing a better performing data fusion algorithm, detail explanation on the positioning algorithms, and finally presents numerical results of the hybrid scheme evaluation.

Portions of this chapter entitled "Comparing Measurement and State Vector Data Fusion Algorithms for Mobile Phone Tracking Using A-GPS and U-TDOA Measurements." and "Hybrid U-TDOA and A-GPS for Vehicle Positioning and Tracking," is published on an international Conference on Hybrid Artificial Intelligence Systems, Springer International Publishing, 2015.

5.2 Comparing Performance of Measurement and State Vector Data Fusion Algorithms using A-GPS and U-TDOA Measurements

As it is discussed in Chapter Two Section 3.8.1, mobile positioning technologies in cellular networks can be either handset-based or network-based positioning. To improve positioning accuracy, coverage and communication latency of positioning technologies, combination of handset-based and network-based positioning techniques (in this research combination of U-TDOA and A-GPS) in association with data fusion technique has recently been proposed.

In relation to this, Section 4.5 discussed the different data fusion algorithms and presented literature reviews on the application of the algorithms. Later in Section 4.8.4, a recommendation was made to compare these two data fusion algorithms (Measurement Fusion and State Vector Fusion) using A-GPS and U-TDOA data and develop the hybrid positioning and tracking scheme based on the algorithm with better fusion performance.

The utilization of appropriate data fusion algorithm in combining measurements from multi-sensors improves accuracy and coverage [40]. Hence, to select a data fusion algorithm suitable to combine moving vehicle position measurements of A-GPS and U-TDOA positioning technologies, we experimentally compared fusion performance of state vector and measurement fusion algorithms.

5.2.1 State Vector Fusion

State Vector Fusion method uses a group of Kalman filters to obtain individual sensor based state estimates which are then fused to obtain an improved joint state estimate and associated covariance.

In this research work, we are interested to locate a mobile phone moving in all journey of a vehicle in 2D using A-GPS and U-TDOA UMTS positioning standards. The state-space model representing the continuous-time dynamics of the mobile phone is described as continuous White Noise Acceleration (WNA) model [238]. In this model, the state vector of the mobile phone is defined as:

$$\mathrm{X(t)} = [\mathrm{x(t)} \;\; \mathrm{y(t)} \;\; \dot{\mathrm{x}}\mathrm{(t)} \;\; \dot{\mathrm{y}}\mathrm{(t)}]^{\mathrm{T}} \tag{5.1}$$

The slight changes of the velocity of the mobile phone are modeled by continuous-time zero-mean white acceleration v (t) which is given as:

$$\ddot{\mathrm{x}}\mathrm{(t)} = \ddot{\mathrm{y}}\mathrm{(t)} = v(t) \;, \quad E[v(t)v^T(\tau)] = Q_c\delta(t-\tau) \tag{5.2}$$

where Q_c is power spectrum density

The continuous-time state equation of the model is expressed as:

$$\dot{x}(t) = A\,x(t) + v(t) \tag{5.3}$$

The discrete-time state equation form of equation (5.3) at sample time ΔT is given by:

$$X(k) = F\,X(k-1) + V(K-1) \tag{5.4}$$

The corresponding measurement equation is defined as:

$$Z(k) = H\,X(k) + W(K) \tag{5.5}$$

where k represents discrete-time index, X(k) is state vector, Z(k) is measurement vector, F is state transition matrix, H is observation transition matrix, V(k-1) and W(k) are zero-mean white Gaussian noise with covariance matrices Q(k) and R(k) respectively.

The KF provided recursive solution for state estimation of the linear system and the optimal state estimation with minimum variance as derived in [239, 240] is given as:

- State Estimate $\hat{X}_K^-$ (priori estimate) before we process the measurement Z_k at time K

$$\hat{X}_K^- = F\hat{X}_{k-1}^+ \tag{5.6}$$

- Covariance of the estimation error of $\hat{X}_K^-$ is P_K^- (priori covariance)

$$P_K^- = FP_{K-1}^+ \; F^T + Q \tag{5.7}$$

- Kalman Gain K_K, a correction term for next propagation step

$$\begin{aligned} K_k &= P_K^- H^T (HP_K^- H^T + R)^{-1} \\ &= P_K^+ H^T R^{-1} \end{aligned} \tag{5.8}$$

- State estimate $\hat{X}_K^+$ (posteriori estimate) after we process the measurement Z_k at time K

$$\hat{X}_K^+ = \hat{X}_K^- + K_K(Z_K - H\hat{X}_K^-) \tag{5.9}$$

- Covariance of the estimation error of $\hat{X}_K^+$ is P_K^+ (posteriori covariance)

$$P_K^+ = (I - K_K H)P_K^- \tag{5.10}$$

5.2.2 Measurement Fusion

Measurement fusion methods directly fuse the sensor measurements to obtain a weight or combined measurement and use a single Kalman filter to obtain the final state estimate based upon the fused observation. Measurement fusion can be done either by simply merging the sensor measurements (augmentation) or using minimum-mean-square-error estimate criterion. In this work, minimum-mean-square-error based fusion is used as it is more efficient than the first one and also, as it is recommended in [196], the dimensions of acquired measurements of A-GPS and U-TDOA positioning techniques is similar. Hence, the fused measurement Z_{MF} and the associated measurement noise covariance matrix $\hat{R}_{MF}$ are defined as:

$$Z_{MF}(k) = Z_{A-GPS}(K) + \hat{R}^{A-GPS}(\hat{R}^{A-GPS} + \hat{R}^{U-TDOA})^{-1}(Z_{U-TDOA}(K) - Z_{A-GPS}(K)) \tag{5.11}$$

$$= \frac{\hat{R}^{A-GPS} X_{U-TDOA}(K) + \hat{R}^{U-TDOA} X_{A-GPS}(K)}{\hat{R}^{A-GPS} + \hat{R}^{U-TDOA}}$$

$$\hat{H}_{MF} = \left[(\hat{R}^{A-GPS})^{-1} + (\hat{R}^{U-TDOA})^{-1}\right]^{-1} * \begin{bmatrix} (\hat{R}^{A-GPS})^{-1} H_{A-GPS} & + \\ (\hat{R}^{U-TDOA})^{-1} H_{U-TDOA} & \end{bmatrix} \tag{5.13}$$

$$\hat{R}_{MF} = \left[(\hat{R}^{A-GPS})^{-1} + (\hat{R}^{U-TDOA})^{-1}\right]^{-1} \tag{5.14}$$

where $X_{A-GPS}(K)$ is A-GPS measurement at time index k.

$X_{U-TDOA}(K)$ is U-TDOA measurement at time index k.

$\hat{R}^{A-GPS}$ is A-GPS measurement noise covariant matrix.

$\hat{R}^{U-TDOA}$ is U-TDOA measurement noise covariant matrix.

H_{U-TDOA} is U-TDOA measurement transition matrix

H_{A-GPS} is A-GPS measurement transition matrix.

The KF algorithm is computed and the state and corresponding covariance time propagation is given as follows.

- State Estimate $\hat{X}_K^{f-}$ (priori fused estimate) before we process the measurement $Z_{MF}(k)$ at time K

$$\hat{X}_K^{f-} = F\hat{X}_{k-1}^{f+} \tag{5.15}$$

- Covariance of the estimation error of $\hat{X}_K^{f-}$ is P_K^{f-} (priori fused covariance)

$$P_K^{f-} = FP_{K-1}^{f+} F^T + Q \tag{5.16}$$

- Fused Kalman Gain $K^f{}_K$ a correction term for next propagation step

$$K^{f}{}_{k} = P_K^{f-} \hat{H}_{MF}^{T} \ (\hat{H}_{MF} \ P_K^{f-} \hat{H}_{MF}^{T} + \hat{R}_{MF})^{-1}$$
$$= \ P_K^{f+} \hat{H}_{MF}^{T} R^{-1} \tag{5.17}$$

- State estimate $\hat{x}_K^{f+}$ (posteriori fused estimate) after we process the measurement $Z_{MF}(k)$ at time K

$$\hat{X}_K^{f+} = \hat{X}_K^{f-} + K^{f}{}_{K} (Z_{MF\,K} - \hat{H}_{MF} \hat{X}_K^{f-}) \tag{5.18}$$

- Covariance of the estimation error of $\hat{X}_K^{f+}$ is P_K^{f+} (posteriori fused covariance)

$$P_K^{f+} = (I - K^{f}{}_{K} \hat{H}_{MF}) P_K^{f-} \tag{5.19}$$

5.2.3 A-GPS and U-TDOA Measurements

A-GPS Measurement

A Java Specification Request 179 (JSR 179) Location Application Programming Interface (API) [241] is utilized (see appendix A) to periodically request location updates from A-GPS mobile phone. We conducted several field tests on Samsung android A-GPS mobile phone moving along all journey of a vehicle. The location updates sent to java application on the central server include latitude and longitude coordinates with their accuracy, the timestamp and speed of the mobile phone. The horizontal accuracy is the root mean square error (RMSE) of easting and northing errors (in meters, 1-sigma standard deviation). The location of A-GPS based in-vehicle mobile is collected in 13 minute trip in urban area of Addis Ababa and a total of 158 valid location updates were measured with in a time rate of 5 seconds in a sample trajectory shown in Figure 5.1.

The positioning error of A-GPS based mobile phone positioning method is obtained from the field test in the form of horizontal and vertical accuracy. The horizontal and vertical accuracy collected at each mobile phone location sample is the RMS composed of the northing (σ_N) and easting (σ_E) standard deviations [242]. Assuming the circular case ($\sigma_N = \sigma_E$), A-GPS based mobile phone location error is generated as Gaussian noise with variance $\sigma = (\mathrm{Acc}_k / \sqrt{2})^2$, where Acc represents the recorded horizontal accuracy at time t_k.

Figure 5.1. Sample trajectory taken from Addis Ababa for moving In-vehicle mobile phone used to collect its location based on A-GPS positioning method

U-TDOA Measurement

The U-TDOA based mobile positioning system determines the position of the mobile phone based on hyperbolic lateration. The hyperbolic lateration mobile phone position method is accomplished in two steps. The first one is the estimation of the time difference of arrival (TDOA) between receivers (Node Bs) through the use of time delay estimation technique. TDOAs are then transformed into range difference measurements between Node Bs to define hyperbolic curves which are then intersected to obtain an estimation position location of the user equipment. As it is illustrated in [243], the accuracy and performance of U-TDOA positioning method is influenced by factors like Signal to Noise Ratio (SNR), signal bandwidth, multipath, Geometric Dilution Of Precision (GDOP), number of measurement and integration time.

U-TDOA UE position estimation method is based on the estimation of the time difference in the arrival signal from the UE (source) to multiple NodeBs (receivers). Assuming that the UE and NodeBs are coplanar, the intersection of hyperbolas obtained as range difference of U-TDOA between UE and Node Bs results in position location estimate of the UE. The hyperbolic lateration is named to be trilateration [39] or hyperbolic position location [244] when the number of NodeBs is three.

Assume NodeB$_1$ received the transmitted signal and it is the one controlling the call. Let ($X_{U\text{-}TDOA}$, $Y_{U\text{-}TDOA}$) be the location of the UE and (X_i , Y_i) be the known location of the ith NodeB, where i= 2, 3, …M. A general model for the two dimension (2D) position location estimate for a UE using M NodeBs is the squared range distance between the ith NodeB and the UE and defined as [244]:

$$R_i = \sqrt{(X_i - X_{U-TDOA})^2 + (Y_i - Y_{U-TDOA})^2} \tag{5.20}$$

$$= \sqrt{X_i^{\,2} + Y_i^{\,2} - 2X_i X_{U-TDOA} - 2Y_i Y_{U-TDOA} + X_{U-TDOA}^{\;\;2} + Y_{U-TDOA}^{\;\;2}}$$

The range difference between NodeBs with respect to NodeB$_1$where the signal arrives first ($R_{i,1}$) is given as:

$$R_{i,1} = cd_{i,1} = R_i - R_1 \tag{5.21}$$

$$= \sqrt{(X_i - X_{U-TDOA})^2 + (Y_i - Y_{U-TDOA})^2} - \sqrt{(X_1 - X_{U-TDOA})^2 + (Y_1 - Y_{U-TDOA})^2}$$

where c is the signal speed ($3\text{x}10^8$ m/s), $R_{i,1}$ is the range difference distance between NodeB$_1$and the ithNodeB, R_1 is the distance between NodeB$_1$ and the UE, and $d_{i,1}$ is the estimated U-TDOA between the NodeB$_1$ and the ith NodeB.

This defines the set of non-linear hyperbolic equations whose solution gives the 2-D coordinates of the UE. Solving the non-linear hyperbolic equation (5.21) is difficult. Many methods have been proposed to solve such kind of non-linear hyperbolic equation. For example, Hamdey and

Mawjoud [243] have compared the three algorithms: Taylor-series expansion, Fang's Algorithm and Chan's algorithm based on complexity, accuracy and their performance limitations. Accordingly, Chan's algorithm gives exact solution and has better accuracy and less complex than Taylor-series and also when compared to Fang's algorithm, Chan's algorithm can support to take redundant measurement. Moreover, Chan's algorithm is a closed-form method, faster and developed for real-time implementation. It is also an approximation of the maximum likelihood estimator which consists of two-step least square (LS) [245]. Hence, Chan's algorithm is the best available option to solve U-TDOA equation [244]and it is employed to locate the UE using U-TDOA measurement.

To linearize equation (5.21), by rearranging the set of non-linear equations (5.21) can be transformed as follows.

$$R_i^2 = (R_{i,1} + R_1)^2 \tag{5.22}$$

Based on equation (5.22), equation (5.20) can be written as:

$$R_{i,1}^2 + 2R_{i,1}R_1 + R_1^2 = R_i^2 = X_i^2 + Y_i^2 - 2X_iX_{U-TDOA} - 2Y_iY_{U-TDOA} + X_{U-TDOA}^2 + Y_{U-TDOA}^2 \tag{5.23}$$

When we subtract equation (5.20) putting i=1 from equation (5.23), the resulting equation is:

$$(R_{i,1}^2 + 2R_{i,1}R_1 + R_1^2) - R_1^2 = (X_i^2 + Y_i^2 - 2X_iX_{U-TDOA} - 2Y_iY_{U-TDOA} + X_{U-TDOA}^2 + Y_{U-TDOA}^2) -$$
$$(X_1^2 + Y_1^2 - 2X_1X_{U-TDOA} - 2Y_1Y_{U-TDOA} + X_{U-TDOA}^2 + Y_{U-TDOA}^2)$$

$$R_{i,1}^2 + 2R_{i,1}R_1 = X_i^2 + Y_i^2 - 2X_{i,1}X_{U-TDOA} - 2Y_{i,1}Y_{U-TDOA} - (X_1^2 + Y_1^2) \tag{5.24}$$

Where $X_{i,1}$is (X_i-X_1) and $Y_{i,1}$ equals (Y_i-Y_1). Equation (5.24) is a set of linear equation with the unknown UE location ($X_{U\text{-}TDOA}$, $Y_{U\text{-}TDOA}$) and R_1which is the distance between the UE and NodeB1 to be solved.

Following the Chan's method [245], for a three NodeB systems (M=3), producing two U-TDOA's, $X_{U\text{-}TDOA}$ and $Y_{U\text{-}TDOA}$ can be solved in terms of R_1 from equation (5.24). The solution is in the form of:

$$\begin{bmatrix} X_{U-TDOA} \\ Y_{U-TDOA} \end{bmatrix} = -\begin{bmatrix} X_{2,1} Y_{2,1} \\ X_{3,1} Y_{3,1} \end{bmatrix}^{-1} \times \left\{ \begin{bmatrix} R_{2,1} \\ R_{3.1} \end{bmatrix} R_1 + \frac{1}{2} \begin{bmatrix} R_{2,1}{}^2 - K_2 + K_1 \\ R_{3,1}{}^2 - K_3 + K_1 \end{bmatrix} \right\} \tag{5.25}$$

where $K_1 = X_1^2 + Y_1^2$, $K_2 = X_2^2 + Y_2^2$, $K_3 = X_3^2 + Y_3^2$

When equation (5.25) is inserted into equation (5.20) with i = 1, a quadratic equation in terms of R_1 is produced. Substituting the positive root back into equation (5.25) results in the final solution. There may exist two positive roots from the quadratic equation that can produce two different solutions resulting in an ambiguity. This problem has to be resolved by using a priori information like value of R_1 can't be negative or root values can't be larger than cell radius.

For four or more NodeB systems ($M \geq 4$), there will be more measurements of U-TDOA's than number of unknowns. Hence the original set of non-linear U-TDOA equations are transformed into another set of linear equations with extra variables. Applying weighted linear least square method repeatedly, an improved position estimate can be acquired. The error vector φ using U-TDOA noise can be derived from equation (5.24) and represented as:

$$\varphi = h - G_a Z_a^0 \tag{5.26}$$

where $Z_a^0 = [X_{U-TDOA} \; Y_{U-TDOA} \; R_1]^T$ which is noise free value.

$$h = \begin{bmatrix} R_{2,1}^2 - X_2^2 - Y_2^2 + X_1^2 + Y_1^2 \\ R_{3,1}^2 - X_3^2 - Y_3^2 + X_1^2 + Y_1^2 \\ \vdots \quad \vdots \quad \vdots \\ R_{M,1}^2 - X_M^2 - Y_M^2 + X_1^2 + Y_1^2 \end{bmatrix}$$

$$G_a = -\begin{bmatrix} X_{2,1} & Y_{2,1} & R_{2,1} \\ X_{3,1} & Y_{3,1} & R_{3,1} \\ \vdots & \vdots & \vdots \\ X_{M,1} & Y_{M,1} & R_{M,1} \end{bmatrix}$$

and the error vector φ is assumed to be normally distributed Gaussian random vector with covariance matrix ψ given by:

$$\psi = E\left[\varphi\varphi^T\right] = c^2 BQB \tag{5.27}$$

where, $B = \mathrm{diag}\{R_2^0, R_3^0, \ldots, R_M^0\}$, $Q = \hat{R}^{U-TDOA} = diag\{\sigma_{2,1}^2, \sigma_{3,1}^2, \cdots, \sigma_{M,1}^2\}$ U-TDOA measurement noise covariant matrix

Still equation (5.26) is non-linear because of elements of Z_a and solving this equation is possible after applying two step procedures. The first one is to assume elements of Z_a are independent and the first–step Least Square (LS) solution of equation (5.26) together with the imposition of the relationship of elements of Z_a in equation (5.20) to the result via another LS computation provides true Maximum Likelihood (ML) estimate of Z_a and given as:

$$\begin{aligned} Z_a &= \arg\min\{(h - G_a Z_a)^T \psi^{-1} (h - G_a Z_a)\} \\ &= (G_a^T \psi^{-1} G_a)^{-1} G^T \psi^{-1} h \end{aligned} \tag{5.28}$$

This equation is a generalized LS solution of equation (5.26). To make equation (5.28) solvable, further approximation is necessary and an approximation of equation (5.28) is:

$$Z_a \approx (G_a^T Q^{-1} G_a)^{-1} G^T Q^{-1} h \tag{5.29}$$

The solution given by equation (5.28) assumes that X_{U-TDOA}, Y_{U-TDOA} and R_1 are independent. However they are related by equation (5.20). Hence incorporating this relationship enables to get improved estimate and defined as:

$$Z_a' = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{bmatrix}^T (\psi')^{-1} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{bmatrix} \right\}^{-1} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{bmatrix}^T (\psi')^{-1} \begin{bmatrix} Z_{a,1}^2 \\ Z_{a,2}^2 \\ Z_{a,3}^2 \end{bmatrix} \tag{5.30}$$

where, $$\psi' = E[\varphi\varphi^T] = 4\begin{bmatrix} Z_{a,1} & & \\ & Z_{a,2} & \\ & & Z_{a,3} \end{bmatrix} \operatorname{cov}(Z_a) \begin{bmatrix} Z_{a,1} & & \\ & Z_{a,2} & \\ & & Z_{a,3} \end{bmatrix} \quad (5.31)$$

The result $Z_a' = \left[X_{U-TDOA}\ Y_{U-TDOA}\ R_1\right]^T$ represents the mobile phone position estimation.

5.2.4 Experimentation Result

To compare the performance of the proposed data fusion algorithms using A-GPS and U-TDOA location measurements of a moving in-vehicle mobile phone, random vehicle route /trajectory on a typical urban area is generated on MATLAB based on the dynamic model represented by equation (5.3). Observation of real vehicle speeds in urban traffic road reveal that the model is practical and motion of vehicles can be modeled as Gaussian Process [238]. Considering typical vehicle motion in urban traffic road [246], average speed of 50 Km/hr. (15m/s) and mean acceleration of 1m/s^2 are applied in the simulation. According to McGuire and Plataniotis [238], the UE acceleration process is a zero-mean Gaussian process with variance σ^2 in both x-and y-coordinate directions with magnitude of Rayleigh distributed random variable with mean of $\sigma\sqrt{\pi/2}$. Hence, the value of σ^2 (i.e., Q_c in 5.2) is estimated as $2*\bar{a}^2/\pi$. Then using equation (5.5), noisy location observations based on measurement noise covariance of U-TDOA, A-GPS and their fusion (based on SF and MF algorithms) are generated along the simulated trajectory.

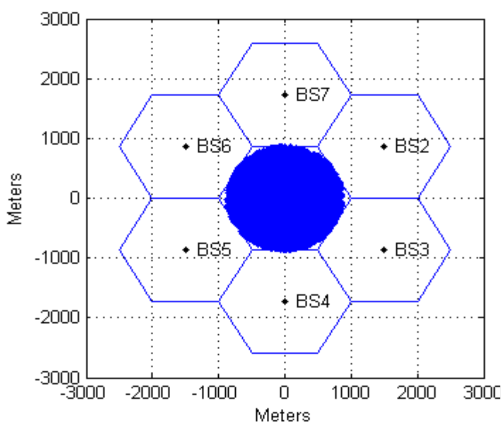
To generate UE position estimations based on U-TDOA positioning technique, a network of 7 NodeBs which include serving NodeB and other 6 neighboring NodeBs is created in a hexagonal cells with radius 1Km on MATLAB as depicted in Figure 5.2 (a).The position coordinates of NodeBs are (0,0), (1500,866),(1500,-866),(0,-1732),(-1500,-866),(-1500,866) and (0,1732). Then true position estimate of UE is generated at every 1000 Monte Carlo run. Assuming U-

TDOA based estimation noise is unbiased Gaussian, location estimation error, which is calculated using Root Mean Square Error (RMSE) , is the squared distance of the estimation to the true UE location and it is given as [240]:

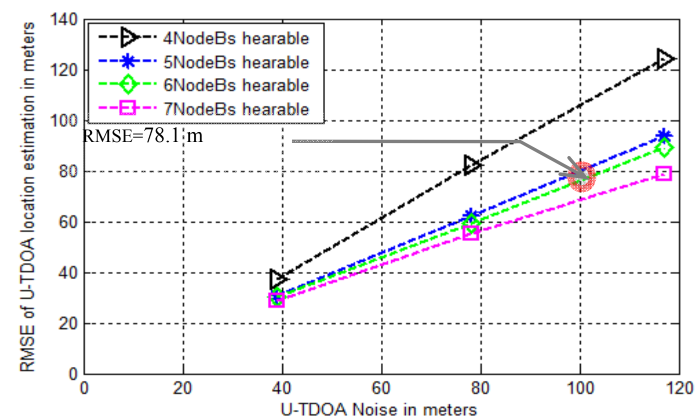
$$\mathrm{RMSE} = \sqrt{\frac{1}{mc}\sum_{k=1}^{mc}(Pos_k^{U-TDOA} - Pos_k^{True})^T(Pos_k^{U-TDOA} - Pos_k^{True})} \quad (5.32)$$

where mc is total number of Monte Carlo performed, $Pos_k^{U-TDOA} = [X^{U-TDOA} \;\; Y^{U-TDOA}]^T$ and for each grid point ,1000 independent Monte Carlo runs are computed.

To determine position estimate of UE, different number of NodeBs ranging from 4 to 7 are chosen to perform UE positioning simulation as shown in Figure 5.2 (b). Assuming signal and noise at each NodeBs is white random process [245], the RMSE of U-TDOA estimation is obtained at noise values of 39m, 78m and 117m which are 0.5, 1 and 1.5 chip periods in UMTS networks. As it can be seen in Figure 5.2(b), positioning accuracy increases with an increase of participating NodeBs. In the case of 7NodeBs, the UE position accuracy is the highest.



(a)



(b)

Figure 5.2 U-TDOA based UE position estimation, (a) Mobile Network Cell Regions and UE distribution (b) Influence of NodeBs number in UE positioning accuracy.

But RMSE of 78.1m (as it is indicated in Figure 5.2(b) where 6NodeBs are hearable with U-TDOA noise of 100m is selected in this simulation. This is because U-TDOA timing measurement accuracy is 3.84Mchips/sec which is 78.125m [247] and measurements in [247] demonstrated that at this estimation noise the positioning accuracies for the probability of 67% and 95% of the calls meet the requirement of E-911.

Hence, using variances of U-TDOA based mobile phone position estimation and A-GPS based mobile phone location measurement, sample mobile phone trajectory together with the generated noisy U-TDOA based mobile phone estimation and A-GPS based mobile phone measurement are generated as depicted in Figure 5.3.

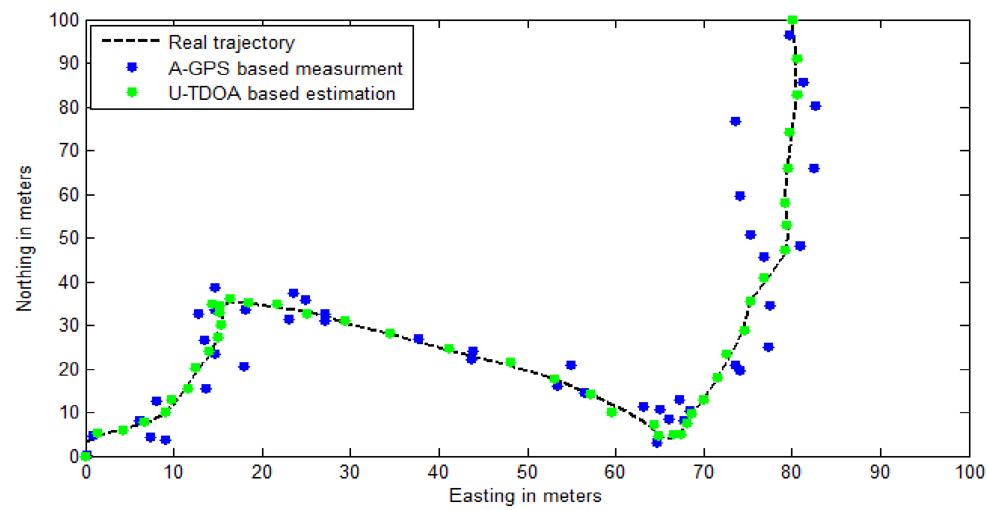


Figure 5.3, Real Mobile phone trajectory vs. the generated A-GPS and U-TDOA based locations.

To perform the tracking activity based on the two data fusion algorithms, initial conditions for KF are determined. According to McGuire and Plataniotis[238],good selection of initial condition for filters is essential for tracking algorithms. Accordingly, the position estimates are initialized by first locations measurements of A-GPS and U-TDOA-based mobile phone positioning. The initial velocity estimates are zeros as at t_0 there is no location information. Initial variances for U-TDOA is based on Cramer-Rao Lower Bound (CRLB) which is derived from [245], for A-GPS based estimates, it is the statistical mean from the accuracy of test data and for velocity estimates, the initial variance is taken based on the fact that initial velocity is between ± 15 m/s.

Filtering on a sample trajectory, the position estimation results are depicted along the trajectory as shown in Figures 5.4 (a), (b), (c) and (d).

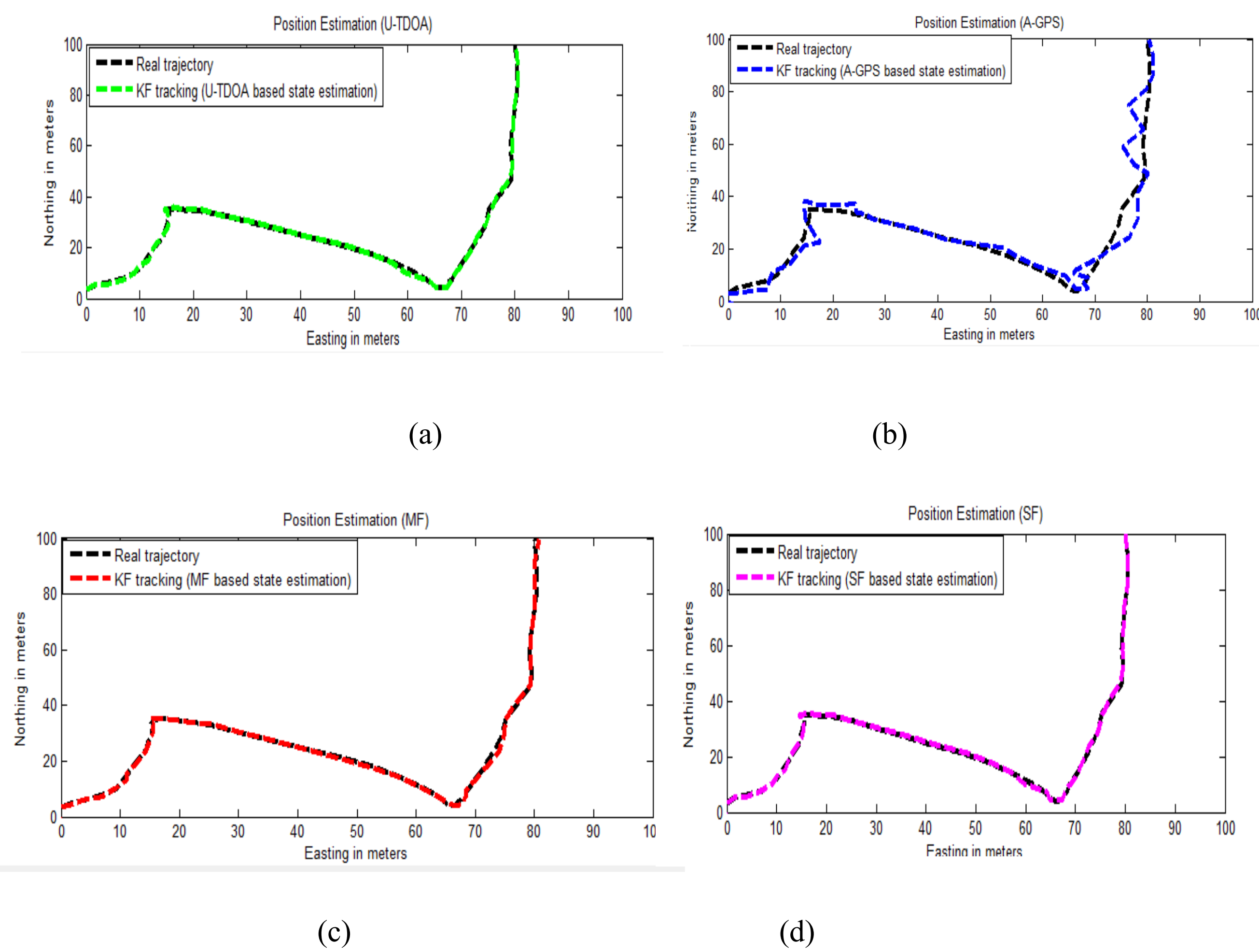
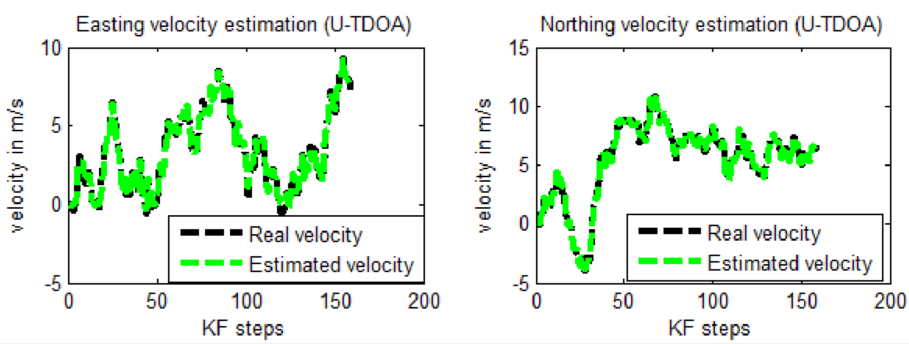


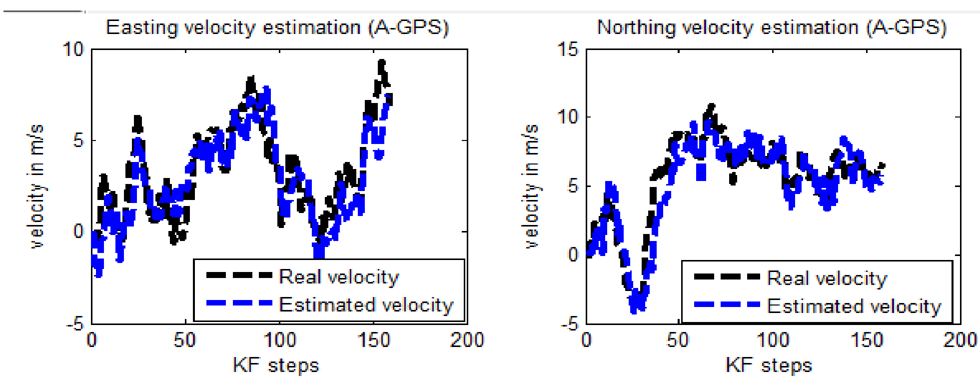
Figure 5.4 Kalman Filter tracking of actual and estimated position for a moving in-vehicle mobile phone on a sample trajectory using U-TDOA, A-GPS measurements, and their fused form using MF and SF algorithms.

As it can be seen from Figure 5.4, KF based tracking of MF algorithm, Figure 5.4 (c), and SF algorithm, Figure 5.4 (d), show better match to the real sample trajectory than the individual measurements. However, MF algorithm has better proximity to the real trajectory than SF algorithm as numerical comparison based on mean and standard deviation of RMSE of position and velocity of these algorithms is shown in table 5.1.

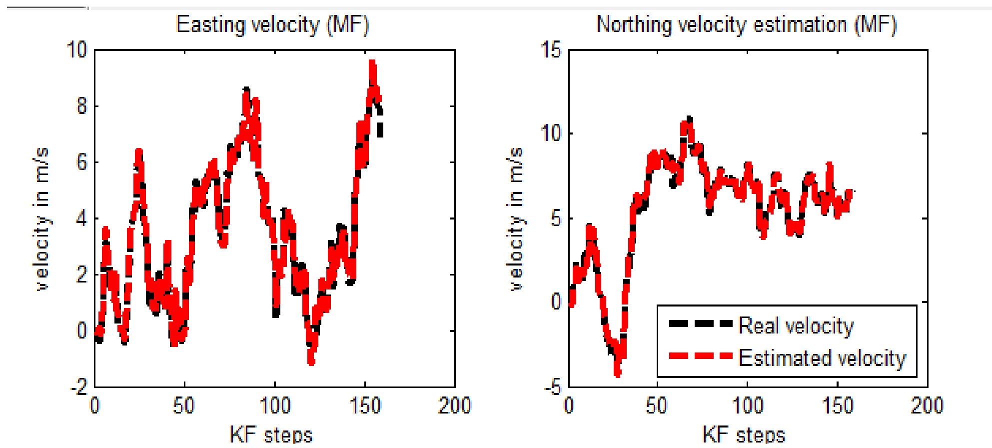
The mobility model applied is White Noise Acceleration (WNA) as described in Section 5.2.1 (see detail explanation in Section 5.3.4) , Kalman filter of real and estimated velocities for each of the noisy measurement and their fusion based on MF and SF algorithms are illustrated in Figure5.5 (a), (b), (c) and (d). Based on the analysis on the figures, the velocity estimates based on fusion data algorithms (MF and SF) are with better match to the real velocity than the velocity estimates of U-TDOA and A-GPS and MF algorithm provides comparatively acceptable velocity estimation accuracy than SF estimation.



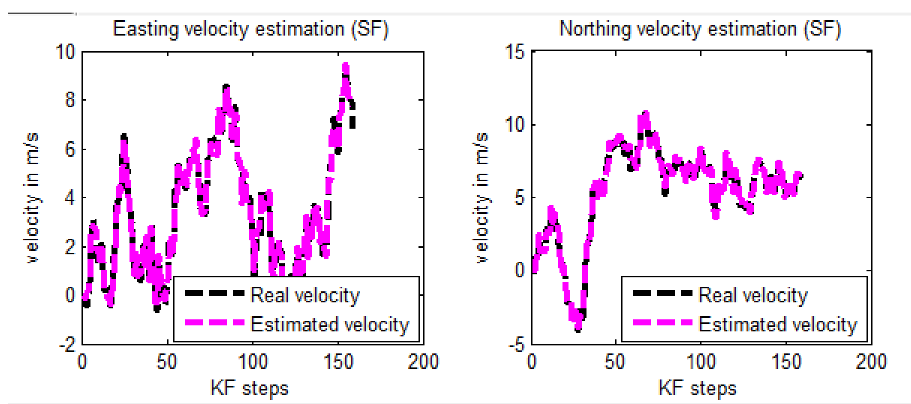
(a)



(b)



(c)



(d)

Figure 5.5. Kalman Filter tracking of actual and estimated velocities for a moving in-vehicle mobile phone on a sample trajectory using U-TDOA, A-GPS measurements and their fused form using MF and SF algorithms.

To further compare estimation performance of U-TDOA, A-GPS and their fusion based on MF and SF algorithms, RMSE of 1000 different sample trajectories where each is filtered at 158 Kalman Filter steps is computed. The RMSE used for performance metrics is defined as [36]:

$$\mathrm{RMSE}_{\mathrm{position}} = \sqrt{\frac{1}{kf}\sum_{k=1}^{kf}[(X_k - \hat{X}_k)^2 + (Y_k - \hat{Y}_k)^2]} \tag{5.33}$$

$$\mathrm{RMSE}_{\mathrm{velocity}} = \sqrt{\frac{1}{kf}\sum_{k=1}^{kf}[(\dot{X}_k - \hat{\dot{X}}_k)^2 + (\dot{Y}_k - \hat{\dot{Y}}_k)^2]} \tag{5.34}$$

where, kf is total number of Kalman filter steps, $[X_k \quad Y_k \quad \dot{X}_k \quad \dot{Y}_k]^T$ and $[\hat{X}_k \quad \hat{Y}_k \quad \hat{\dot{X}}_k \quad \hat{\dot{Y}}_k]^T$ are real and state estimation at filter step k respectively.

The sample mean (μ_{RMSE}) from RMSE of position and velocity is calculated on these 1000 different sample trajectories generated and filtered with 158 filter steps each. As it is shown in Table 5.1, position and velocity estimation accuracy of MF algorithm is better than SF algorithm.

Table 5.1 Sample mean and standard deviation of position and velocity estimation using RMSE for MF and SF based Hybrid UE positioning methods

	$RMSE_{position}$		$RMSE_{velocity}$	
	$\mu_{RMSE\,1000traj.}$	$\sigma_{RMSE\,1000traj.}$	$\mu_{RMSE\,1000traj}$	$\sigma_{RMSE\,1000traj.}$
U-TDOA	22.9695	3.2589	3.4611	0.5016
A-GPS	48.1372	3.6992	7.5482	0.6478
MF	19.5369	2.9142	2.7244	0.4493
SF	21.4497	3.2023	2.9871	0.4887

To conclude, comparison between the state vector fusion and measurement fusion algorithms using a real-world A-GPS and simulation-based U-TDOA data is made. In this experimentation-based comparison, the performance analysis made on the estimation accuracy of position and velocity revealed that MF algorithm is performing better than SF algorithm in aligning the estimate values to the real position and velocity of mobile phone moving in all journey of the vehicle as mean of RMSE for MF is smaller than that of SF. Hence, to develop hybrid positioning scheme and also perform road traffic state estimation activity of this research, measurement fusion algorithm is employed.

5.3 Measurement Fusion-Based Hybrid Positioning and Tracking Scheme

To develop a hybrid positioning and tracking scheme, in addition to selecting appropriate type of data fusion algorithm, the choice of multi-sensor data fusion architecture is an important issue. This is due to the fact that data fusion architecture can affect the quality of fused result, nature of algorithm to be used, complexity of processing logic and communication bandwidth between the sensors and fusion processing component [194]. There are three basic multi-sensors data fusion architecture approaches: centralized, distributed and hybrid. Currently, there exist two commonly used centralized multi-sensor data fusion methods for Kalman filter including centralized measurement fusion and centralized state-vector fusion [49]. The centralized measurement fusion method directly fuses measurements or observations to obtain merged or weighted measurements and then use Kalman filter to find final state estimate based on fused measurement. Whereas, centralized state-vector fusion method use a group of local Kalman filters to obtain individual sensor based state estimates which are then fused to get improved joint estimate. In this research, centralized measurement fusion architecture is used and the hybrid positioning and tracking scheme based on centralized measurement fusion architecture is depicted in Figure 5.6.

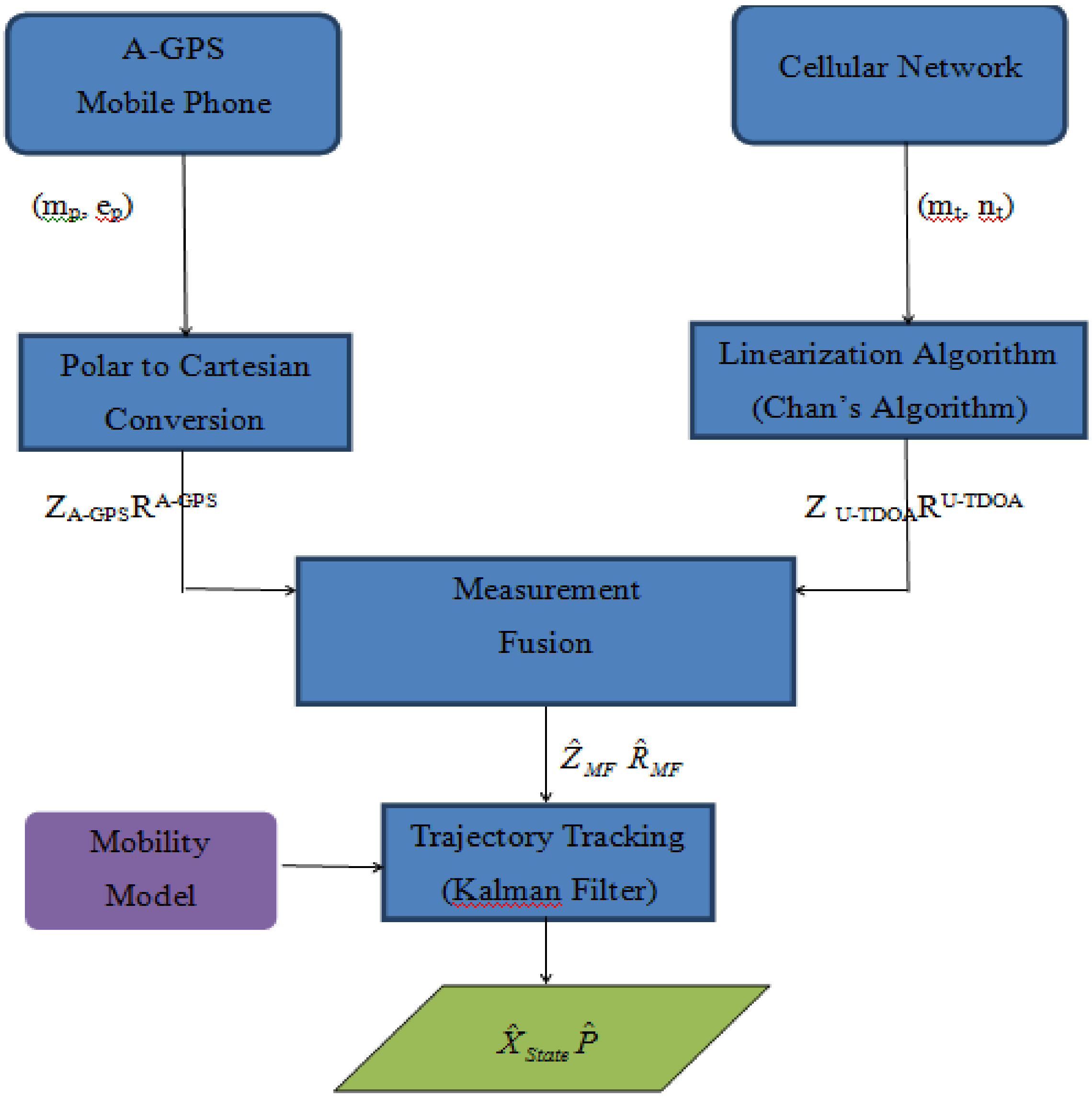


Figure 5.6 Flow chart for the hybrid positioning and tracking scheme

5.3.1 A-GPS and U-TDOA Measurements

As it is discussed in detail in Section 5.2.3, to gather A-GPS-based measurements, A-GPS mobile phone installed with JSR 179 location API software (see appendix A) and moving in all journey of the vehicle is used. The JSR 179 location API software periodically requests the location updates from the mobile phone and reports to a central server. This software provides two dimensional (2D) geographic coordinates of the mobile position $\mathbf{m_p} = [p_{lat} \;\; p_{lon}]^T$ together with horizontal accuracy $\mathbf{e_p}$. The location updates sent to java application on the central server include latitude and longitude coordinates with their accuracy, the time-stamp and speed of the mobile phone.

To gather U-TDOA-based measurements simulation experiment is applied. For the experiment, a network of 7 NodeBs, which include serving NodeB and other 6 neighboring NodeBs, is created in a hexagonal cells with radius1Km on MATLAB as depicted in Figure 5.2.Then true position estimate $\mathbf{m_t}$ of mobile phone is generated at every 1000 Monte Carlo run based on WCDMA network parameters and the U-TDOA measurement noise $\mathbf{n_t}$ is found based on zero-mean Gaussian random variable.

5.3.2 Location Estimation and Noise Variance

The geographic coordinates of the mobile position $\mathbf{m_p} = [p_{lat}\ \ p_{lon}]^T$ are converted to the Cartesian coordinate $\mathbf{Z_{A\text{-}GPS}} = [x_{lat}\ \ y_{lon}]^T$. The horizontal accuracy $\mathbf{e_p}$ is related to the variance $R^{A\text{-}GPS}$ of measurement noise. The time measurement using U-TDOA is converted into hyperbolic equations and these equations are solvedto get mobile location estimation result $\mathbf{Z_{U\text{-}TDOA}} = [x_{U\text{-}TDOA}\ \ y_{U\text{-}TDOA}]^T$ (see section 5.2.3 for detail explanation). The variance $R^{U\text{-}TDOA}$ represents the estimation uncertainty.

5.3.3 Fusion of the Measurements

Centralized measurement fusion is done by fusing the measurements $\mathbf{Z_{A\text{-}GPS}}$ and $\mathbf{Z_{U\text{-}TDOA}}$ to new fused measurement $\hat{Z}_{MF} = [\hat{x}_{MF}\ \ \hat{y}_{MF}]^T$. Weighted least square criterion is applied to determine the measurement fusion result including the covariance $\hat{R}_{MF}$. The fused measurement

$\hat{Z}_{MF}$ and the associated measurement noise covariance matrix $\hat{R}_{MF}$ are defined in equation (5.11)-(5.14) in Section 5.2.2.

5.3.4 Position and Velocity State Estimation

This subsection discusses location and velocity estimations of the moving in-vehicle UE using Kalman Filter (KF) from the fused measurement $\hat{Z}_{MF}$. To determine all possible states of the moving in-vehicle UE on the road network, the mobility model applied is also described.

Mobility Models

Mobility models represent a state-space model that describes the motion of user equipment located in a road vehicle. A state-space model represents the time evolution of the system state of the user equipment in terms of differential equation in continuous-time but inputs change at discrete-time observed (measured) instances which are modeled as sample-data systems [239]. In general, a state-space representation of continuous-time dynamics can be written as:

$$\dot{x}(t) = A(t)x(t) + B(t)u(t) + v(t) \tag{5.35}$$

where x is state vector , u is input control vector

v is process noise vector , A is transition/system matrix

B is input gain at continuous-time

The solution of x (t) at some arbitrary time t_k is given as:

$$x(t_k) = e^{A\Delta t}\, x(t_{k-1}) + \int_{t_{k-1}}^{t_k} e^{A(t_k-\tau)}[B(\tau)\, u(\tau) + v(\tau)]\, d\tau \tag{5.36}$$

If $F_k = e^{A\Delta t}$ and $G_k = \int_{t_{k-1}}^{t_k} e^{A(t_k-\tau)} B(\tau)\, d\tau$ then equation (5.36) becomes

$$x(t_k) = F_{k-1}x\,(t_{k-1}) + G_{k-1}xu\,(t_{k-1}) + \int_{t_{k-1}}^{t_k} e^{A(t_k-\tau)} v\,(\tau) d\tau \tag{5.37}$$

The covariance of the state is defined as:

$$P_k = E[(x_k - \bar{x}_k)(x_k - \bar{x}_k)^T] \tag{5.38}$$

If we assume the process noise entering the state equation (5.36) is zero-mean continuous white noise, its covariance is written as:

$$E[v(t)v^T(\tau)] = Q_c\delta(t-\tau)\text{, where } Q_c \text{ is power spectrum density} \tag{5.39}$$

Vehicle Motion Kinematics

Kinematic state models are defined by setting certain derivative of the position zero and if there is no random input, the motion is characterized by a polynomial in time [248]. Several kinematic models are available for tracking maneuvering and non-maneuvering targets. However, simplified state estimation kinematic models like White Noise Acceleration (WNA),the Wiener process acceleration (WPA), and the Keplerian State (KPS) model are preferable for state estimation with short observation periods as these models are effective in reducing complexity, delay of tracking algorithm with small or no loss in estimation accuracy [51].

Both WNA and WPA models are widely used in estimating state of moving targets because of the less complexity compared to KPS model [51] . But WNA is commonly used for tracking non-maneuvering targets whose motions deviate little from the straight line path and with low initial measurement accuracy WNA and WPA models are very consistent when compared to KPS [241]. Hence, in this research work, the moving user equipment located in a road vehicle is modeled as a dynamic linear system driven by continuous white noise acceleration. Consequently, continuous-time equation is written first and by applying discretization, discrete-time transition equation is expressed. Assume the user equipment located in a vehicle is moving in 2D Cartesian coordinate system. The state vector of the moving user equipment is defined as:

$$X(t) = [x(t) \;\; y(t) \;\; \dot{x}(t) \;\; \dot{y}(t)]^T \tag{5.40}$$

where, $x(t)$ and $y(t)$ are user equipment locations, $\dot{x}(t)$ and $\dot{y}(t)$ are velocities of the moving user equipment.

The motion of the moving user equipment is described as continuous White Noise Acceleration (WNA) model [248]. In this model the velocity, although assumed constant, has slight changes and it can be modeled by continuous-time zero-mean white acceleration v (t) as:

$$\ddot{x}(t) = \ddot{y}(t) = v(t) \tag{5.41}$$

The continuous-time state equation ofthe model is expressed as:

$$\dot{x}(t) = Ax(t) + v(t) \tag{5.42}$$

i.e.

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \ddot{x} \\ \ddot{y} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ n_1 \\ n_2 \end{bmatrix} \tag{5.43}$$

After discretization, the discrete-time state equation with sampling period ΔT in the sample-data system is given as:

$$X(k+1) = F\,X(k) + V(K) \tag{5.44}$$

With the transition matrix

$$F = e^{A\Delta t} = \begin{bmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.45}$$

and the process noise vector $V(K)=[0\ 0\ v(k)\quad v(k)]^T$ has a covariance given as

$$Q = E[V(k)V(k)^T] = \begin{bmatrix} \frac{1}{3}\Delta T^3 & 0 & \frac{1}{2}\Delta T^2 & 0 \\ 0 & \frac{1}{3}\Delta T^3 & 0 & \frac{1}{2}\Delta T^2 \\ \frac{1}{2}\Delta T^2 & 0 & \Delta T & 0 \\ 0 & \frac{1}{2}\Delta T^2 & 0 & \Delta T \end{bmatrix} Q_c \tag{5.46}$$

Where Q_c is process noise intensity whose choice should follow the guideline that the changes in the velocity over a sampling period Tare of the order $\sqrt{Q_{22}}=\sqrt{Q_c T}$ and should be small relative to the actual velocity level [248].

Measurement Models

The discretized version of the state vector (5.20) is related to the location observation Y(k) by the measurement equation defined by:

$$Z(k) = H\,X(k) + W(K) \tag{5.47}$$

Where $H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$, which takes the measurement observation not the velocity and the measurement noise vector W (k).

The measurement noise can be modeled as:

$W(k) = \begin{bmatrix} w(k) \\ w(k) \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} R & 0 \\ 0 & R \end{bmatrix}\right)$, where R = $\delta_x = \delta_y$ is the measurement error variance. It is assumed that the variances in both x and y directions are the same and independent.

KALMAN Filter

To Track the user equipment moving in entire journey with the vehicle at real-time, discrete-time Kalman filter (KF) is used for A-GPS and U-TDOA based noisy location measurements. The KF provided recursive solution for state estimation of the linear system described by (5.24) and (5.27). These transition and measurement equations can simply be written as:

$$\begin{cases} X_k = FX_{k-1} + V_{k-1} \\ V_{k-1} \sim N(0,Q) \end{cases} \tag{5.48}$$

$$\begin{cases} Z_k = HX_k + W_k \\ W_k \sim N(0,R) \end{cases} \tag{5.49}$$

where, Q and R are covariance matrices for process noise vector V_{k-1} and the measurement noise vector W_k respectively. The optimal state estimations with minimum variance as derived in [248] and [239] are given as follows.

- State Estimate $\hat{X}_K^-$ (priori estimate) before we process the measurement Z_k at time K

$$\hat{X}_K^- = F\hat{X}_{k-1}^+ \tag{5.50}$$

- Covariance of the estimation error of $\hat{X}_K^-$ is P_K^- (priori covariance)

$$P_K^- = FP_{K-1}^+ \ F^T + Q \tag{5.51}$$

- Kalman Gain K_K a correction term for next propagation step

$$\begin{aligned} K_k &= P_K^- H^T (HP_K^- H^T + R)^{-1} \\ &= P_K^+ H^T R^{-1} \end{aligned} \tag{5.52}$$

- State estimate $\hat{X}_K^+$ (posteriori estimate) after we process the measurement Z_k at time K

$$\hat{X}_K^+ = \hat{X}_K^- + K_K(Z_K - H\hat{X}_K^-) \tag{5.53}$$

- Covariance of the estimation error of $\hat{X}_K^+$ is P_K^+ (posteriori covariance)

$$P_K^+ = (I - K_K H)P_K^- \tag{5.54}$$

The matrices F, Q, H and R are defined before tracking the moving user equipment starts. Hence, equations (5.51), (5.52) and (5.54) can be evaluated offline and this feature favored a real-time moving user equipment tracking application.

5.4 Evaluation of the Hybrid Mobile Phone Positioning and Tracking Scheme

The proposed hybrid In-Vehicle mobile phone positioning and tracking scheme depicted in Figure 5.6 is evaluated using simulation of a typical vehicle motion in urban area on MATLAB. In the simulation, first a random vehicle route /trajectory is generated based on the dynamic model represented by equation (5.3). Observation of real vehicle speeds in urban traffic road reveal that the model is practical and motion of vehicles is modeled as Gaussian Process[238]. Considering the typical vehicle motion in urban traffic road[246], average speed of 50 Km/hr. (15m/s) and mean acceleration of $1m/s^2$ are applied in the simulation. According to McGuire and Plataniotis [238], the UE acceleration process is a zero-mean Gaussian process with variance σ^2 in both x-and y-coordinate directions with magnitude of Rayleigh distributed random variable with mean of $\sigma\sqrt{\pi/2}$. Hence, the value of σ^2 (i.e., Q_c in equation (5.46)) is estimated as $2*\bar{a}^2/\pi$. Then, using equation (5.47), noisy location observations using measurement noise covariance of U-TDOA, A-GPS and their measurement fusion are generated along the simulated trajectory.

Sample UE trajectory together with the generated noisy U-TDOA-based UE estimates, A-GPS based UE measurement and their fusion measurement using the described model are generated as depicted in Figure 5.7.

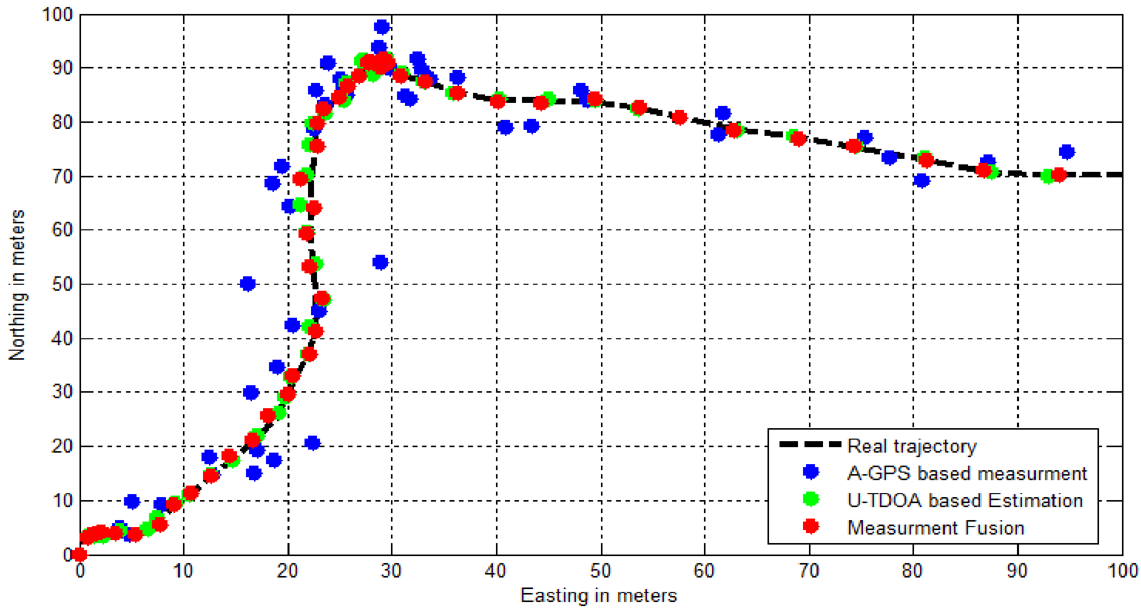


Figure 5.7: Real UE Trajectory vs. the generated A-GPS, U-TDOA and MF based locations

Discrete Kalman filter (described in Section5.3.4) is applied to truck the moving in-vehicle UE at real-time for each of the noisy location measurements. According to McGuire and Plataniotis[238], good selection of initial condition for filters is essential for tracking algorithms. Accordingly, in this simulation for the KF, the position estimates are initialized by first locations measurements of A-GPS and U-TDOA based UE positioning. The initial velocity estimates are zeros as at $t_0$there is no location information. Initial variances for U-TDOA is based on Cramer-Rao Lower Bound (CRLB) which is derived from [245], for A-GPS based estimates, it is the statistical mean from accuracy of test data and for velocity estimates the initial variance is taken based on the fact that initial velocity is between ± 15 m/s. Filtering on a sample trajectory, the position estimation results are depicted along the trajectory as shown in Figure 5.8 (a), (b) and (c).

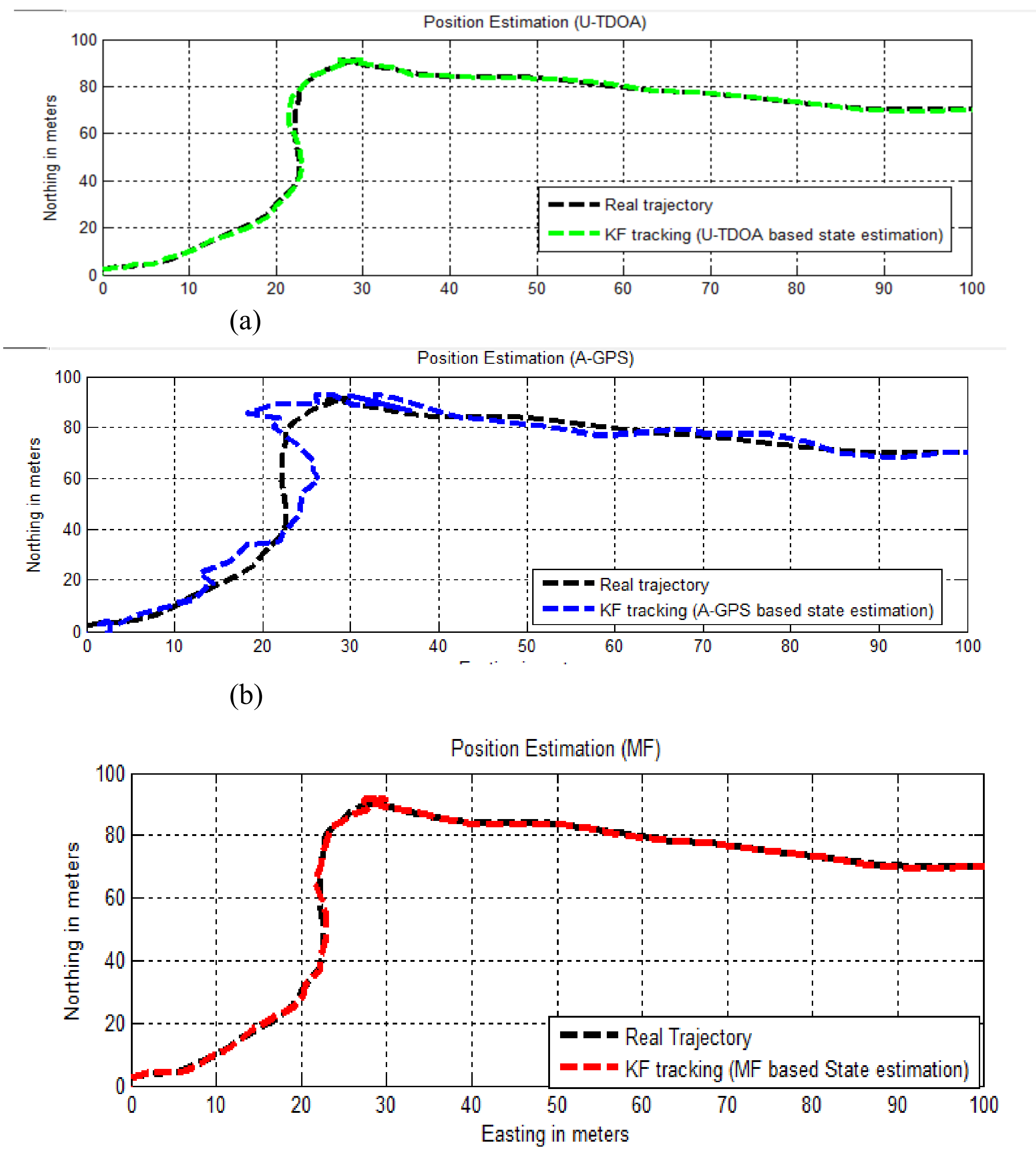
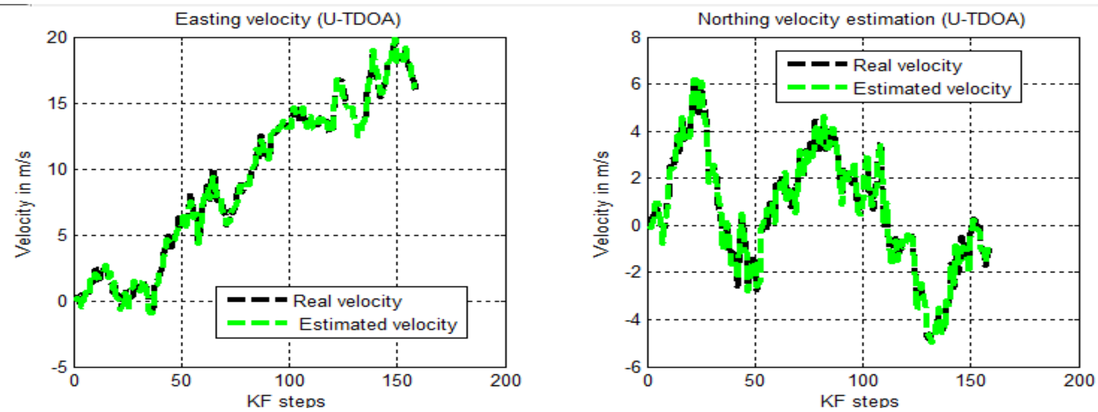


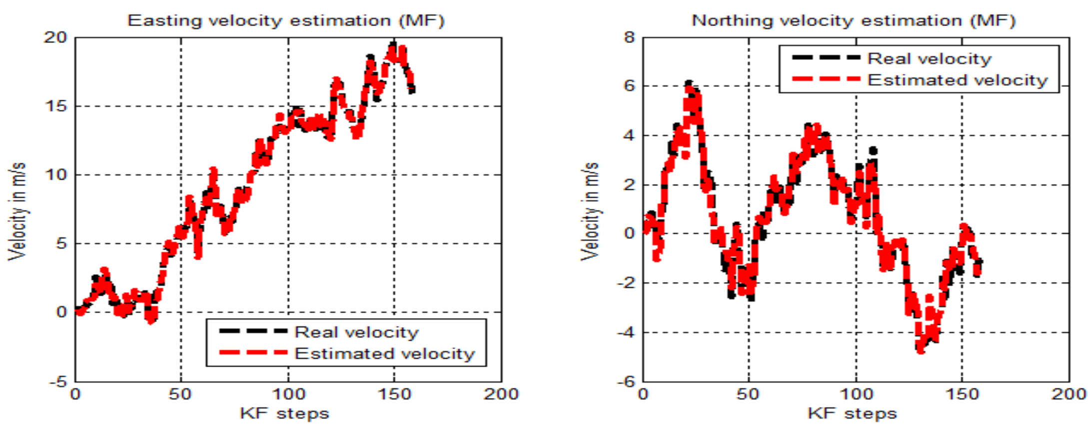
Figure 5.8: Kalman Filter tracking of moving in-vehicle UE on a sample trajectory using U-TDOA, A-GPS and hybrid (Measurement Fusion) methods, actual and estimated position.

As it can be seen from Figure 5.8, the tracking of the hybrid state estimation, Figure 5.8 (c), shows better match to the real sample trajectory.

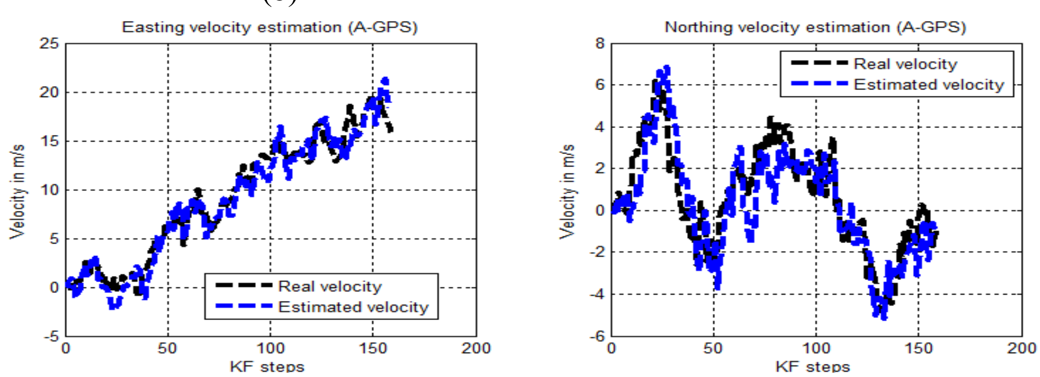
Because the mobility model applied is White Noise Acceleration (WNA) as described in Section 5.3.4, Kalman Filter of real and estimated velocities for each noisy measurement is illustrated in Figure 5.9(a), (b) and (c).



(a)



(b)



(c)

Figure 5.9 Kalman Filter tracking of moving in-vehicle UE on a sample trajectory using U-TDOA, A-GPS and hybrid (Measurement Fusion) methods, actual and estimated velocities

As it is shown in Figure 5.9 (c), the estimated velocity of moving in-vehicle UE matches with the actual velocity and we can say the hybrid positioning method (MF) is better from U-TDOA and A-GPS UE positioning methods.

To compare the estimation accuracy of U-TDOA, A-GPS and the Hybrid (MF) methods, RMSE of 1000 different sample trajectories with 158 Kalman Filter each is computed and totally took 6 min. The RMSE used for performance metrics is defined as [36]:

$$\text{RMSE}_{\text{position}} = \sqrt{\frac{1}{kf}\sum_{k=1}^{kf}[(X_k - \hat{X}_k)^2 + (Y_k - \hat{Y}_k)^2]} \tag{5.55}$$

$$\text{RMSE}_{\text{velocity}} = \sqrt{\frac{1}{kf}\sum_{k=1}^{kf}[(\dot{X}_k - \hat{\dot{X}}_k)^2 + (\dot{Y}_k - \hat{\dot{Y}}_k)^2]} \tag{5.56}$$

Where kf is total number of Kalman filter steps, $[X_k \quad Y_k \quad \dot{X}_k \quad \dot{Y}_k]^T$ and $[\hat{X}_k \quad \hat{Y}_k \quad \hat{\dot{X}}_k \quad \hat{\dot{Y}}_k]^T$ are real and state estimation at filter step k respectively.

The sample mean (μ_{RMSE}) and standard deviation (σ_{RMSE}) from RMSE of position and velocity is calculated based on 1000 different sample trajectories generated and filtered with 158 filter steps each. As it is shown in Table 5.2, the performance of the Hybrid (MF) UE positioning method is better from A-GPS and U-TDOA methods with minimum estimation error of position and velocity (μ_{RMSE}=21.9301m, μ_{RMSE}=3.3089 m/s) and the error is less dispersed (σ_{RMSE}=2.9142m, σ_{RMSE}=0.4493m/s).

Table 5.2: Sample mean and standard deviation of position and velocity estimation using RMSE

	$RMSE_{position}$		$RMSE_{velocity}$	
	$\mu_{RMSE\,1000traj.}$	$\sigma_{RMSE\,1000traj.}$	$\mu_{RMSE\,1000traj}$	$\sigma_{RMSE\,1000traj.}$
U-TDOA	24.1355	3.2589	3.5592	0.5016
A-GPS	47.9638	3.6992	7.1873	0.6478
MF	21.9301	2.9142	3.3089	0.4493

To compare the positioning accuracy of the positioning methods U-TDOA, A-GPS and the Hybrid MF with respect to the E-911 requirements specified in[249], cumulative distribution function (CDF) curves under the estimation errors of 1000 sample generated trajectories which independently filtered at 158 KF steps are drawn. According to the analysis in Figure 5.10 (a) & (b), in urban environment the network based positioning method U-TDOA and the handset based positioning method A-GPS meets the E-911 requirement.

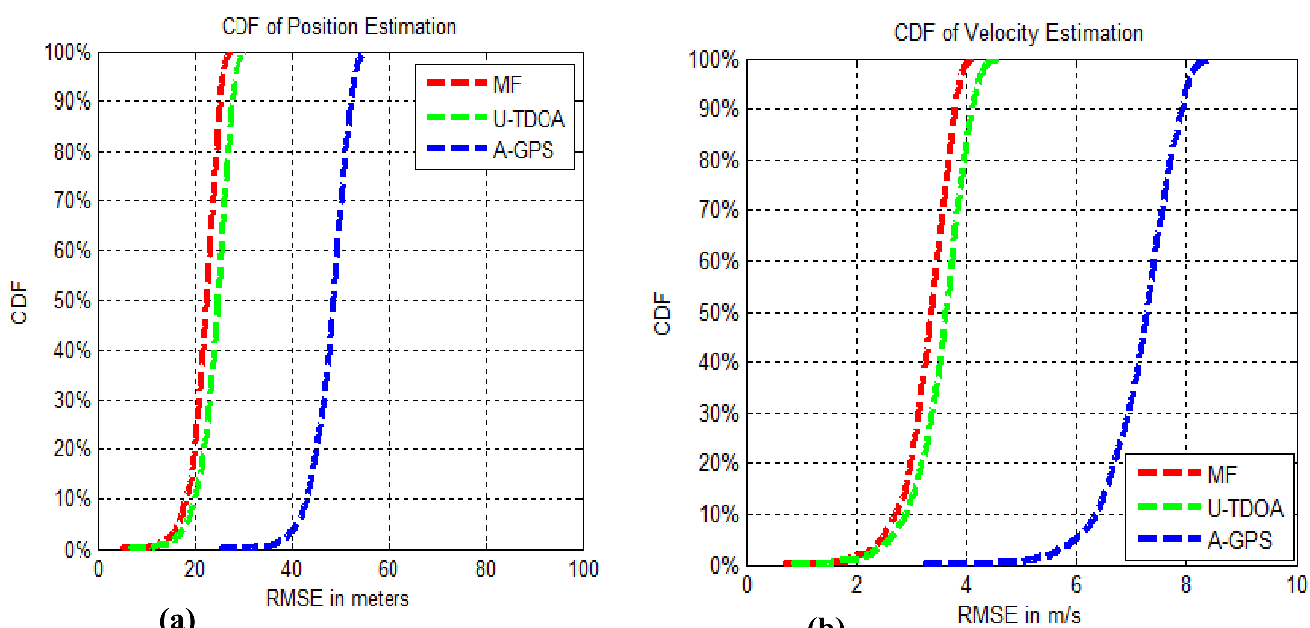


Figure 5.10: CDF of position and velocity estimation based on RMSE of U-TDOA, AGPS and MF

5.5 SUMMARY

Hybrid UE-based Vehicle position and tracking based on the UE moving along all journey of the vehicle has been implemented and simulated based on the suggestion made at the end of Chapter Three. To develop the hybrid positioning and tracking scheme selection of appropriate data fusion algorithm as well as fusion architecture was necessary. Accordingly, the experimentation made in comparing state vector fusion and measurement fusion algorithms showed that MF is better to estimate position and velocity of a mobile phone moving together in all journey of a vehicle. Besides, statistical computation made on estimation error on RMSE of 1000 independently generated trajectories proved that MF-based hybrid positioning method is better than SF-based hybrid UE positioning method. Thus, MF is recommended to be used in developing the hybrid scheme as well as other activities of this research. Moreover, to get fused results of UE position estimation from the network-based positioning method-U-TDOA and handset-based positioning A-GPS, centralized measurement fusion architecture is applied.

To generate noisy location measurements along a sample trajectory based on U-TDOA, A-GPS and MF measurement noise variances, dynamic white Noise Acceleration (WNA) model is employed. Kalman filter is used to track the position and velocity state estimations of U-TDOA,A-GPS and MF-based measurements. The evaluation of the hybrid positioning scheme indicated that MF-based measurements are with better match to real trajectory than the individuals. Moreover, computing RMSE of estimation errors with 1000 independent sample trajectories with a filter of 158 filter points each revealed that MF-based UE position estimations are with less sample mean estimation error and less dispersed than U-TDOA as well as A-GPS based positioning methods.

Hence, the dynamic model of vehicle kinematics and Kalman Filter position and velocity tracking algorithms developed are used in the next chapter in estimating real-time urban traffic condition.

Chapter Six: Urban Road Traffic State Estimation using In-Vehicle Mobile Phones as a Probe

6.1 Introduction

With rapid increase of urban development and vehicle number increase, estimation of road traffic flow condition becomes more important particularly these days to our daily life than ever before. Real-time road traffic flow information is utilized for various purposes such as dynamic route guidance, incident detection, vehicle emission monitoring and it is also useful for successful deployment of Intelligent Transport System (ITS) applications-Advanced Traffic Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS). Particularly, ATMS and ATIS need accurate real-time road traffic flow information and short term traffic state estimation of the future for smooth traffic flow [250] and to deliver integrated road traffic flow information to road users.

Road traffic state estimation comprises different activities, road traffic data collection is the primary step and also backbone in estimating urban road traffic flow. Traffic flow information can be obtained using different road traffic surveillance technologies. These technologies can be either fixed sensor technologies or mobile probe-based road traffic surveillance technologies.

As it is discussed in Chapter Three, fixed sensor technologies can support to gather spot road traffic data which can't reflect road traffic flow of the entire network. Besides, these technologies can't be deployed to cover wide area road network due to maintenance cost.

Mobile probe-based road traffic surveillance technologies are alternatives to this luxury, fixed road side infrastructures. Mobile probe-based road traffic surveillance systems collect and process road traffic data locating the vehicle via GPS (Floating vehicle technologies) or mobile phones over the entire road network [75]. Floating vehicle technologies also provide limited sample size [29] and the data collected can't be representative for all vehicles on the entire road network [30].

Contrary to fixed sensor technologies and floating vehicle technologies, using the existing cellular network infrastructure to gather road traffic data offers large coverage capability as traffic data can be obtained continuously and also it is faster to set up, easier to install and needs less maintenance [31].

Mobile positioning technologies which aim to collect road traffic data in cellular networks can be either handset-based or network-based. Each of these positioning technologies can't provide an improved positioning accuracy and area coverage simultaneously.

Thus, to improve positioning accuracy, coverage and communication latency of positioning technologies, combination of handset-based and network-based positioning techniques (Hybrid of A-GPS and U-TDOA) has been proposed in Chapter Three Section 3.8.1 and the performance of the hybrid positioning technology using measurement fusion algorithm is evaluated and meet E-911 estimation accuracy requirement as it is discussed in Chapter Five Section 5.3.

Once traffic data for moving vehicles on urban roads is gathered, the next step is the estimation of road traffic flow status for every road link of the entire road network. Over the years, variety of traffic state like travel time and traffic flow estimation models have been developed. But, existing road traffic state estimation techniques can be either model based or data driven based approach [116]. As it is discussed in Chapter Three Section 3.8.5, hybrid method of combining Artificial Neural Network (data driven approach) and the microscopic simulation model SUMO (model based approach) is proposed to be used in estimating road traffic flow on sample road networks of Addis Ababa city, Ethiopia. The proposed road traffic state estimation method is used to evaluate a real-time road traffic state estimation framework which is developed based on the estimation procedures.

Hence, in this chapter, a real-time road traffic state estimation framework that utilizes the existing cellular network infrastructure for road traffic data collection with a neural network model estimator is presented and discussed. To evaluate the framework, a hybrid method of combining a three-layer Artificial Neural Network model and the microscopic simulation model SUMO is used.

Portion of this chapter entitled "Road Traffic state estimation framework based on hybrid assisted global positioning system and uplink time difference of arrival data collection methods," is published on AFRICON, 2015, IEEE, 2015.

Portion of this chapter entitled "Cellular Network Based Real-Time Urban Road Traffic State Estimation Framework Using Neural Network Model Estimation," is published on Computational Intelligence, 2015 IEEE Symposium Series on IEEE, 2015.

Portion of this chapter entitled "A Neural Network Model for Road Traffic Flow Estimation," is published on Advances in Nature and Biologically Inspired Computing, Springer International Publishing, 2016. Pp. 305-314.

This chapter is published as book chapter entitled "Artificial Neural Network Based Real-Time Urban Road Traffic State Estimation Framework" on a book of title "Computational Intelligence in Wireless Sensor Networks," Springer International Publishing AG 2017.

6.2 Road Traffic Sate Estimation System

The core milestones of real-time road traffic state estimation based on cellular network signaling include location data collection, mobile phone mobility classification, map matching and route determination, road traffic condition estimation and dissemination of traffic information to road users. In line with this, the architecture for road traffic flow estimation system consists of three layers [251, 226, 44]. The data collection layer is responsible to collect real-time location data of vehicles on the road and send the data to the next layer- estimation server. The road traffic state estimation layer does the data preprocessing, updates data to the database server, estimates real-time traffic flow and provide the information to road users on mobiles or on to the Internet. The third layer, database server, stores digital map which is used for road traffic state estimation and information dissemination processes.

In this dissertation, we build our real-time road traffic state estimation framework based on road traffic state estimation procedures discussed in Chapter Four where the cellular network is used as the source of road traffic data. This framework, depicted in Figure 6.1, does not restrict the models and methods to be applied, for example, the proven hybrid A-GPS, U-TDOA data collection systems only. This is because in the last twenty years, with the advancement of Information and Communication Technologies, gradual shift was observed toward traffic data collection systems that collect both individual as well as aggregate properties of traffic streams over space. Examples include floating car data collection systems, cellular network based location data collection systems and video-based traffic data collection systems. Hence, the framework presented in Figure 6.1 is a general framework for urban road traffic state estimation. As it is indicated in Figure 6.1, the framework has five basic components

6.2.1 Traffic Data Collection Component

This component represents the data sources which provide real-time road traffic measurements on the basis of which real-time road traffic flow condition is estimated. As it is indicated in the framework, the cellular network is used as road traffic data source where road traffic data can be gathered. For example, in our research, the UMTS cellular network positioning standards, Assisted Global Positioning System (A-GPS) and Uplink Time Difference of Arrival (U-TDOA) were used to gather real-time road traffic data like speed, location and time-stamp of a moving vehicle on a traffic road.

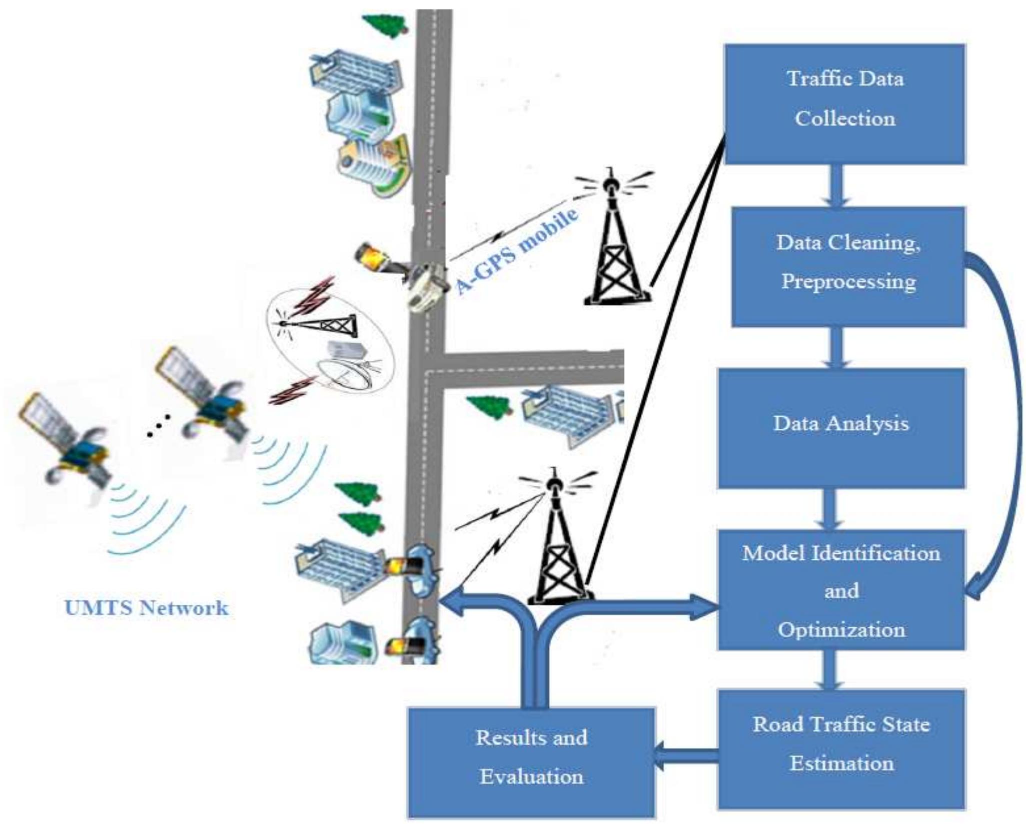


Figure 6.1: General Framework for Short term urban road Traffic State Estimation

As it is discussed in Chapter Five, after cleaning and preprocessing of the collected road traffic data , measurement fusion algorithm, which is found to be superior from state vector fusion particularly to combine measurements of vehicles on the road, is employed to get a hybrid based measurement and the experiment done on the positioning accuracy of the cellular network revealed that reliable road traffic data with acceptable accuracy (i.e., with in the E-911 requirement) can be gathered using the existing cellular network infrastructure as road traffic data source.

6.2.2 Data Cleaning and Preprocessing

Usually the raw traffic sensor data is not good enough to use it directly for road traffic management activity. Primarily, data cleaning activities enable to remove abnormal data including abnormal velocity, wrong direction and time duplication. Then other preprocessing activities like data checking, data completion and data correction will be performed [44]. Besides, when In-vehicle mobile phones are used as traffic probes, activities like mobility classifications and map matching are done during the preprocessing phase. For example, as it is explained in Chapter Five, traffic data is collected based on the UMTS cellular network positioning method of A-GPS and U-TDOA positioning methods. Preprocessing activities like coordinate transformation of A-GPS measurements, linearization of U-DOA based traffic data, classification, map matching and fusion of the measurements were done in this module of the framework as it is depicted in Figure 6.2.

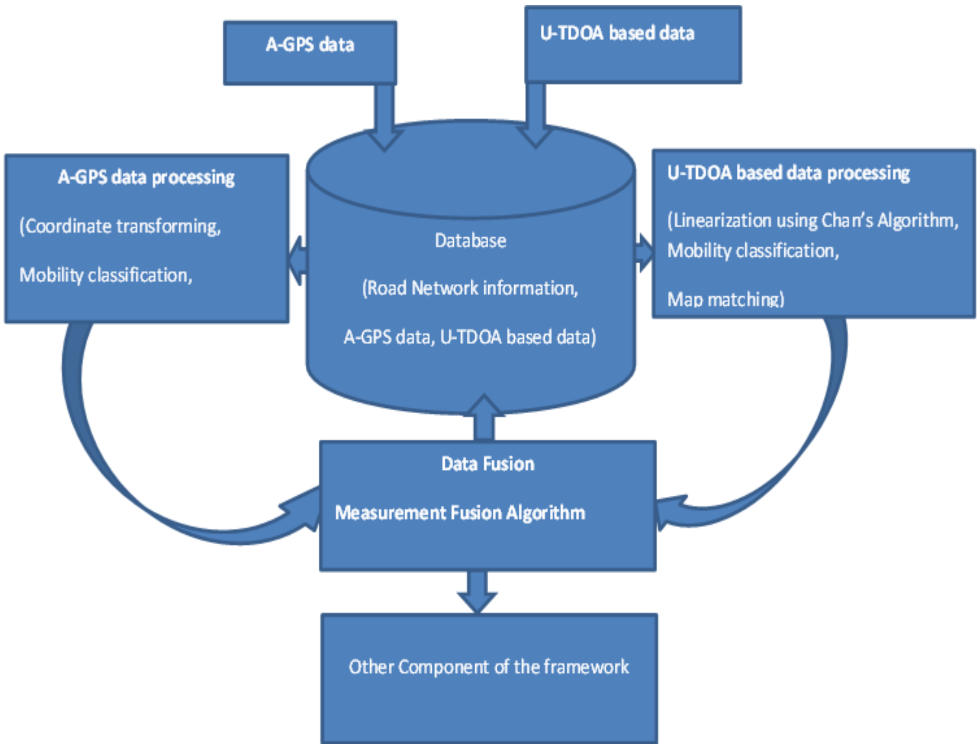


Figure 6.2 Preprocessing activities on Fusion based A-GPS, U-TDOA-based traffic data

6.2.3 Data Analysis

This component of the framework represents the statistical activities performed for data sampling from raw traffic sensor data which was cleaned and preprocessed using appropriate techniques/procedures. For acceptable quality of urban road traffic state estimation with probe based monitoring, the percentage of vehicles/mobile serving as traffic probe, i.e. penetration rate is with high concern [252,253]. Accordingly, mobile probe based urban freeway traffic monitoring can provide sufficient data when the penetration rate is from 3% to 5%. Though the minimum sample size of probe vehicles is dependent on factors like road type, link length and sample frequency [254], for arterial roads' reliable speed estimation, a minimum penetration rate of 7%, i.e. at least 10 probe vehicles traversing a road section (every road link) successfully is required [252, 253,254].

The other crucial issue in road traffic state estimation using mobile phones as traffic probes is the sampling frequency. For example, A-GPS mobile phones receive location updates at every 1-3 seconds and collection of data from large number of mobile probes may cause network carrier congestion. To solve this problem, three approaches are proposed: temporal (report vehicle information at prescribed time), spatial (probes send information when passing predefined location) and pinpoint method (report based on vehicle velocity change rate) [226].

The above sampling frequency approaches, temporal and spatial can't necessarily help to collect useful data for traffic state estimation. Pinpoint method is useful in addressing problem of these methods but it may not enable to collect sample size data as the probe is forced to report vehicle information only when the velocity change rate value is large. Hence, in this dissertation, we propose a dynamic "Pinpoint-Temporal" sampling frequency method which is a combination of pinpoint and temporal. In this method, the required sample size data incorporating vehicle information at change of state points is collected.

During sampling, to avoid road traffic state estimation biases due to sampling frequency, the initial sampling time-stamp is not taken to be fixed as the vehicle could be anywhere while sampling. Figure 6.3 explains pinpoint-temporal sampling strategy. For example, if the initial sampling time-stamp is i, and sampling time-stamp interval is 10 seconds, then the next temporal sampling frequencies will be $i+10$, $i+20$, $i+30$ etc. Combining pinpoint with this temporal strategy, the points where the data recording takes place are depicted in Figure 6.3.

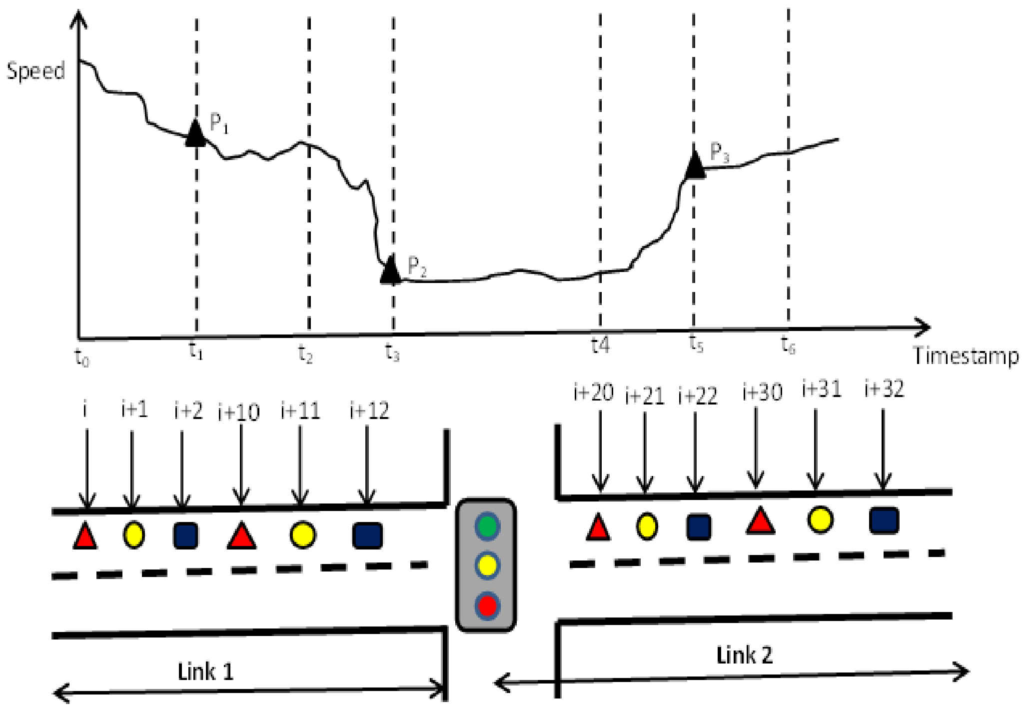


Figure 6.3, Pinpoint-Temporal sampling based vehicle information recording at different links

As it is indicated in Figure 6.3, different combinations of temporal sampling frequencies with different initials like i, i+1, i+2,etc. could improve road traffic state estimation accuracy [255]. In the process, the vehicle change state points, p_1, $p_2$and p_3 unless repeated, will be considered in the sample.

6.2.4 Model Identification and Optimization

This component of the proposed real-time road traffic state estimation framework represents appropriate approaches used to estimate road traffic sate with acceptable accuracy. Current practices of road traffic state estimation techniques applied include either model based or data driven approaches [116] . However, as it is discussed in Chapter Three Section 3.8.5, no single predictor had yet been developed that presented itself to be universally accepted as the best, and at all times, an effective traffic state forecasting model for real-time traffic operation . Hence, selection of appropriate methodological approach is a major issue in traffic state estimation [135]. Thus, for this research hybrid method of combining Artificial Neural Network (data driven approach) and the microscopic simulation model (model based approach) is proposed to be used in estimating road traffic flow on sample road networks of Addis Ababa (see detail in Chapter Three Section 3.8.5).

Artificial Neural Network Model for Urban Arterial Road Traffic State Estimation

Different types of artificial neural networks (ANN) have been proposed in the past few years for estimation purpose. The most popular connected multilayer perceptron (MLP) neural network architecture is chosen in this study as it is extensively applied in transportation applications, has very good capability, and easy to implement so long as there are enough neurons in the hidden layer [256]. The architecture of ANN is composed of a set of nodes and connections organized in layers. In this dissertation, a three layer ANN is used: input layer, hidden layer and output layer. The input layer enables to receive external information and the output layer is the layer where problem solution is acquired. Usually, one or two hidden layers are used between the aforementioned layers but single hidden layer is proved to be enough for ANNs to estimate non-linear functions [256]. It is the hidden nodes in the hidden layer that allow the neural network to detect the feature to capture the pattern in the data, to perform non-linear mapping between input and output variables.

As it is discussed in subsection 6.2.1, the cellular network is used as road traffic data source and the data collected based on mobile phones as probes contain vehicle position, time-stamp and vehicle speed on the road link. Hence, position, time-stamp and speeds are used as input data in the ANN model. The structure of the ANN model, which is experimentally proved with different traffic demand including 20% demand increase, 50% demand increase and 100% demand increase, is utilized from Zheng and Zuylen [255] as shown in Figure 6. 4. According to the author, the accuracy of the ANN model is sensitive to position input whereas the speed input is not crucial factor influencing the ANN performance.

The mathematical model for the input layer, hidden layer and output layer is as follows.

Input layer

$$\text{x (i)} = \begin{bmatrix} x_1(i) \\ \vdots \\ x_n(i) \end{bmatrix} = \begin{bmatrix} p(i) \\ r(i) \\ t(i) \\ v(i) \end{bmatrix},\ p(i) = \begin{bmatrix} p_1(i) \\ \vdots \\ p_n(i) \end{bmatrix},\ r(i) = \begin{bmatrix} r_1(i) \\ \vdots \\ r_n(i) \end{bmatrix},\ t(i) = \begin{bmatrix} t_1(i) \\ \vdots \\ t_n(i) \end{bmatrix},\ v(i) = \begin{bmatrix} v_1(i) \\ \vdots \\ v_n(i) \end{bmatrix} \quad (6.1)$$

where p(i) is position vector, r(i) is link id vector, t(i) is time-stamp vector and v(i) is speed vector

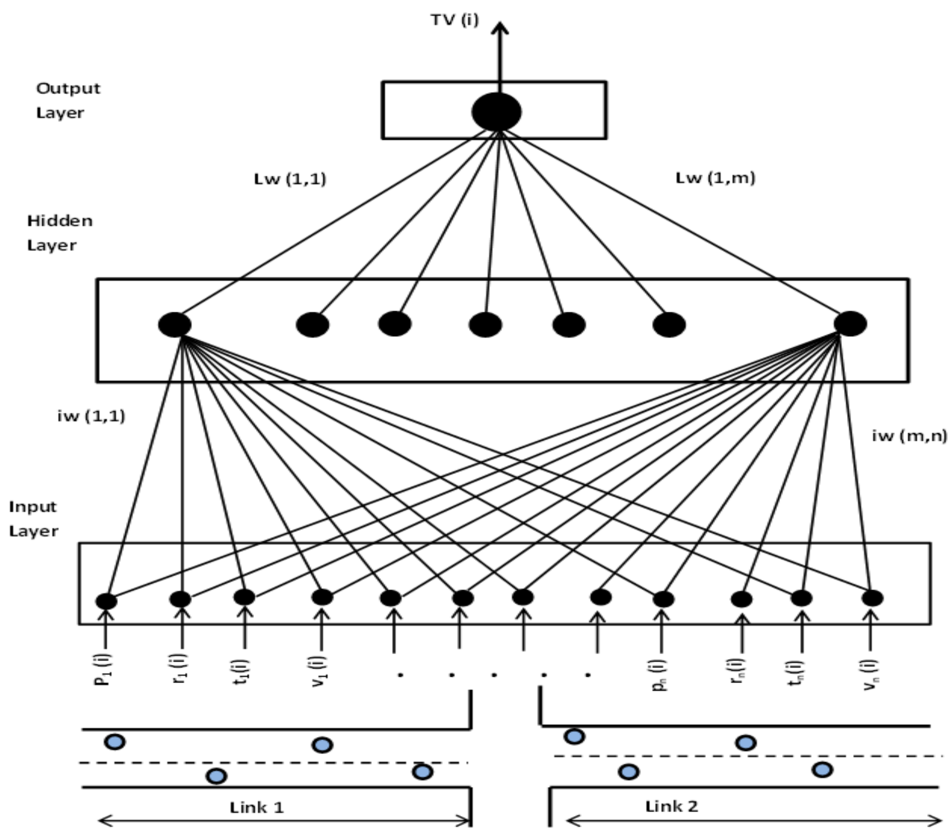


Figure 6.4, Artificial Neural Network for link traffic flow estimation

Hidden layer

$$H(i) = \begin{bmatrix} h_1(i) \\ \vdots \\ h_m(i) \end{bmatrix} = \begin{bmatrix} \varphi(\sum_{j=1}^{N} w_{j,1} x_j(i) + b_1) \\ \vdots \\ \varphi(\sum_{j=1}^{N} w_{j,m} x_j(i) + b_m) \end{bmatrix} \tag{6.2}$$

where, $h_m(i)$ denotes the value of the mth hidden neuron, $w_{j,m}$ represent the weight connecting the jth input neuron and the mth hidden neuron, b_m is bias with fixed value for the mth hidden neuron and φ is the transfer function.

Output layer

$$y(i) = TV(i) = \varphi(\sum_{k=1}^{m} w_k h_k(i) + b) \tag{6.3}$$

where, $y(i)$ and $TV(i)$ denote estimated traffic speed of probe vehicle i on the link under consideration, w_k represent the weight connecting the kth hidden neuron and the output neuron, b is bias for the output and φ is the transfer function.

6.2.5 Road Traffic State Estimation

This component of the framework represents techniques/ procedures employed to estimate traffic flow at every link of vehicles' route. Theoretically, road traffic state can be calculated without using any estimation models when all the vehicles travelling on the road are used to collect traffic data [257]. However, it is difficult due to some factors like public's awareness of privacy protection [247] and some information sharing problems [249].

Road traffic state estimation is performed based on a transforming criterions (methods) on the calculated average speed of vehicles on the road links [257]. Basically there are three ways of calculating road traffic speed of vehicles: Average Method, Integral Method and Fitting Method.

Average Method (AM)

This method is the simplest one and road traffic speed of vehicles is calculated using arithmetic mean of vehicle location points [258]. For a set of vehicle localization points with speed $(V_t{}^r = \{v_{i,t}{}^r\},\ (i = 1,2....n))$, on segment r at an interval time (t), the average road traffic speed is given by:

$$V_t^r = avg_{i=1}{}^n (v_{i,t}{}^r) \tag{6.4}$$

The average method has been applied in different studies for road traffic state estimation activity, Tao et al. [126], Chenet al. [259] are some of them.

Integral Method (IM)

This method determines traffic speed as traveled distance (D) divided by the time (T) spent on the distance. If a vehicle (m) is traveling on a road segment (r) at time interval (t), the vehicle mean speed using integral is given as:

$$V_t^{r,m} = D/T = \int_t^{t+1} v dt / T \tag{6.5}$$

According to Quiroga [260], it may be necessary to approximate equation (6.5) as speed and time of a vehicle traveling on a road will not have relationship and the approximation is:

$$v_t^{r,m} \approx \frac{1}{T}\{v_{0,t}{}^{r,m}(\frac{t_1 - t_0}{2}) + \sum_{n-1}^{N-1} v_{n,t}{}^{r,m}(\frac{t_{n+1} - t_{n-1}}{2}) + v_{N-1,t}{}^{r,m}(\frac{t_N - t_{N-1}}{2})\} \tag{6.6}$$

where n is the point index of one vehicle, if multiple vehicles (m>1) are passing on the segment at time t the calculation is done by averaging $v_t^{r,m}$.

Fitting Method (FM)

This method uses the position information of the vehicle. According to kong et al, [261], if L is the total length of road r, the speed of a vehicle during an interval time (T) on the whole segment is given by:

$$v_t^{\,r} = \left[\int_{(k-1)T}^{KT} v_t^{\,r} \, dt \right] / T \tag{6.7}$$

Most studies, for example Qiankun, et al [262], Kong, et al [263], Tao, et al[126], conducted on road traffic state estimation employed the Average Method (AM) to estimate traffic flow on road links. However, an experimental evaluation on the performance of these methods revealed that as the number of vehicles on arterial road becomes at least 7, the performance of Integral Method (IM) is better than the other two [257]. We propose to use IM method in the road traffic state estimation process.

6.2.6 Results and Evaluation

This component of the framework evaluates and disseminates road traffic flow information to road users on their mobile phones or on the Internet for universal access. During evaluation, comparison of road traffic state estimation model result and ground truth based traffic state data is done and if accuracy and coverage of estimation result is not acceptable, optimization of the identified road traffic state estimation framework is done with different techniques like improved probe penetration rate and sampling frequency [126], special point elimination method , dynamic boundary method and IM-FM fusion method [257]. However, evaluation of the results from field tests is not suitable for statistical analysis particularly for arterial roads [126].Hence, simulation based individual vehicle tracks and aggregate traffic states can be used as ground truth during evaluation [264].

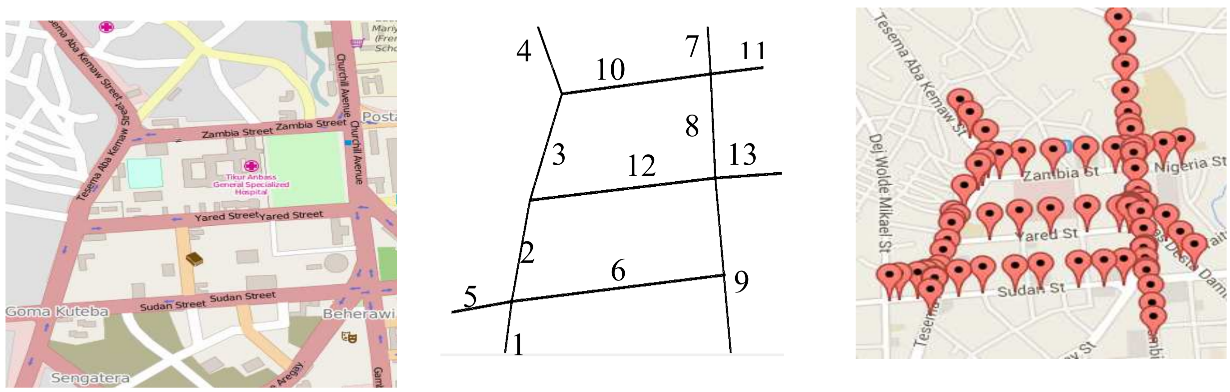
6.3 Framework Application

In Section 6.2.1, it was discussed that the UMTS cellular network is used as road traffic data source. For the application of the framework, real-world data was gathered based on a java application utilizing JSR 179 API on A-GPS mobile phone. But, due to security reason, it was impossible to get U-TDOA based traffic measurements on a traffic road. As UTDOA is network based positioning method, it can only be used by the network operator to gather traffic data. Hence, to model the arterial road traffic, a microscopic simulation package “Simulation of Urban Mobility” (SUMO) [81, 123] is employed. To generate road network and vehicle route, the SUMO packages NETCONVERT and DFROUTER are used. From SUMO simulation, aggregated speed information for each road link named “aggregate edge states” and floating car data (FCD) export file are generated for further analysis. The information on aggregate edge states include road edge IDs, time intervals, mean speeds, etc. The aggregate speeds are used to determine ground truth of traffic flow. Whereas, the FCD output file records the location coordinates of every moving vehicle on the sample road at every time-stamp, vehicle speed, edge IDs and this data file is used as simulation for in-vehicle mobile based traffic information system.

To evaluate the framework depicted in Figure 6.1, SUMO is used to simulate the urban road network and the corresponding traffic flow. From simulation, the location of each vehicle and “ground truth” traffic states are generated. The generated vehicle location data is firstly preprocessed to reflect “realistic” location sample that A-GPS mobiles may provide in real world situation. Next, data analysis activities like penetration rate, sampling frequency algorithms are employed on the preprocessed location data. Using appropriate proportion of the data, training of Artificial Neural Network (ANN) model of the selected road network is done. Then, speed estimates of the trained ANN are allocated to each of the sample road links and aggregated on predefined time interval. For performance assessment of the identified state estimation model, accuracy of speed estimation is evaluated using Mean Absolute Error (MAE) as well as comparison with the "ground truth" speed value of SUMO aggregate state. Finally, estimated speed values are classified into different traffic flow conditions using threshold techniques and presented as colored road segments on road users' mobile phones or on the Internet.

6.3.1 Urban Road Network for Testing the Framework

As it is shown in Figure 6.5 (a), a part of Addis Ababa city road network is chosen as simulation case study. The OpenStreetMap (OSM) xml file of the selected road network is edited using Java OpenStretMap (JOSM) [265] to remove road edges that can't be used by vehicles like road ways to pedestrian etc., and also for simplicity all road edges are set to one-way. The simplified road network consists of 13 nodes, 12 links with length range from 169m to 593m and 4 traffic lights as shown on Figure 6.5(b). On SUMO command window, network file encoding traffic light logic, speed limit of road links and road link priorities are generated from the JOSM file using NETCONVERT. Then, using DUAROUTER random routes of vehicles traveling on the road network, number of vehicles to be emitted to the road, start and end of traffic flow are determined. These randomly generated vehicles and their routes are run on SUMO and as a result of 3600-seconds interval, 718 probe vehicles are generated with random trips. In order to mimic the real traffic situation on this road, free flow traffic demand is used with maximum speed 30Km/hr., which is the speed limit on the real situation of the sample road network of Addis Ababa. Besides, the data sets from the simulated network, real data set was collected by a car with A-GPS device driving on the sample road networks and location updates in terms of longitude and latitude, time-stamp and speed were recorded every 3 seconds. The real A-GPs location data collected within 45 minutes is depicted in Figure 6.5 (c).



(a) (b) (c)

Figure 6.5 Sample road network for simulation: (a) sample road networkfrom OpenStreetMap (b) simplified diagram from SUMO (c) Real A-GPS based moving vehicle location data.

6.3.2 Data Preparation

The SUMO simulation is conducted for 1-hour without incident. Data from the first 15 seconds of simulation were considered to be warm-up period and were not used in the analysis. Every second, position, time-stamp and speeds of vehicles were recorded. Data from theoutput files "aggregate edge states" and FCD output were screened and preprocessed before applied for , further analysis.

Data Screening and Preprocessing

The first challenge in using the cellular network based mobile probe system is distinguishing non-valid probes (pedestrians etc.). But probe data in this system come from our service subscribers and validity of traffic probes is not an issue. Other criteria considered in the screening and preprocessing activity include:

- Speed estimates greater than 13.89m/s of speed limit are eliminated as the speed limit in Addis Ababa city vary from 8.3 m/s (30km/hr) to 13.89m/s (50km/hr).
- Location estimates with distance to nearest link larger than 20m is eliminated. As the positioning accuracy of A-GPS positioning method is maximum of 20m [89] and also to differentiate closely spaced parallel urban roads, an accuracy of 20m is expected [266].
- In-vehicle mobile location estimate with coordinate (0, 0) and with zero speed are eliminated.

Aggregation of link speeds

From the SUMO simulation conducted for 1 hour, to characterize traffic flow condition on every road link of the sample road networks, aggregation of link speed estimates over a specific time interval is performed. Previous works on road traffic state estimation [252, 267] discussed a 10 minutes aggregation time is a reasonable choice considering real-time requirement and data availability. The average speed along road link r during the time interval $\lfloor t_{k,} \, t_{k+\Delta T} \rfloor$ is given as:

$$V_{av}{}^{r}\left(t_{k,} t_{k+\Delta T}\right) = \frac{1}{n^{r}{}_{t_k, t_{k+\Delta T}}} \sum_{k=t_k}^{t_{k+\Delta T}} v_r(k) \tag{6.8}$$

where $v_r(k)$ is the available speed estimate on link r and $\frac{1}{n^{r}{}_{t_k, t_{k+\Delta T}}}$ is total number of available speed estimates. The mean traveling speed of the road links on a 10-minutes time interval is recorded in the “aggregated edge states “and it is depicted in Figure 6.6.

From Figure 6.6, all road links except link 1 and link 5 are expected to have smooth traffic flow as their speed is above 7m/s (link speed limit is 30km/hr). However, link 5 has medium traffic flow and link 1 is with medium traffic flow from 10 to 20 and 50 to 60 minutes. From 20 to 50 minutes the traffic flow on this road link is improved.

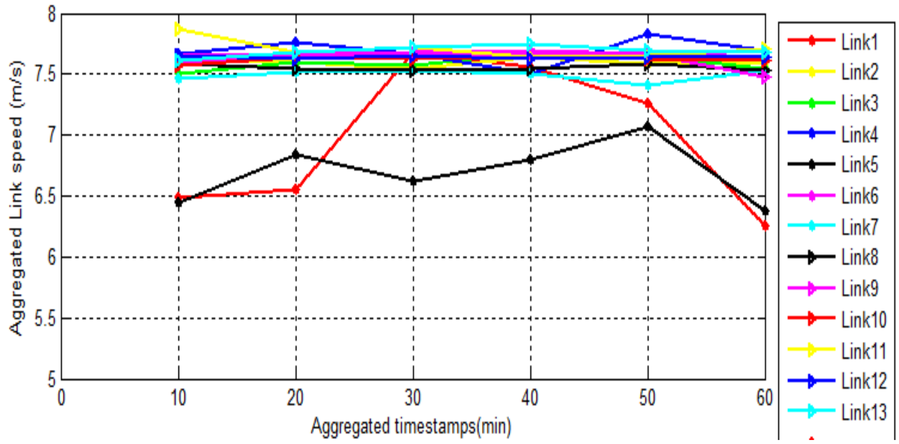


Figure 6.6 Aggregated road link speeds –"ground truth speed".

Data Sampling Process

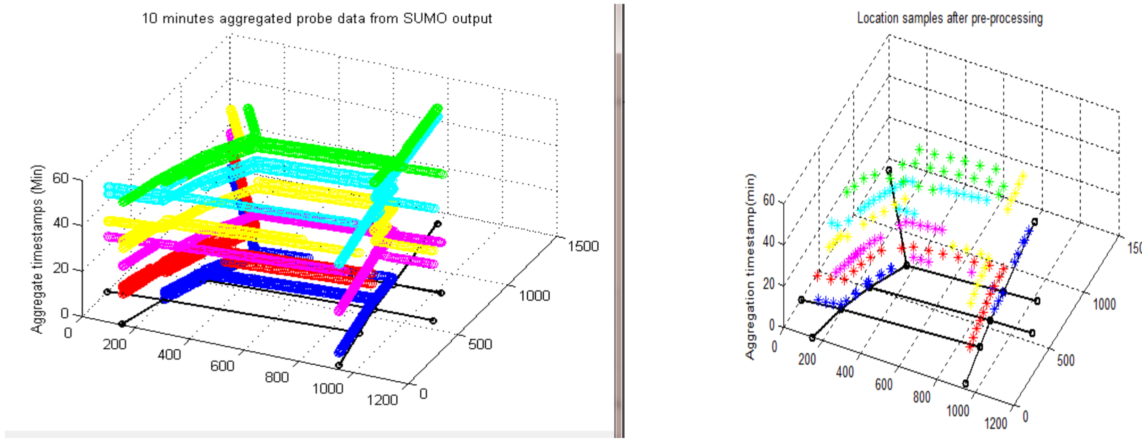
From the 1 hour SUMO simulation, the simulation output file**,** FCD output, generates large amount of simulated mobile probes at real time. At every second, location updates (in terms of x, y or longitude, latitude) for the mobile probes are recorded. There are in total 437 probes and the time they spent range from 10 seconds to 202 seconds. Figure 6.7 (a) shows location data collected from these probes, which are aggregated in 10 minutes. The FCD output file contains detail information of each vehicle/mobile and grows extremely large. Hence, converting this location data into more compressed one is necessary [126]. Accordingly, to degrade location data, one can set up a specified percentage of simulated vehicles/mobiles to be traffic probe. As it is discussed in Section 6.2.3, previous studies suggest that for arterial roads reliable speed estimation, a minimum penetration rate of 7%, i.e. at least 10 probe vehicles traversing a road section (every road link) successfully is required [252, 253, 254] although factors like road type, link length and sample frequency affect the minimum sample size.

In this research work, the sample is taken considering the road link length as it is indicated in Table 6.1 and sampling frequency is based on "Pinpoint-Temporal" which is elaborated in section 6.2.3.

Table 6.1 Number of probes taken for the sample from the FCD output based on road link length

Link #(Street Name)	Link length (m)	Number of sample probes	Number of location updates per probe
1 (Tesema Aba Kemaw Street)	274.6	10	15
2(Tesema Aba Kemaw Street)	233.4	10	15
3(Tesema Aba Kemaw Street)	258.8	10	15
4(Tesema Aba Kemaw Street)	194.2	10	15
5 (Sudan Street)	194.2	10	15
6 (Sudan Street)	695.8	20	15
7 (Churchill Avenue)	593.9	15	15
8 (Churchill Avenue)	233.3	10	15
9 (Churchill Avenue)	531.4	15	15
10(Zambia Street)	484.3	15	15
11(Nigeria Street)	69.5	10	15
12 (Yared Street)	601.7	20	15
13 (Ras Damtew Street)	214.6	10	15

As it is presented in Table 6.1, for road link length 300m and below 10 probes are taken (which is the minimum recommended in the literature), 300m to 600m 15 probes and more than 600m link length 20 probes and totally 165 probes (37.6%) are considered in the sample. The sampling frequency employed is "Pinpoint-Temporal" with 10seconds time interval and 15 location updates of each probe is collected including the first and last probe information as the proposed state estimation method, which is discussed in Section 6.2.5 is integral method (IM). Figure 5.7 (b) plots location data of the sample probes aggregated in 10 minutes.



(a) (b)

Figure 6.7 Positioning data of mobile probes of this research aggregated at every 10-minute : (a) Probe location data generated from FCD output file, (b) Sample probe location data

Data for Training and Evaluation

After the sampling process, the extracted data were used for training the neural network and estimating the link travel speed. A total of 165 probe data were simulated and using random approach of dividing the available dataset for ANN development [268], 110 probe data (two-third of the data) were used for training process and the other 55 probe data (one-third of the data) were used for performance evaluation.

6.3.3 Neural Network Training

A training process is needed before the ANN model can be applied to estimate traffic state. In the process three procedures including training, testing and validation were conducted. The total training data set (110 probe data) were divided in to three subsets [269] which are 88 probe data (80%) for training, 11 probe data (10%) for testing and 11 probe data (10%) for validation. During the training process, different hidden neurons like 10, 15, 20 and 25 were chosen. During testing the performance in terms of Mean square error (MSE) for the case of 10, 15, 20 and 25 neurons is compared and 15 hidden neurons were used to build the network.

Levenberg-Marquardt algorithm (Trainlm) [270] was chosen so that the over fitting phenomenon can be avoided. Moreover, the algorithm can provide fast convergence even for large networks with few hundred weights. The trained ANN model, which took 2 seconds, is applied to estimate link traffic state under free flow (implemented within 1.5 seconds) but proved even in over saturated condition as it is indicated in [255].

6.3.4 Evaluation

To evaluate how the ANN model performs, the performance indicators Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are adapted from [255] and defined as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(v_{pv,k} - v_{true,k})^2} \tag{6.9}$$

$$MAPE = 100 * \frac{1}{n}\sum_{k=1}^{n}\left|\frac{v_{pv,k} - v_{true,k}}{v_{true,k}}\right| \tag{6.10}$$

where, $v_{pv,k}$ is the estimated travel speed of the kth probe vehicle and $v_{true,k}$ is the true link speed of the kth probe vehicle recorded by data collection points.

Results based on Simulation Data

The trained ANN model is used to estimate link travel speed with a simulation data input. A correlation between the estimated link travel speed based on ANN model and the true link travel speed which is computed from the simulation data using the integration method (IM) of calculating vehicle speed is performed. As it is depicted in Figure 6.8, the estimated link travel speed has very high correlation with the true link travel speed (R^2>99%). The linear regression between the estimated and true (simulated) link speed that predicts the best performance among these values has an equation y = 0.997*x + 0 indicating the trained ANN model can help to predict road traffic flow, where x represents true speed and y estimated link travel speed.

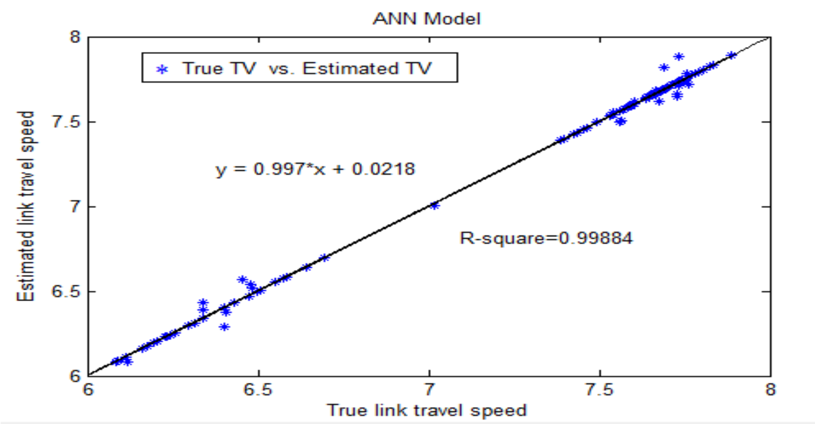


Figure 6.8, Correlation between estimated link travel speed and true link travel speed using simulation data.

The performance of the estimation method in terms of RMSE and MAPE is 0.029325 and 0.127% respectively with average speed of 7.191m/s.

Results based on Real A-GPS Data

The trained ANN model was also applied to estimate travel speed based on real A-GPS data. A car with A-GPS based mobile phone traveled on the sample road network and location updates in terms of longitude, latitude, time-stamp, speed and accuracy is recorded at every 3seconds for about 45minute (see Figure 6.5).A sample using "Pinpoint-Temporal" method with 10seconds time interval is taken and at every road link, 15 location points i.e. total of 195 A-GPS based vehicle location points are taken. The estimation result is shown in Figure 6.9. Each point represents travel speed on each trip i.e. at every road link. From the regression formula in the figure, it can be seen that the trained ANN model performs very good. The RMSE and MAPE are 0.101034 and 1.1877% respectively which show the possible application of the ANN model to real link travel speed measurements.

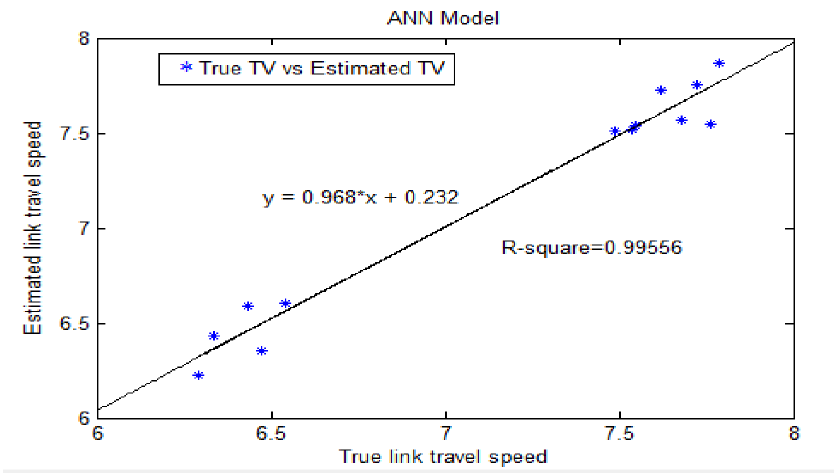


Figure 6.9, Correlation between estimated link travel speed and true link travel speed using real A-GPS data.

6.4 State Estimates of Road links

As it is presented in Sections 6.3.5 and 6.3.6, the trained ANN model provides a very good link travel speed estimation using both simulated as well as real A-GPS data. In this section, the trained ANN model is applied to estimate sample road link states using link travel speeds and a comparison is made against the ground truth speed estimates named as "aggregated edge states". For this analysis, a sample of 195 probe vehicle points are taken from SUMO FCD output file based on "Pinpoint-Temporal" sampling frequency method with a 10minutes time interval. The result of the analysis is shown in Table 6.2.

Two performance indicators Mean Absolute Error (MAE) and Estimation Availability are used to evaluate the ANN model estimation accuracy and system coverage respectively. MAE is defined as mean of absolute difference between the ground truth speed on a link and the estimated speed. The estimation speed availability is the fraction of links having speed estimation in the time interval considered.

Table 6.2 Ground truth vs. ANN model based average link speeds of the research result

Aggregated Ground Truth Speed (**A**)			ANN model based Speed Estimates with 10min Interval (**B**)										
Link # (Street Name)	0-10min		10-20min		20-30min		30-40min		40-50min		50-60min		MAE
	A	B	A	B	A	B	A	B	A	B	A	B	
1(Tesema Aba Kemaw St.)	6.48	6.29	6.56	6.91	7.69	7.01	7.56	7.43	7.26	7.07	6.26	6.29	0.28
2(Tesema Aba Kemaw St.)	7.61	7.37	7.60	7.82	7.55	7.31	7.64	7.53	7.59	7.99	7.60	7.56	0.21
3(Tesema Aba Kemaw St.)	7.50	7.11	7.60	7.91	7.57	7.15	7.68	7.69	7.65	7.66	7.55	7.20	0.23
4(Tesema Aba Kemaw St.)	7.67	7.63	7.77	7.53	7.67	7.48	7.50	8.35	7.84	8.02	7.69	7.82	0.23
5 (Sudan St.)	6.45	6.62	6.84	6.69	6.63	6.02	6.80	6.61	6.98	6.67	6.38	6.89	0.32
6(Sudan St.)	7.59	7.28	7.65	7.97	7.67	7.98	7.65	7.27	7.68	7.48	7.64	8.09	0.33
7 (Churchill Avenue)	7.47	7.09	7.52	7.17	7.53	7.52	7.50	7.79	7.41	7.98	7.53	7.84	0.32
8 (Churchill Avenue)	7.59	7.49	7.55	7.07	7.54	7.08	7.55	7.33	7.59	7.56	7.54	7.84	0.26
9 (Churchill Avenue)	7.66	8.06	7.67	7.58	7.68	8.07	7.70	7.77	7.67	7.78	7.48	7.33	0.21
10 (Zambia St.)	7.57	7.07	7.64	7.35	7.62	7.36	7.62	7.97	7.62	7.55	7.62	7.86	0.29
11(Nigeria St.)	7.87	7.81	7.68	7.69	7.72	7.52	7.64	7.55	7.65	7.91	7.71	7.93	0.14
12 (Yared St.)	7.65	7.41	7.62	7.05	7.65	7.85	7.62	7.81	7.65	7.68	7.64	7.80	0.23
13(Ras Damtew St.)	7.61	7.88	7.69	7.49	7.72	8.00	7.75	7.72	7.70	7.82	7.68	7.52	0.18

Considering the state-of-the-art traffic speed classification in urban areas [259], speed thresholds are employed to classify the estimated road traveling speed. Accordingly, three traffic condition levels : Green, Yellow and Red where green level (smooth traffic) if link speed is above 7m/s, yellow level (medium traffic condition) when link speed is between 4m/s and 7m/s and red level (congested traffic condition) when link speed is below 4m/s are used as it is shown in Table 6.2. From the table, it is shown that medium traffic condition is detected on link 5 and partly on link1. The average estimation accuracy based on MAE is 0.28m/s and all sample road networks have link speed estimation using the trained ANN model. Moreover, these estimated traffic conditions will be color-coded on the road network and presented on road users' mobile display for real-time analysis.

6.5 Summary

In this research, a method of real-time urban traffic state estimation is presented. A three-layer Artificial Neural Network model is proposed to estimate complete link traffic state. The inputs to the ANN model include probe vehicle's position, time stamps and speeds. Based on the microscopic traffic simulation SUMO, "aggregate edge state" which is the ground truth link travel speed and FCD output data is generated. From the FCD output, a sample based on "Pinpoint-Temporal" method is extracted and the dataset is divided to train as well as evaluate the ANN model. Besides, real A-GPS data gathered using A-GPS mobile phone on a moving vehicle on the sample roads is used to evaluate the ANN model. The performance of the ANN model is evaluated using the performance indicators RMSE and MPAE and on average the MPAE is less than 1.2%.

The trained ANN model is also used to estimate the sample road link speeds and compared with ground truth speed (aggregate edge states) on a 10-minute interval for 1hour. The estimation accuracy using MAE and estimation availability indicated that reliable link speed estimation can be generated and used to indicate real-time urban road traffic condition.

Chapter Seven: Evaluation and Validation of the Research Process and Result

7.1 Introduction

Evaluation is considered as one of the core milestones of design science research process. Evaluation strategies, methods and criteria are determined based on the developed artifact[61]. Different authors of design science research proposed different evaluation strategies and methods. According to Carcary and Marian [70], evaluation is not only a design activity but should be considered from the beginning of the research process. Hence, in this chapter evaluation in terms of validity and reliability of the research process and result, accuracy of the experiment results, completeness and practical utility of the developed framework is discussed.

7.2 Validity and Reliability of the Research Process and Result

Validity, according to Creswell [59] represents the accuracy of the research findings and reliability is about the consistency of the research procedures which are employed in the research process. Although different techniques exist for validation checking, descriptive evaluation on the relevant literatures used in the process of artifact design process and utility evaluation can help to validate a research work in design science research [61].Accordingly, review of relevant literatures is the basis in the formulation of the framework attributes evaluation method and tool identification process. To improve the relevance of the literatures, emphasis was given to age and matching of sources to the topic. These, we believe, contributed to the validity of the research process.

Besides, communication of the problem relevance, the framework and its design procedures, evaluation methods and results to the research community in the form of journal article, conference paper or poster can help to improve the validity of the research findings as peer review system judges validity and originality of research work [271]. In relation to this, as it is indicated at the beginning of every chapter in the report all findings from the three iterations of the research process, the literature review as well as the methodology were communicated to the research community. Particularly the framework, it was reviewed and conference presentation was made on three different conferences and also published as a book chapter.

Regarding the reliability of the research process and findings, the data collection and analysis procedures in Chapter two provided the justification on the consistence of the procedures.

7.3 Accuracy of the Experiment Results

This research work employed experimentation to evaluate the performance of the designed framework and proposed positioning algorithm. The tools applied in the experiment are selected based on the recommendation of the literature. For example, the fusion algorithm used in the hybrid positioning scheme development is selected after conducting experimental comparison among the commonly used fusion algorithms-state vector fusion and measurement fusion algorithm. Road vehicle data collection technologies are selected after systematic review on the positioning standards of the 3G cellular network. The three layers ANN traffic state estimator employed in the evaluation of the developed framework is also recommended in the literature. The work of Vlahogiann et al.[136] for example, justifies that ANN is preferable from other road traffic modeling tool as it is flexible in producing accurate multi-step ahead forecasting with less effort and strongly adaptable to learn from past.

The analysis of the experiment is conducted with respect to accuracy, error rate and the performance. The evaluation is done using the performance indicators RMSE and MAPE. To validate the correctness of the framework experts' comments and interview results are used.The use of well-known and appropriate experimental tools in a research like this adds validity to the work [272].

7.4 Completeness and Practical Utility of the Framework

Evolution in design science research can be either natural (based on observation, interview etc) or artificial (using simulation and laboratory experiment). Depending on the artifact and the attributes to evaluate, natural, artificial or both evaluation methods could be useful. According to Venable [273], mixing naturalistic and artificial evaluation method leads a robust evaluation process.

In this research the developed real-time road traffic state estimation framework is evaluated with respect to estimation accuracy through simulation and filed based data. To evaluate feasibility of studying and designing state estimation framework and also to test the completeness of the framework expert evaluation is conducted.

As it is explained in the methodology chapter, to conduct expert evaluation comments given by reviewers on published papers only on the framework, reviewers' comments gathered during paper presentations and expert interviews are used.

Although all results of the research process including the proposal were communicated to the research community in the form of conference papers and book chapter, only on the design and evaluation of the framework including the book chapter, four manuscripts were prepared and published on relevant conferences. The first conference paper was accepted and presented in a poster session of IEEE AFRICON 2015 Addis Ababa Ethiopia. The paper (title is not written for anonymity reason) basically discusses purpose of the components and gives emphasis on data collection component. Comments of reviewers’ and conference participants during the poster presentation were used to include missing components and their interaction. Similarly, a conference paper on the estimation framework together with its experimental evaluation was submitted to IEEE Symposium on Computational Intelligence in Vehicles and Transportation Systems (IEEE CIVTS'15) (Cape Town South Africa) and comments are used to enhance the framework and the experimentation process. A conference paper on the estimation framework particularly on the ANN estimation model and its performance is presented and published in the 7th world congress of nature and biologically inspired computing (NaBIC 2015) (Pietermaritzburg, South Africa) from which comments were also used to improve the framework. A book chapter about the framework, its experimental evaluation and expert evaluation is submitted and expected to be published with a title “Computational intelligence in wireless sensor networks: recent advances and future challenges”. Comments given from the chapter reviewers’ are used to refine more on the components, component interactions and experimentation and evaluation processes of the framework.

The bottom line is comments of conference paper as well as book chapter reviewers’ and comments of conference participants during conference paper presentations are indications to the feasibility of the study and completeness of the framework.

To evaluate the practical utility of the designed framework, an e-mail interview was performed. The evaluation method involved supplying copy of the real-time state estimation framework including the description of the components to an interviewee and then asked to answer a number of questions as per the structured interview presented in appendix B. The structured interview questions are open ended and to improve reliability, these questions are adopted from [274].

As it is presented in the research methodology the research site was Addis Ababa city. The researcher visited FDRE ministry of transport office as well as Ethiopian road transport authority and learned that road traffic flow information gathering technologies are not used in the country including Addis Ababa though some surveillance cameras are deployed on few road intersection of Addis Ababa for security purpose. To adjust the duration of traffic light with respect to traffic congestion, Addis Ababa traffic police is expected to present weekly report whether duration of a traffic light at some location was enough to support smooth traffic flow or not so that change can be made. Besides, experts in these offices are not professionals of Information Technology related discipline.

Because experts in the research site have neither practical experience on read traffic flow data collection technologies and estimation process nor Information Technology related profession, the researcher decided to conduct the expert evaluation using researchers and practitioners of intelligent transport systems as an interviewee. Conducting the expert evaluation based on experts other than the research site, according to Bias [275] helps to minimize biases and supports cross-validation.

The interviewees for the expert evaluation are selected as they were conference paper presenters at IEEE Series of Symposiums on Computational Intelligence 2015 (IEEE SSCI 2015) conference in Cape Town South Africa where the researcher also was invited for paper presentation. These experts have publications on Intelligent Transport Systems, in the five day conference of IEEE SSCI'15 for example their conference paper was categorized under this theme. Hence, using these experts in the practical utility evaluation of the state estimation framework is appropriate.

To conduct the evaluation the researcher employed an e-mail interview. According to Meho [276], e-mail interview is preferable to face-to-face interview as it allow to access diverse participants regardless of their geographical location, cost effective, eliminate time for prescribing and scheduling appointment, gives ample time to participants to think about their response and encourages respondents' self-disclosure. Conducting the evaluation through an e-mail interview of the interviewee helps to generate rich and quality data [277] about the utility of framework.

First the researcher send permission request to 11 experts and only 7 of them have accepted the invitation to participate in the e-mail interview. These 7 experts, 4 of them are academic professors and the remaining 3 are practitioners, are from seven different geographical locations. The interview questions together with the interview guide is sent via e-mail to the 7 interviewees with the questions embedded in the e-mail message as response rate of embedded questions is higher than those from attachment messages [278].

The interview items are composed of 5 open ended questions that the experts are responded accordingly. The first two questions are more general that represent the real-time road traffic state estimation framework and its importance to road traffic management activity. The remaining three questions tried to assess the understandability, completeness and usefulness of the framework to practitioners, researchers and other traffic management activity stakeholders.

The first question presented to each of the interviewee was “what do you understand by the term road traffic state estimation framework? Have you ever come across with such term, in a research or related to your organization?” There was two ways of understanding the term as the interviewee replied. The practitioners understood the term traffic state estimation framework in relation to the estimation models like Kalman Filter, neural network and the academic professors understood the term as a representation of road traffic state estimation process named it process architecture. When asked if the term road traffic state estimation framework was used in their activity, organization three interviewees replied that each of them wrote papers for publication in the application of estimation algorithms.

The second question asked was on any advantage or disadvantage the interviewee perceived in using the framework. Different Reponses were given. The advantages of using the framework as mentioned by the interviewee include traffic flow pattern generation, future traffic flow estimation, support route selection decision, support dynamic traffic light duration and preparation of plans to support smooth traffic flow. The only disadvantage mentioned during the interview was the resource requirement as the data to be gathered and processed will be huge.

The third question evaluated how well the interviewee understood the framework. All the respondents have found the framework easy to understand as they are experts in the research area. The fourth question asked was on any missing element in the framework that the interviewee felt. One respondent mentioned that sensor road traffic data collection technologies like loop detectors are missing. Although the framework developed can entertain this technologies if a need arises, we argue that these technologies are with a number of limitations, that is why this research proposed the existing cellular network to be used as road traffic data source.

The final question on the structured interview was ascertaining if the interviewee perceived any potential use of the framework in their organization or research activity. All have accepted its use with respect to road traffic management activity stakeholder, road users including pedestrians, researchers and also practitioners. But one respondent mentioned privacy, security and required resource needs higher emphasizes.

7.5 Summary of the Evaluation Results

A design science research advocates the importance of evaluating the process of the research as well as the end result. Taking this into consideration a multi-method evaluation approach was employed for the evaluation and validation of this research work. Considering the literature support on the process and the artificial and expert evaluation conducted to validate utility of the research result, the process and result of this research work is valid, feasible, and acceptable.

Chapter Eight: Conclusion, Contributions and Future Works

8.1 Introduction

The research presented in this dissertation sought to develop real-time road traffic state estimation framework which utilize the existing cellular network as data collection technology. Because of the nature of urban road traffic problems different domains like data collection technologies, data fusion methods, traffic flow estimation methods etc. had to be drawn together for a comprehensive theoretical and practical understanding of the problem.

This chapter aims to present conclusions, contributions and future works. As it can be seen from Chapter one, this research aimed to address five research questions which are mapped to five specific objectives. A discussion about objectives and how they are addressed in the research is made on the concluding remarks.

8.2 Conclusion

Road traffic problems like traffic accident, environmental pollution and congestion are becoming critical issue that affect everyday life of people living in large cities of the world. Different possible solutions have been proposed and implemented since several years ago. To efficiently utilize the existing road infrastructures, the deployment of road traffic monitoring systems which employ road-side detectors and probe vehicles as source of traffic data have been taken as big step in mitigating the problems.

However, these data collection technologies cannot support to collect data from the entire road network and also suffer from deployment and maintenance cost. The use of the existing cellular network is considered as a promising solution to collect vehicle location data and generate road traffic flow information in cost effective way.

In relation to this, different studies conducted field experiment to show the feasibility of using cellular network to gather road traffic data for the purpose of generating road traffic flow information. But, most of the researches were done based on 2G cellular network and tried to address the problem of the old GPS. A few have considered 3G cellular network but utilized hybrid of two handset-based positioning technologies to gather road traffic data. According to the literature, to optimize accuracy, coverage and availability a hybrid of network-based and handset-based positioning technologies is recommended.

In addition to data collection technologies, other issues like data fusion methods, traffic flow estimation, etc. need to be investigated so as to generate accurate and reliable road traffic flow information. In this dissertation, among the others, In-vehicle mobile phone positioning and tracking based on a 3G hybrid positioning technology and the development of real-time road traffic state estimation framework and its evolution using hybrid of model-based and data-driven state estimation approaches are addressed. Validation of the research process and result, completeness and practicability of the framework are presented.

The research started with detail investigation on the different positioning technologies of each of the cellular network generations i.e. 2G, 3G and 4G. With systematic literature review on the different positioning standards, hybrid positioning technology combining handset-and network-based localization method with good compromise between positioning accuracy and availability (area coverage) for vehicle positioning, was proposed. To develop a hybrid mobile phone positioning and tracking algorithm, suitable data fusion algorithm, measurement fusion, was selected after comparing the fusion algorithms through laboratory experiment. The developed hybrid positioning and tracking algorithm was implemented, its positioning accuracy was evaluated and found to be appropriate to locate position and velocity of In-vehicle mobile phone moving in all journey of the vehicle.

The other issue addressed in this dissertation is the development and evaluation of real-time road traffic state estimation framework using the cellular network as source of road traffic data. Among other procedures, road traffic data collection is the first and backbone to road traffic state estimation activity. Considering road traffic state estimation procedures, experiment results of the hybrid positioning technology and literature findings on road traffic state estimation models, a general real-time road traffic state estimation framework was proposed. The framework and different perspectives of the components are discussed.

To evaluate the applicability of the framework hybrid of model based and data driven approach was proposed. From the model based the microscopic model SUMO and ANN from the data driven approach employed.

A three layer Artificial Neural Network (ANN), which was tested on different road traffic demand, was used to estimate road traffic flow on selected road networks of Addis Ababa. The inputs to the ANN model include probe vehicle's position, time stamps and speeds. To train and validate the ANN model, a sample based on "dynamic pinpoint–temporal" sampling method was taken from data generated from the simulation of the urban road using the microscopic simulator SUMO.

The performance of the ANN model is evaluated using the performance indicators RMSE and MPAE and on average, the MPAE is less than 1.2%.The estimation performance of the trained

ANN was also tested using a real-world data gathered using A-GPS mobile phone installed with JSR 179 API software.

The analysis made using linear regression and correlation coefficient also indicated that reliable traffic flow information can be generated using the proposed framework. The color-coded road traffic speeds on all road networks showed the capability of the proposed framework to provide road traffic flow information on every link of an urban road network and this information can also be communicated to road users on their mobiles or other device connected to the network.

As it is clearly said in the methodology chapter, this research work is guided by a design science research process. Accordingly, validation of the research process and result is necessary. To validate the research process the theoretical support and justifications to the reliability of the instruments are discussed. Besides, expert evaluation and laboratory experiment are employed to evaluate the practical utility of the research result. The results of the evaluation confirmed that the research process and result are valid, reliable and acceptable.

8.3 Contributions

The contributions of this dissertation can be analyzed in the following issues:

Measurement Fusion Algorithm to Combine Measurements from Multiple Sensors for Road Traffic Application

Multi-sensor data fusion algorithms are important in integrating measurements from multiple sources. The utilization of appropriate data fusion algorithm improves positioning accuracy and coverage. There are two commonly used Kalman Filter based data fusion algorithms, state vector fusion and measurement fusion algorithm. This research compared the performance of these algorithms and the overall estimation performance of measurement fusion algorithm is better than state vector fusion algorithm. This contribution is unique as no research work make experimental comparison on these algorithms and proposed a data fusion algorithm suitable for transport applications. This contribution is useful to road transport research community to make integration of road traffic data from multiple sources and apply for further analysis.

Hybrid of Handset-and Network-based UMTS Positioning Algorithm to Localize a Moving Vehicle and Track its Trajectory

Road traffic flow information is useful for drivers and road traffic officers for route selection and to perform road traffic management activities respectively. Road traffic data can be gathered using different technologies. However, the current state-of-the-art data gathering tools can support only to gather traffic data on limited sections of road networks, i.e., at road intersection pointes. These tools also suffer from high deployment and maintenance cost. Hence, utilization the existing cellular network as a road traffic data source can help to get continuous traffic data flow, with wide road network coverage and minimum cost of deployment.

In relation to this, a hybrid scheme of network-based and handset-based positioning technology of 3G cellular network is proposed and the positioning and tracking capability of the hybrid positioning scheme is experimentally evaluated and found to meet the E-911 requirement.

This contribution of the research is the first in its kind which addresses the requirements of the network operators, helps to use any kind of mobile phone as traffic data collection probe and more importantly it provides high degree of accuracy as it satisfies the 3GPP recommendation.

This experimentally evaluated hybrid UMTS positioning technology is useful to perform different transportation management activities. For example, it can enable road traffic management officers to gather traffic data of vehicles from the entire road networks at any time, any weather condition and urban environment. Besides, it can support in the preparation of road traffic monitoring strategies and guide lines. Researchers also can acquire traffic data from different parts of road networks, make analysis to get patters of flow with respect to different time zone, working days and hours, road infrastructure etc.

Cellular Network based Real-Time Road Traffic State Estimation Framework

With the raise of urban development, road traffic sate estimation has become more important to our daily life than ever before. It is essential for ITS applications, dynamic vehicle navigation, traffic signal control, emergency dispatch etc. For road traffic flow information to be useful, the estimation should be with acceptable degree of accuracy. One source of problem during road traffic state estimation was the data collection technologies which are either situated at intersection points or has limited area coverage and costly to deploy.

In this study, a real-time road traffic state estimation framework is developed. The framework uses the existing cellular network as source of road traffic data. The framework comprises different components. To evaluate the framework, hybrid of data-driven and model-based road traffic state estimation approaches is applied. The concept of hybrid model for road traffic state estimation using 3G cellular networks as a source of traffic data is developed for the first time in this dissertation. Besides, the developed framework can be used in any environment with different data collection and state estimation scenarios as the components are not specific to any positioning technology as well as estimation model.

Therefore, this framework is useful to practitioners, for example it can be used as a guide line to develop road traffic monitoring and management system, to the research community to get traffic data and perform pattern analysis related to different road safety factors and also to road traffic management personnel to perform traffic flow monitoring, future traffic flow prediction and development of road traffic strategic plans.

In achieving these main contributions to the body of knowledge a number of secondary contributions were achieved including the following:

- Dynamic Pinpoint-Temporal Data Sampling Method

When cellular network is used as source of traffic data, the data gathered will be huge and difficult for processing. Hence, taking sample from the gathered data is a crucial step. In this dissertation, we proposed and used a dynamic "Pin-point-Temporal" sampling frequency method which is a combination of Pinpoint and Temporal. In this method the required sample size data incorporating vehicle information at change of state points with variable initial time-stamp is collected. During sampling, to avoid road traffic state estimation biases, the initial sampling time-stamp is not taken to be fixed as the vehicle could be anywhere while sampling.

- Comprehensive Literature Review on Road Traffic Flow monitoring and Estimation Activity

To understand road traffic flow monitoring and estimation activity a literature review on different domains was conducted. Review of the data collection technologies including sensor technologies and cellular networks with their positioning standards, map matching algorithms, mobility classification models, traffic flow estimation methods (model based and data driven approaches) is systematically presented and themes, gaps are identified. This comprehensive literature review is useful for other researchers who are interested to do research in road traffic monitoring and management activity.

- Methodological Contribution

This research work is guided by design science research approach. Although the aim of the research was to develop road traffic state estimation framework, addressing other sub problems related to data collection technology, data fusion algorithm, estimation and modeling techniques was important. The research approach employed provided good opportunity to integrate sub problems and their solutions to the problem and solution of the research agenda. Hence, the research approach, methods and techniques used in this research are new contributions which support to solve a problem with other sub problems and it is useful for researchers with similar type of research problem context.

- Developing Country Context

Although the framework developed considers real time road traffic state estimation on urban roads of any country, the local context was very important to perform the evaluation on the hybrid positioning technology as well as state estimation framework. In this regard, the framework can be used in developing countries like Ethiopia where there is no any road traffic monitoring technology and practice but deployed 3G cellular network all over the country to support voice and data communication of the society. In this countries road traffic is a major cause of death and urban pollution.

8.4 Concluding Remarks

The aim of this research was to use the existing cellular network as a solution to the problems of the current state-of-the-art road traffic data collection technologies. To provide real-time road traffic flow information to road users and other stake holders, a state estimation framework that applies hybrid positioning technology of 3G network was proposed. Accordingly, the research process was geared to answer five research questions that are mapped to five specific objectives. A design science research model is adopted to guide the research activity.

The Investigation began with the comparative study of various road traffic data collection technologies including sensor technologies and mobile probe-based surveillance technologies. As learned from the literature, the current road traffic data collection technologies (sensors) like loop detectors have limitations with respect to area coverage, performance and deployment and maintenance cost. Contrary to fixed sensor technologies, the existing cellular network is given higher emphasis as it can help to alleviate problems of sensor technologies.

Therefore, detail literature review on the different generations of the cellular network (2G, 3G, and 4G) was presented. Particularly 3G and 4G cellular network generations provide mobile phone positioning facilities and recommended to be used for location-based services including fleet management systems.

Because 3G cellular network is deployed and used in the research site of this research, the different positioning technologies and their positioning accuracy of 3G (UMTS) was systematically reviewed.

With the comparison of the positioning accuracy and availability of vehicle location, the requirements of the network operators and recommendation of the 3GPP standard, hybrid of U-DOA and A-GPS positioning technologies of UMTS network was proposed (Research question 1, Specific objective 1). This hybrid positioning technology is unique from others as it addresses expectations of operators, can provide high positioning accuracy and can support to use any type of mobile phone as a traffic probe..

To combine measurements of A-GPS and U-TDOA positioning technologies using a data fusion algorithm, review of the different data fusion algorithms was conducted. However, as the data fusion algorithm has great impact in the accuracy and coverage of the fused result, performance comparison of state vector fusion and measurement fusion algorithms was conducted.

The estimation performance comparison among the multi-sensor data fusion algorithms was conducted using real world A-GPS data and Simulation based U-TDOA data. The experiment result indicated that performance of measurement fusion algorithm is better than state vector fusion algorithm (Research question 2, Specific objective 2). Hence, measurement fusion algorithm is proposed to be used in the integration of data from multiple sources of road traffic sensors for the first time.

To develop a hybrid positioning scheme of A-GPS and U-TDOA positioning technologies, measurement fusion algorithm was applied. To evaluate the performance of this algorithm, measurements of A-GPS (real world data gathered based on JSR 179 API) and U-TDOA data through simulation was used. To represent the time evolution of the mobile phone state while it is moving on road network together with the vehicle White Noise Acceleration (WNA) mobility model was employed. The experiment result indicated that the developed hybrid positioning scheme can estimate the position and track the trajectory of In-vehicle mobile with a positioning accuracy that E-911 required (Research question 3, Specific objective 3). This hybrid algorithm is distinguished from other solutions in that measurements of UMTS positioning standards A-GPS and UMTS are fused at the measurement level.

Next, the focus of the dissertation was on the problem of real-time road traffic state estimation. In relation to this, detail literature review on road traffic state estimation procedures, tools and methods that are available and appropriate to use at every state estimation activity is discussed.

Depending on the road traffic state estimation procedures, research result on traffic data collection technologies and review of state estimation model, a real-time road traffic state estimation framework is designed (Research question 4, Specific objective 4).

To evaluate the operational effeteness of the framework, hybrid of model based and data driven road traffic state estimation approaches was used. The experiment result indicated that the framework is useful to generate road traffic flow information at every road link on the urban road networks (Research question 5, Specific objective 5).

Because the whole research process is guided by a design science research approach, evaluation of the research process and result is needed. Accordingly, Validity of the research process as well as practical utility of the result was conducted. This is through the theoretical literature support to evaluate the research process and experimental and survey result was employed to access validity and practicality of the research result. The reliability of the instruments used in this research and the interview questions for the survey is checked and discussed. Based on the results evaluation, the process and result of this research are valid, acceptable and practical.

8.5 Recommendation

This research work discussed how the already deployed cellular network infrastructure can be used to gather road traffic flow data on urban road networks. This is due to the fact that:

- The accuracy of positioning technologies of the cellular network is highly affected by buildings and other obstructing objects on urban areas. Hence, utilization of a positioning technology with better positioning accuracy and coverage is required.
- Besides, road traffic problems like pollution, traffic accident and congestions highly affect urban areas than rural areas.

However, problems of positioning accuracy and the traffic are limited on rural areas and results of this research work therefore can be extended to be used on rural and remote areas as long as there is cellular network coverage.

One contribution of this research work is the hybrid A-GPS and U-TDOA positioning technology for road traffic application. In this hybrid technology if the A-GPS data is not with good accuracy due to obstruction, the U-TDOA can continue be used as it helps to collect data on the operator network. To improve detection rate urban roads other technologies like city wide Wi-Fi and Bluetooth can be used although the mobile user can disable the services and the later has high battery consumption.

8.6 Future Works

The results discussed in Chapter Five, Chapter Six and Chapter Seven demonstrate that this dissertation is successful in achieving the research objectives stated in Chapter One. However, there are other activities left for future work.

The first one is, the UMTS network operator in Ethiopia (Ethiopian Telecommunication Corporation (ETC)) made the U-TDOA based data confidential. Hence, in this dissertation the

U-TDOA based location data is gathered through simulation based on statistical models. So, it would be interesting if the proposed hybrid (A-GPS and U-TDOA) based mobile phone positioning and tracking algorithm is evaluated based on real-world data.

The other issue to be addressed in the future is the mobility model. In this dissertation the vehicle motion dynamics applied is WSA (see Chapter Five). But, there are also other models that entertain the human factor like pedestrians. Hence, the adoption of advanced mobility models can be considered as future research direction.

Finally, the proposed real-time road traffic state estimation framework is not fully implemented. Therefore, requirements from different stakeholders including government, network operators, drivers etc. needs to be addressed. The full fledged implementation of the framework, its evaluation based on the stakeholders need and demonstration using real-world In-Vehicle mobile phone location data covering large area road network would be interesting.

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APPENDIX A

This appendix contains source code of JSR 179 API based application installed on A-GPS enabled mobile phone to collect real world data about the mobile location, speed , accuracy while moving in all journey of a vehicle.

```
public class LBSSample extends MIDlet implements CommandListener, LocationListener, ProximityListener
{
//Creating Form objects
   private Command exitCommand;
    private Command startCommand;
    private Command saveCommand;
    private Command mapCommand;
    private Command contCommand;
private String URL = "http://192.168.42.246/serversetup/LocationServer.php?";
//URL of the DB server
    private Command stopCommand;
    private Command createCommand, locationCommand,newWaypointCommand;
    private Form locationForm,waypointForm,noAPIForm;
    private int lat,lon,alt,speed,course,dist,proximity,state;
    private int waylat,waylon,wayrad,wayalt;
    private double wplat,wplon,wpalt,wprad;
    private Display display;
    private Coordinates oldCoordinates = null, curCoordinates = null;
    int az = 0;
    LocationProvider lp = null;
    private float distance = 0;
    public LBSSample(){
    locationForm = new Form("Location Details");
    waypointForm = new Form("New Waypoint");
    noAPIForm = new Form("No Location API");
     exitCommand = new Command("Exit", Command.EXIT, 1);
     startCommand = new Command("Start", Command.OK, 1);
     createCommand = new Command("Create", Command.OK, 1);
     locationCommand = new Command("Location",Command.EXIT,1);
     saveCommand= new Command("Save",Command.OK,1);
     mapCommand= new Command("MAP",Command.OK,1);
     contCommand=new Command("cont Mod",Command.OK,1);
     newWaypointCommand = new Command("New Waypoint",Command.OK,1);
       lat = locationForm.append(new StringItem("Latitude ", ""));
```

```
    lon = locationForm.append(new StringItem("Longitude ",""));
    alt = locationForm.append(new StringItem("Altitude ",""));
    speed = locationForm.append(new StringItem("Speed ",""));
    course = locationForm.append(new StringItem("Course ",""));
    dist = locationForm.append(new StringItem("Distance ",""));
    state = locationForm.append(new StringItem("",""));
    proximity = locationForm.append(new StringItem("",""));
   waylat = waypointForm.append(new TextField("Latitude     ","",9,TextField.DECIMAL));
 waylon = waypointForm.append(new TextField("Longitude    ","",9,TextField.DECIMAL));
 wayalt = waypointForm.append(new TextField("Altitude (m) ","",9,TextField.DECIMAL));
 wayrad = waypointForm.append(new TextField("Radius (m)   ","",9,TextField.DECIMAL));
 noAPIForm.append(new StringItem("This device does not support the JSR 179 Location API","")); }

protected void startApp() {
//What to do at start up
        display = Display.getDisplay(this);
        waypointForm.addCommand(createCommand);
        waypointForm.addCommand(locationCommand);
        waypointForm.setCommandListener(this);
        locationForm.addCommand(exitCommand);
        locationForm.addCommand(startCommand);
        locationForm.addCommand(saveCommand);
        locationForm.addCommand(mapCommand);
        locationForm.addCommand(contCommand);
        locationForm.addCommand(newWaypointCommand);
        locationForm.setCommandListener(this);
        noAPIForm.addCommand(exitCommand);
        if (hasLocationAPI())
        {
            createLocationProvider();
            display.setCurrent(locationForm);
        } else{
             display.setCurrent(noAPIForm);
        }
  }

  protected void pauseApp() {   }
  protected void destroyApp(boolean arg0)
  {   }
```

```
public void commandAction(Command command, Displayable displayable)
   {
  //Action for different commands
     if(command == exitCommand)
          { destroyApp(false);
            notifyDestroyed();
          }
          else if(command == startCommand)
          {Thread getLocationThread = new Thread()
                        {
                        public void run()
                          {    setListener();
                           }
                        };
                    getLocationThread.start();  }
          else if(command == saveCommand)
          {
           new Thread()
           {
            public void run()
            {
            try
            {
            boolean result = saveLocation(locationProvider, URL);
               if (result)
               {
this.strLat.setText("Your location has been saved in database!!");
               }
               else
               {
this.strLat.setText("Failed to save location!!");
               }
            }
            catch (Exception e)
            {
               this.strLat.setText(e.getMessage());
            }
            }
           }.start();

          }
```

```
            else if (command == newWaypointCommand)
            {
                  display.setCurrent(waypointForm);
            }
            else if (command == createCommand)
            {
                  wplat = Double.valueOf(((
                              TextField)waypointForm.get(waylat)).getString()).doubleValue();
                  wplon = Double.valueOf(((
                              TextField)waypointForm.get(waylon)).getString()).doubleValue();
                  wpalt = Double.valueOf(((
                              TextField)waypointForm.get(wayalt)).getString()).doubleValue();
                  wprad = Double.valueOf(((
                              TextField)waypointForm.get(wayrad)).getString()).doubleValue();

                  final Coordinates waypoint = new Coordinates((float) wplat,(float) wplon,
                              (float) wpalt);
                  Thread getProximityThread = new Thread()
                        {
                        public void run()
                        {
                              setProximity(waypoint,wprad);
                        }
                  };
getProximityThread.start();
            }
            else if (command == locationCommand)
            {   display.setCurrent(locationForm);
            }
    }

public boolean hasLocationAPI()
    {
//Check if the mobile device can support JSR 179 API
 if (System.getProperty("microedition.location.version") == null)
            {
               return false;
            } else
            {
              return true;
```

```
        }
    }

void createLocationProvider() //location provider
    {
        if ( lp==null )
        {
            Criteria cr = new Criteria();

            try
            { lp = LocationProvider.getInstance(cr);
            }
            catch (LocationException le)
            {   le.printStackTrace();
            }
        }
    }


private void setListener()//listener to change location update
    { lp.setLocationListener(this,10,-1,-1);
    }

private void setProximity(Coordinates waypoint, double wprad)
    {  try
            {LocationProvider.addProximityListener(this,waypoint,(float) wprad);
            }
            catch (LocationException e)
            {  e.printStackTrace();
            }
    }



public void locationUpdated(final LocationProvider locProvider, final Location loc) //updating location as time goes with change
of speed
    { Thread getLocationThread = new Thread()
            {   public void run()
                {                        getLocation(locProvider,loc);
                }
            };
```

```
        getLocationThread.start();    }

public void providerStateChanged(LocationProvider locProvider, int newstate)
    {
                ((StringItem)locationForm.get(state)).setLabel("Location Provider State Changed. Location Provider now ");
                if (newstate == LocationProvider.AVAILABLE)
                        ((StringItem)locationForm.get(state)).setText("AVAILABLE");
                else if (newstate == LocationProvider.TEMPORARILY_UNAVAILABLE)
                        ((StringItem)locationForm.get(state)).setText("TEMPORARILY_UNAVAILABLE");
                else if (newstate == LocationProvider.OUT_OF_SERVICE)
                        ((StringItem)locationForm.get(state)).setText("OUT_OF_SERVICE");
        }
        public void monitoringStateChanged(boolean arg0)
    {
((StringItem)locationForm.get(state)).setLabel("Monitoring State Changed. ");
                if (arg0 == false)
                        ((StringItem)locationForm.get(state)).setText("Not currently monitoring");
                else if (arg0 == true)
                        ((StringItem)locationForm.get(state)).setText("Currently Monitoring");
        }

public void proximityEvent(final Coordinates coordinates, final Location loc)
    {   Thread getLocationThread = new Thread()
        {
                        public void run()
            {
                                getLocation(coordinates,loc);
                        }
                };
                getLocationThread.start();
        }

        private void getLocation(LocationProvider locProvider, Location loc)
    {
                getLocation(loc);
                ((StringItem)locationForm.get(proximity)).setLabel("You are outside the " +
                                wprad +   " meter radius of the defined zone");
        }
```

```
private void getLocation(Coordinates c, Location loc)
    {
        getLocation(loc);
        ((StringItem)locationForm.get(proximity)).setLabel("You are " +
                                        loc.getQualifiedCoordinates().distance(c) +
                                        " meters from (lat/long/alt)" +
                                        c.getLatitude()+"/"+c.getLongitude()+"/"+c.getAltitude());
                setProximity(c,wprad);
        }

        private void getLocation(Location loc)
    {
                final double []arr = new double[3];
        final double Hacc, Vacc;



      try {
                        QualifiedCoordinates c = loc.getQualifiedCoordinates();
                        if (null == oldCoordinates)
            {
                                oldCoordinates = new Coordinates(c.getLatitude(),c.getLongitude(),c.getAltitude());
                         }
                        else
            {
                                distance += c.distance(oldCoordinates);
                                curCoordinates = new Coordinates(c.getLatitude(),c.getLongitude(),c.getAltitude());
                                az = (int)oldCoordinates.azimuthTo(curCoordinates);
                                oldCoordinates.setAltitude(c.getAltitude());
                                oldCoordinates.setLatitude(c.getLatitude());
                                oldCoordinates.setLongitude(c.getLongitude());
            }
                        if (c != null)
            {
                                ((StringItem)locationForm.get(lat)).setText(String.valueOf(c.getLatitude()));
                                ((StringItem)locationForm.get(lon)).setText(String.valueOf(c.getLongitude()));
                                ((StringItem)locationForm.get(alt)).setText(String.valueOf(c.getAltitude())+" m");

        ((StringItem)locationForm.get(speed)).setText(String.valueOf(loc.getSpeed()/1000*3600)+" km/h");
                                ((StringItem)locationForm.get(course)).setText(String.valueOf(az)+"
"+findDirection(az));
                                ((StringItem)locationForm.get(dist)).setText(String.valueOf(distance/1000)+" km");
```

```
                    //savelocation()
                    arr[0]=c.getLatitude();
                    arr[1]=c.getLongitude();
                    arr[2]=(loc.getSpeed())/1000*3600;
                    //Hacc = c.getHorizontalAccuracy();
                    //Vacc=c.getVerticalAccuracy();

saveLocation (URL, arr[0],arr[1],arr[2],c.getHorizontalAccuracy(),c.getVerticalAccuracy());//Save location speed accuracy to server
          }
                    }
          catch (SecurityException se)
          {
The MIDlet is not authorized to retrieve location information
                    }
          }
```

APPENDIX B

This appendix contains copy of the e-mail interview questions used to evaluate road traffic state estimation framework. The evaluation result is discussed in Chapter Seven.

Interviewee position ☐ Academic professor ☐ Practitioner

Q_1what do you understand by the term road traffic state estimation framework? Have you ever used this term in your research or such a framework exist in you institution/organization?

Q_2After viewing the framework do you think there are advantages and also limitations of developing and using the framework in road traffic management activity?

Q_3 Do you understand the road traffic state estimation framework?

Q_4 In your opinion is there any missing component in the road traffic state estimation framework?

Q_5 Do you envisage any potential use of the framework for road users, researchers, practitioners or/and in your organization?