Addis Ababa university

Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Telecommunication Engineering Graduate Program

Thesis Tittle

Geolocation of Narrow Band Radio Frequency Emitter Using RSS based Localization Techniques: The Case of Addis Ababa

By

Kebe Adugna Gelmecha

Advisor

Murad Ridwan (PhD)

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Signed by the Examining Committee:

Internal examiner:	Dr. Yihenew Wondie	Signature __________	Date __________
External examiner:	Dr. Beneyam Berehanu	Signature __________	Date __________
Adviser	Dr. Murad Ridwan	Signature __________	Date __________

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Dean, School of Electrical and Computer Engineering

Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

Name: **Kebe Adugna Gelmecha**

Signature: ___________________

Place: Addis Ababa

Date of Submission: ________________

This thesis has been submitted for examination with my approval as a university advisor.

Murad Ridwan (PhD) ______________________

Signature

Abstract

Currently, determining the coordinate of fixed or moving objects using propagation features of radio waves such as signal strength, propagation delay, signal phase, and angle of arrival have been a subject of interest in radiodetermination. Radiodetermination can be categorized into radiolocation, ranging, and radio navigation. Ranging is to estimate the distance between the receiver and the transmitter. Radiolocation (geolocation for the object on the earth) predicts the position of an object. Radio navigation encompasses both ranging and radiolocation. Triangulateration and trilateration (range-based) techniques use for radiolocation purposes. Triangulateration technique relies on line of bearing from receiver to emitter incorporating with antenna arrays. Whereas, Trilateration considers received signal strength (radio-wave propagation path loss models) and propagation delay. Following radio wave properties and applied technologies, measurements have been taken by deploying radio wave measurement systems on the ground, or in aircraft.

In this thesis, passive radio frequency (RF) emitter geolocation was analyzed by considering received signal strength (RSS) techniques to compare and analyze the performance of RSS-based geolocation techniques and algorithms. For this purpose, data were gathered using a mobile radio spectrum monitoring unit (receiver), and it was analyzed using software tools such as excel and Python. Radio wave propagation is statistically modeled using the lognormal shadowing model and regressive methods to determine the distance. The results indicate that the error of estimated distance with regressive and clustering approach on average by 96% over the non-clustered approach. With this approach, weighted least square (WLS) estimates location with the error of 170 meters, whereas linear least-squares (LLS) estimate with the error of 206 meters. The lognormal model estimates distance with a minimum error than the regressive method when the standard deviation of data is less than 2dB. At the end, there is a positive correlation between estimated distance and location. It means the error of estimated location increases, as the error of estimated distance increases.

Key words: Geolocation algorithms, RSS-based geolocation techniques, radio wave measurement, range-based geolocation*,*

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Lists of Acronyms

A-GPS	Assisted global positioning system
AOA	Angle of arrival
BW	Bandwidth
CWLS	Constrained weighted LS
DF	Direction finding
DOP	Dilution of Precision
ECA	Ethiopian communication authority
E-CID	Enhanced Cell Identification
E-OTD	Enhanced Observed Time Difference
FM	Frequency modulation
GPS	Global positioning system
KNN	K-nearest neighbor
LAN	Local area network
LLS	Linear least square regression
LOB	Line of bearing
LOCA	Location On the Conic Axis
LOS	Line of sight
LOS	Line of sight
MLE	Maximum Likelihood Estimation

MUSIC	Multiple Signal Classification
NLOS	No line of sight
NLS	Nonlinear least square regression
OSL	Ordinary least square
OTDOA	Observed Time Difference of Arrival
PDF	Probability distribution’s function
RF	Radio frequency
RMSE	Root mean square error
RSS	Received signal strength
SVM	Support vector machine
TDOA	Time difference of arrival
TOA	Time of arrival
UTDOA	Uplink Time Difference of Arrival
UTM	Universal Transverse Mercator
WLS	Weighted least square regression
WSN	Wireless sensor network

1 Introduction

Any communication requires a channel, whether it is wired or wireless, to convey the information. This channel can be manmade or natural resource. Radio channel is one type of natural resource used for radio service, which is highly relied on the availability of radio frequency spectrum. The value of this natural is increasing from time to time. This is due to: increasing of radio services with different platforms, high demand to use radio services, growing of radio access networks and systems, enhancement of technologies and wireless products [1]. Using radio spectrum effectively and efficiently is a mandatory in today's wireless industry. But it is difficult to manage and control this natural resource and corresponding radio services without optimized radio spectrum management and monitoring systems. As shown in figure (1.1) there are five radio spectrum monitoring platforms which are integrated through telecommunication infrastructures to perform data collection: portable, transportable, mobile, fixed, and airborne monitoring unit. Satellite platform can also be used in case of global and space positioning purpose. Up on measurement data, different activities can be performed and analyzed. For examples, radio planning, radio determination, radio system optimization, and etc.

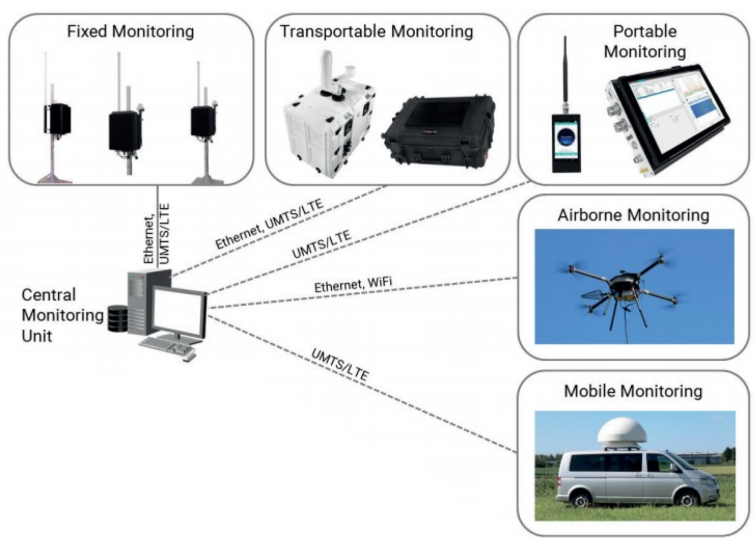


Figure1.1 Integrated radio spectrum monitoring system[2]

Radio determination is one types of radio service which used to calculate the position and velocity of an object, by means of the propagation properties of radio waves. There are three types of radio determination: radiolocation, ranging, and radio navigation. Ranging is to estimate the distance from receiver to transmitter, whereas radiolocation is to estimate the position of an object. Radio navigation encompasses both ranging and radiolocation.

In the radiolocation process, critically important parameters are time, the physical position of the object of interest, and related information. The process of locating this object on the earth using the features of radio propagation is called geolocation. These features are signal strength, propagation delay, signal phase, and angle of arrival[1]. Upon these features there are well known techniques which are relied on measurement data to estimate the location of the object of interest. They are: angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), and received signal strength (RSS).

The role of geolocation in radio service has received considerable attention across different sectors in recent years. To list some of such sectors: private, public services, military operations, radio spectrum regulators, public safety, location-based services, intelligence arena, and etc. Geolocation system can play a significant role in determining the position of object of interest in these sectors. So, understanding the complexity and dynamics of geolocation problem is vitally important. For example, radio frequency interference is a major problem for regulators and radio service operators. It may be originated from: co-channel, adjacent channels, unauthorized users, and jammers. In fact, national radio spectrum regulators may have a detail plan of the radio frequency spectrum, but identifying and geolocating this radio frequency interferer is a challenging activity due to: Environmental factors, behaviors of radio channels, intentional jammers, propagation modes, and lack of advanced radio wave measurement devices and systems [3].

In the case of the Ethiopian communication authority (ECA), radio spectrum monitoring system is not effective. Currently, ECA cannot address the problem of geolocation, due to the lack of advanced radio spectrum measurement devices and systems. But geolocation is a key element of radio spectrum monitoring. ECA has only a single mobile radio monitoring unit, which it is directional antenna does not work properly. It can only measure the received power of the signal. As stated in [1] geolocating targeted transmitter with TDOA and AOA has higher accuracy when compared with RSS. However, they are too expensive to be used for this thesis. This thesis considers the limitation of ECA’s monitoring device and tried to model propagation environments and geolocate the targeted emitter based on RSS measurement techniques and range-based algorithms. The selected propagation models are lognormal shadowing model and regressive method. These models were compared and analyzed. By the same way two range-based localization algorithms are also compared and analyzed using field measurement data. Data were collected using a single mobile monitoring unit by moving around street of Addis Ababa city in different areas. Two FM transmitters (97.1FM, 101.1FM) are considered for this field measurement purpose. The key parameters of the dataset are the power of the received signal (dBm) and the coordinates of a receiver. As indicated in result section lognormal model estimation of distance is better than the regressive method for 97.1FM, but for 101.1FM transmitter, regressive method estimation is better. The performance of these models depends on the standard deviation of the measured power. If the standard deviation of measured power is less than 2dB lognormal shadowing model performs better. But for standard deviation greater than 2dB a regressive method has given a better estimation of distance. As explained in the result section, performance of estimating the location of interested emitter with the weighted least square regression algorithm is better than the linear least square regression algorithm. At the end, the accuracy of RSS-based emitter localization depends on the accuracy of the radio wave propagation model, the number of spatially separated receivers for data collection, and data analysis tools.

1.1 Statement of the Problem

To maintain the integrity of radio services any radio frequency interferences and security threats must be detected, localized, and solved as much as possible in a short period of time. As radio spectrum monitoring trends shows that, integrated radio spectrum monitoring system are needed to locate the physical position of radio interferers or object of interest. In integrated system many radio receivers can be placed in spatial distributed manners with different platforms. They are used to measure the features of radio wave propagation such as signal strength, propagation delay, signal phase, and angle of arrival for geolocation or others purposes. And then they are integrated through telecommunication infrastructures and monitored from the central monitoring unit. But currently, there are no such spectrum monitoring facilities and experiences in Ethiopia.

To date, electromagnetic wave-based localization techniques and corresponding algorithms have still not been comprehensively analyzed in the context of Addis Ababa's propagation environments. In addition, electromagnetic wave-based localization techniques and corresponding algorithms are not well reviewed in context of different radio services and technologies in Addis Ababa city. Knowing the features and performance of these localization techniques can help the decision of implementing the right project for radio frequency spectrum monitoring activities.

1.2 Objectives

1.2.1 General Objective

The main objective of this thesis is to compare the performance of the lognormal shadowing model and regressive method for distance estimation and range-dependent algorithms least-square linear regression and weighted least-squares linear regression algorithms for location estimation.

1.2.2 Specific Objectives

The achievement of the general objective requires the pursuit of the following specific objectives:

- To evaluate the performance of selected range-based localization algorithms
- To study relevant literatures and key parameters used for localization purpose
- To acquire data from two FM stations for data analysis
- Tuning the parameters of propagation models for better estimation of distance
- To study key factors that affect the accuracy of range-based geolocation problem

1.3 Methodology

This thesis work starts by reviewing relevant literatures in the area of radio frequency spectrum management and monitoring, electromagnetic wave-based localization techniques and algorithms, radio wave propagation environments, radio wave propagation models, localization performance analysis and evaluation. Figure1.2 illustrate the overall applied methodology in this thesis. The primary data was collected through field measurement using a single radio monitoring unit. This monitoring equipment has the capability of measuring: frequency range up to 3GHz, power of the received signal in dBm, and its position. The strategy used for fieldwork was taking measurements of received signal power(dBm) and corresponding coordinates (latitude, longitude) at each measurement position using a single mobile spectrum monitoring unit. Due to the fluctuating of transmitted signal with distance and enviroments, the average power was taken at each specific coordinate. With this principle 240 average values of transmitted powers and associated coordinates were collected from two FM transmitters. Then, data preparation was done using selected software tools and techniques. These tools are python and excel tools along with statistical data analysis methods. The distance was derived from the best-fit propagation model. And then algorithms were compared using root mean square error (RMSE).

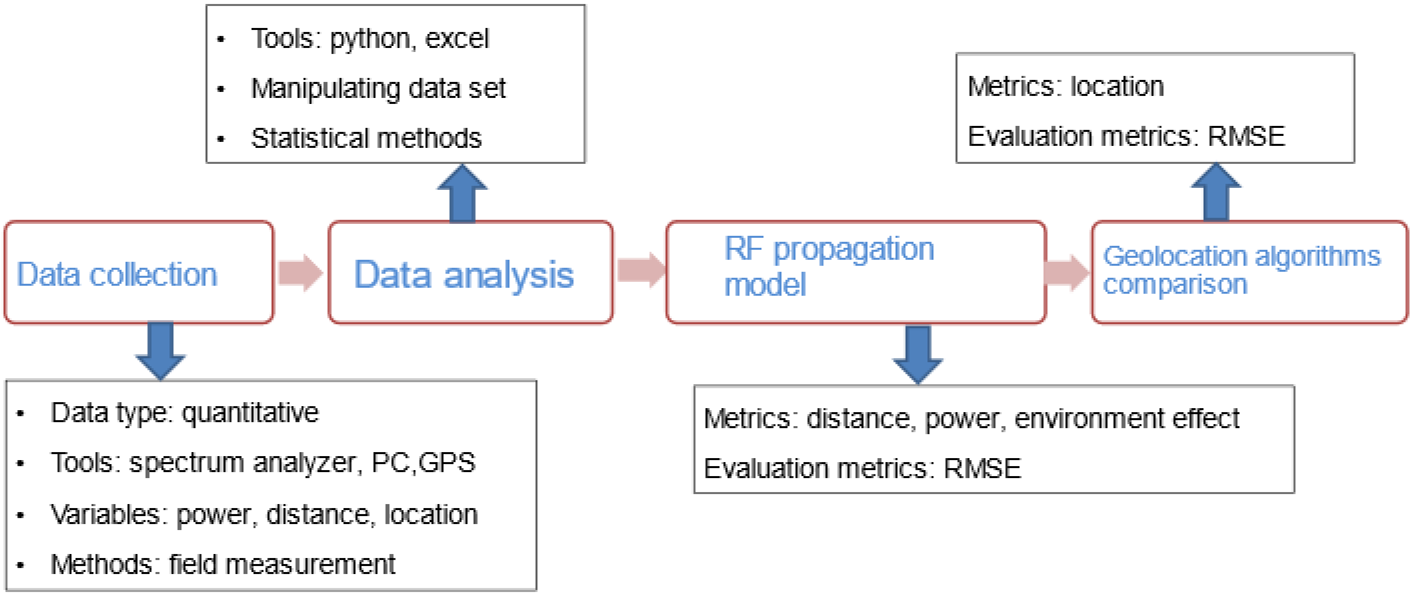


Figure1.2 Block diagram to illustration overall applied methodology

1.4 Related Works

Verities of theories and perspectives have been drawn from the literature regarding the positioning of the interesting object. Even though the main principles of object positioning are the same both for an object placed on the ground and in space, the systems deployment and techniques to be used are may not be necessary the same because of: the accessibility of measurement, technologies, radio services types, propagation types matter, and frequency range[3]. This review scoped to two themes: estimation of path-loss model parameters with different methods, and comparisons of RSS-based geolocation techniques and algorithms in the context of Addis Ababa city's environments.

RF emitter positioning problems rely on the characteristics of RF signals propagation. These features of radio propagation are signal strength, propagation delay, signal phase, and angle of arrival. These features may be affected by factors. Propagation environments and distance are the main factors that affect the RF wave and its propagation. When an RF signal encounters an object, it may diffract, reflect, absorbed, refract, and scatter. These behaviors can bring the sequences of different delay profiles for the same signal, attenuated signal, and bias geolocation problem[1]. Especially for propagation model-based (RSS approach), the RF emitter geolocation process is highly biased. The performance of RSS-based geolocating depends on the distance, path loss model from the distance from the receiver to emitter is determined, so as much as possible, this model should be optimally modeled to geolocate targeted objects with minimum errors.

Many types researches have been done in the area of objects geolocation in three domains of environment: ground to ground, ground to space, space to space and via verses. As stated in [4][5] there are three well-known geolocation techniques, used for detecting and geolocating the source of RF signals: Triangulation (AOA bearing based), range-based (TOA, TDOA, FDOA RSS) or Trilateration, and Multilateration (hybrid approaches). These techniques may depend on a single receiver basis or the network of receivers deployed at spatially distributed manners for a specific environment. Their provision can be; fixed or mobile, or hybrid. Once data is collected through these techniques and structured using different tools, the physical position of the target emitter can be determined upon prior knowledge offered from the received signal, and then location estimation algorithms process these parameters to estimate the coordinates of the targeted objects accordingly. These algorithms are Linear least square regression (LLS), Nonlinear least square regression (NLS), Weighted least square regression (WLS), Multiple Signal Classification (MUSIC), Maximum likelihood (ML), Constrained weighted LS (CWLS), and Location on the Conic Axis (LOCA)[4]. The selection of these algorithms depends on the parameters of the dataset. For example, MUSIC is based on AOA techniques to estimate the location of an object by considering the direction of arrival information.

To estimate the distance between the receiver and targeted transmitter based on RSS measurements can be done with a best-fit propagation model. This technique may apply for applications in which high range accuracy does not necessarily need because the accuracy can be highly affected by multipath and shadow fading [4]. In [6] the propagation models can be categorized into three types: empirical, deterministic, and stochastic model. The empirical model is based on the statistical analysis of field measurement data. It can be subcategorized into non-time dispersive and time dispersive. Time dispersive is to offer information such as propagation delay, whereas the non-time dispersive model is to estimate the distance from the transmitter to receiver. Examples of empirical model are: lognormal shadowing model, hata model. The deterministic model relies on the detailed priority information of propagation environments, for example, ITU-R P.1546, ITU-R. P1812 required digitalized terrain data[7]. The stochastic model is to model the propagation environments with a series of random variables. An empirical model is selected for this thesis work.

In [8] building an accurate model for the representation of radio propagation path loss is the primary step in RSS based geolocation process from a set of measurements of the RSS at specific known locations, N samples of the RSS have been taken (p_i; $0 < i \leq N$} in dBm), at coordinates of (x_i, y_i) and distances of (r_i ; $0 < i \leq N$) [8]. whereas, these distances have been derived from the best-fit propagation model. In this reference two propagation path loss methods are followed. In the first method, path loss exponent is calculated, while in second method path loss exponent and received power at reference point are calculated based on the cost function, which is defined as in equation (1.1)

$$(p_o , \alpha) = \frac{1}{N}\sum_{i=1}^{N}(\text{predicted power} - \text{measured power})^2 \tag{1.1}$$

Mainly four parameters can affect the accuracy of RSS-based position estimation: propagation model uncertainties, sensors or receiver's placement, noises, algorithms used, and quality of collected data. As stated in[9][10] Cramer Rao Lower Bound, RMSE, and Dilution of Precision techniques are used to evaluate for best fit. In addition, in the presence of noise and multipath environments, the statistical model is preferable over deterministic Cramer Rao Lower Bound, RMSE, and Dilution of Precision techniques are used for best fit. The statistical model is preferable to the deterministic model.

1.5 Scope and Limitations

1.5.1 Scope of the Thesis

In this thesis two empirical models, lognormal and linear regressive, are applied to compare their distance estimation performance from radio wave propagation. Up on the estimated distance two range-based localization algorithms, Linear least square regression and Weighted least square regression, are also compared and analyzed. For this statistical data analyze field measurement was conducted using a mobile radio monitoring unit in Addis Ababa city.

1.5.2 Limitations of the Thesis

Mainly limitations of the thesis are:

- Dataset was collected only from two FM stations (97.1 and 101.1 MHz). This means the analysis couldn't claim the impacts of power, technology, and frequency range on the process of range-based localization.

- Since data collection methods was limited to single mobile monitoring unit, the covered propagation area (environments) is small. Due to this it is difficult to get dominant propagation model which represent the whole area of the city.
- The location estimation performance of others range-based localization techniques and algorithms is not analyzed with field measurement data. They are studied only by reviewing literatures.

1.6 Significance of the Study

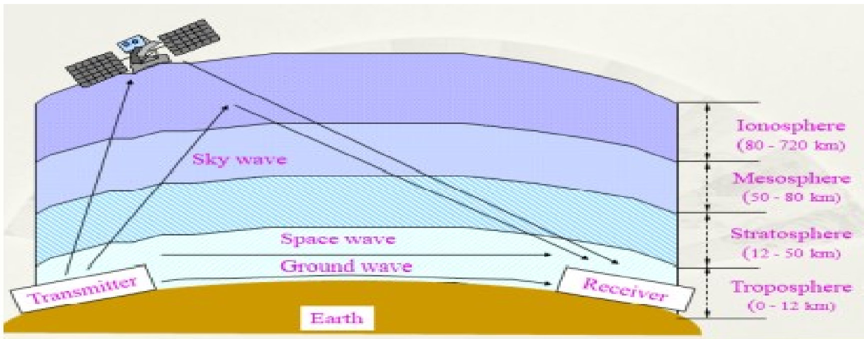
As per my knowledge geolocation techniques are not analyzed and compared in Addis Ababa's propagation environments context. In this work, two significant points are drawn: RSS based localization techniques can use for building radio maps for fingerprint-based localization, and also it may be used for predictive analysis for cases such as regulatory activities (implementing project): coverage compliance, coordination of RF stations, and locating the object of interest or interferers. Propagation model can also be used to predict coverage area, frequency assignment and interference. For example, in the case of radiofrequency interferences that happened to radio services from RF transmitters whose physical locations are unknown, passive localization techniques are expected to solve such problems. Detecting, localizing, and resilience these unknown RF interferers as fast as possible can: improve radio services coverage and capacity, improve the efficiency of the spectrum, increase the integrity of radio services, minimize unnecessary costs, etc.

1.7 Thesis Organization

This thesis is comprised of six main sections. Section I, the introduction, consists of the background of the study, reasons for choosing the topic, statement of the problem, objective of the study, the significance of the study, limitation of the study. Section II presents a review of radio wave propagation models. Section III reviews localization techniques and algorithms. Reviewing different localization techniques such as time of arrival, angle of arrival, time difference of arrival, received signal strength, and internet protocol-based localization in cyberspace. Section IV is the methodology section which consists of research design, materials and tools, data collection and analysis methods, and procedures. Section V presents results and discussions whereas, section VI presents conclusions and future works.

2 Radio Wave Propagation Models

As discussed in [6] propagation channel is the physical environment where radio waves propagate from transmitter to a receiver. This environment may contain only free space, free space with oxygen and water absorption, and blocking objects in the middle of the propagation paths. As shown in figure 2.1 mode of RF waves propagation can be categorized into ground wave, skywave, and space wave.



Classification Band	Initials	Frequency Range	Characteristics
Extremely low	ELF	< 300 Hz	Ground wave
Infra low	ILF	300 Hz - 3 kHz	
Very low	VLF	3 kHz - 30 kHz	
Low	LF	30 kHz - 300 kHz	
Medium	MF	300 kHz - 3 MHz	Ground/Sky wave
High	HF	3 MHz - 30 MHz	Sky wave
Very high	VHF	30 MHz - 300 MHz	Space wave
Ultra high	UHF	300 MHz - 3 GHz	
Super high	SHF	3 GHz - 30 GHz	
Extremely high	EHF	30 GHz - 300 GHz	
Tremendously high	THF	300 GHz - 3000 GHz	

Fig 2.1 Types of radio wave propagation via frequency range [8]

Due to this propagation characteristics and the distance of propagation, the occurrence of pathloss is real. Pathloss is the overall attenuation of RF signals. It can be modeled with empirical model to find optimum function which fit the measurement dataset. As shown in figure 2.2 free space propagation of radio waves propagate without encounter of the object in the middle, and the attenuation of signals is in the function of frequency and distance (path loss). But if the propagation environment is not the line of sight, radio wave impinges upon the object which encounters in between, the multipath and shadowing fading phenomenon become alive[11].

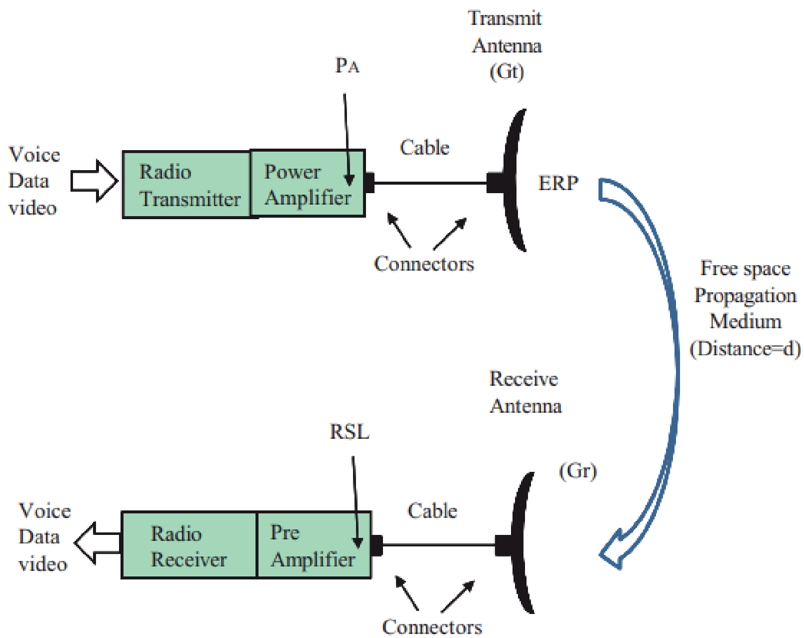


Figure 2.2 System model for free space radio wave propagation[12]

$$ERP = P_a - 2L_C - L_{Ca} + G_t$$

$$\mathrm{RSL} = \mathrm{ERP} - 2L_c - L_{ca} + G_r - L_p \tag{2.1}$$

$$\mathrm{RSL} = \mathrm{ERP} - 32.5 - 20\log(\mathrm{f}) - 20\log(\mathrm{d}) + G_r - L_{Ca} - 2L_c$$

Where Pa is the output power, ERP is effective radiated power, RSL is received signal level, L_C is connector loss, L_{Ca} is cable loss, G_t is the transmitter gain, G_r is receiver gain, and L_p is pathloss.

In [1] complex propagation environment can be modeled by considering three components:

- Pathloss: it is deterministic, distance and frequency dependent
- Shadowing (blockage): random, lognormal
- Multipath fading (reflections, diffraction, refraction, scattering, absorption) it is random

2.1 Multipath Fading Models

In [13] multipath fading is happened due to many factors: object between the transmitter and receiver, atmospheric ducting, and ionosphere refraction. Since these factors are random in nature they sequence randomly delayed of the same signal.

The well-known models for multipath fading are:

- Rayleigh fading model: by taking two random variables
- Rician fading model: consider strong a single line of sight signal (ratio of signal power for dominant components)
- Hoyt fading model: consider two gaussian distribution and random in phase and quadrature signals
- Nakagami fading model: gaussian and statistical independent signal and square root of their sum
- Weibull fading model: two gaussian distribution with equal variance
- Generalized gamma fading model

2.2 Shadowing Models

As discussed in [13] shadowing effects can be modeled with lognormal shadowing and gamma shadowing model. The statistical model is considered to estimation of path-loss model parameters with lognormal shadow model. Figure 2.3 illustrates the variation of the signal amplitude in dBm as a function of the distance and environments between the transmitter and the receiver. In free space the signal is decaying as the distance between transmitter and receiver is increasing. But the instantaneous received signal amplitude in a multipath environment always varies with small change of receiver position and distance.

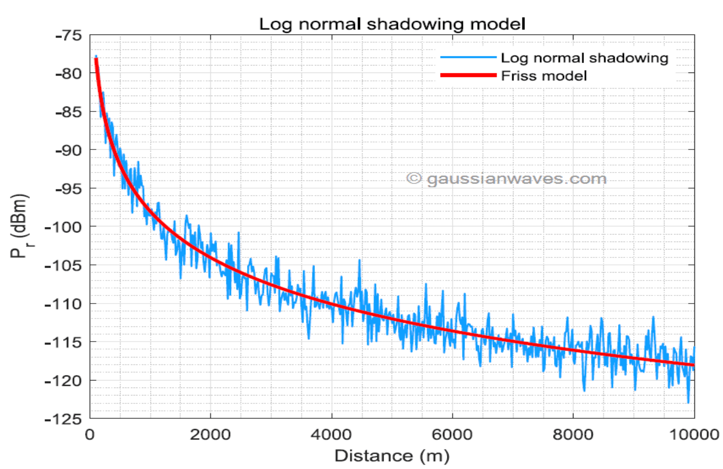


Figure 2.3 Lognormal shadowing model via free space model [13]

3 RF Signal Emitter Geolocation Techniques and Algorithms

3.1 Introduction

In this section, localization scenarios, basic concepts, measurements and mathematical equations of localization techniques and algorithms are reviewed. "Geolocation of RF signal is defined as the problem of precise localization of sources emitting electromagnetic energy in the form of radio signals observing their received signals features (power, propagation delay, and line of bearing) using spatially separated receivers" [14]. Estimation of the position of the source of RF emitter is performed within different position systems. As illustrated in figure 3.1 positioning system can be categorized into: global and local positioning system. Global positioning system encompass the global coverage and it can be achieved through satellite approach (GPS). Local positioning systems considers specific location. It can be active or passive location system and the features of radio waves can be measured by using integrated radio frequency monitoring system.

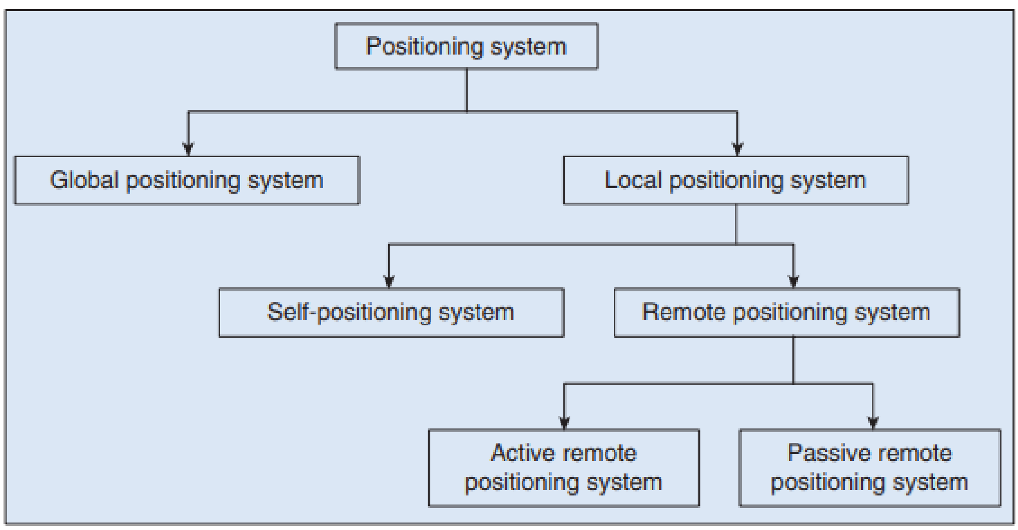


Figure 3.1 Classification of positioning system [1]

The demand of locating the objects of interest are growing due to the enhancement of localization technology and the increasing of location-based services. For examples, sectors such as the military, public services, private companies, and others are using localization system for different purpose [15][3][16]. Locating the position of the targeted object in interconnected systems and complex environments is tough. In addition, this object may be uncooperative in the localization process, which means it can be unauthorized spectrum users or intentional interferers, and they don't want to expose their position. On the other hand, it is difficult to geolocate transmitter that doesn't have a GPS antenna and receiver using GPS technology. This scenario may be possible if the signal propagated toward the satellite position.

The quality of locating the object mainly depends on environmental effects, systems, and techniques used. Propagation environmental can come up with the challenge of shadow fading, multipath fading, multipath RF channels interferences, distance[17][18]. In addition, the localization accuracy can also be affected by the quality of receivers (the device which performs measurements), receiver placement, measurement quality, and mathematical equation (algorithms) which process the measured metrics.

RF propagation-based localization techniques are categorized into range-based and bearing angles. Range-based techniques are TOA, TDOA, and RSS. These techniques try to estimate the distance between receivers and targeted objects by observing signal properties such as power and propagation delay. AOA relies on the bearing angle drawn from the receiver to the emitter. TOA and TDOA techniques are to determine the distance by measuring measures propagation delay. The RSS techniques rely on the measurements of RF signal power and RF propagation models to drive the distance from it. Up on the estimated distance under specific environment, range-based localization is compared and analyzed. The comparison parameter for both the propagation model and algorithms is an error of the distance. AOA and TOA techniques have high accuracy. However, they are computationally complex, consider LOS and synchronization time. On the other hand, RSS is inexpensive and needs low computational capacity. Also, it does not require synchronization time, but it relies on the accurate model of propagation environment [15].

Figure 3.2 illustrate the overall RF based localization process. At first stage the RF signal measurement system have to consider the wanted RF signal features. For example, if there are no directional and antenna arrays in the deployed system it is impossible to apply AOA techniques as well as associated algorithms. In addition, the RF signal measurement system also has to consider the localization scenarios, whether the transmitter is uncooperative or active. For uncooperative scenario it is difficult to apply TOA techniques [6]. Once the needed RF signal features are captured, the next stage is to structure and manipulate the raw data and then feeding this structured data to the selected algorithms. At final stage to optimize the localization process by using different performance evaluation metrics.

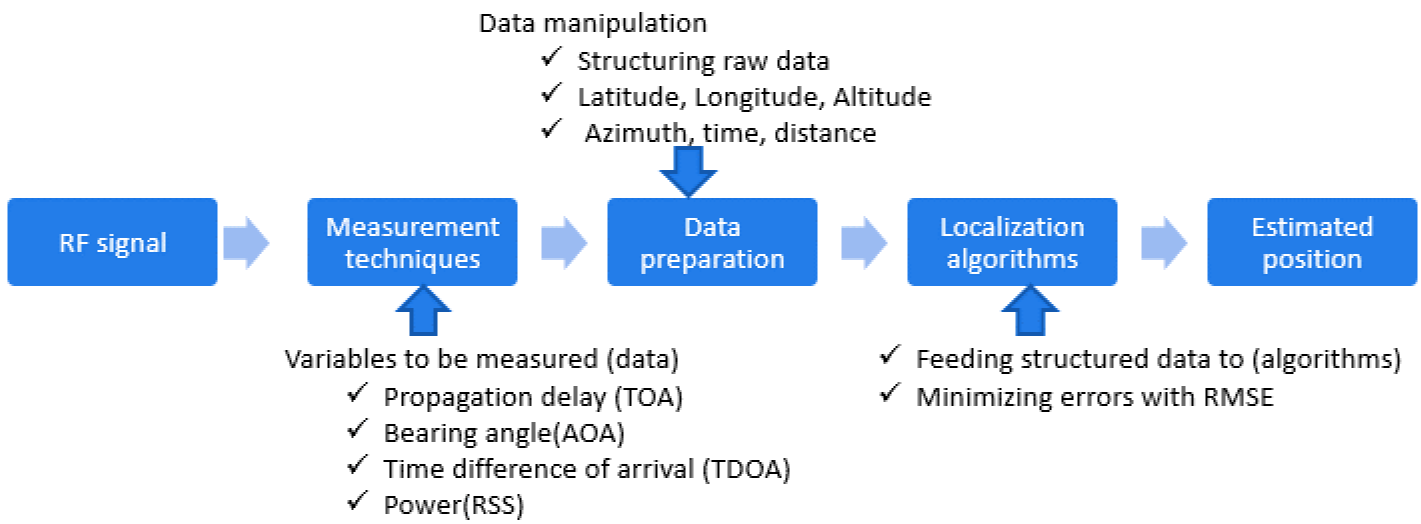


Figure 3.2 Block diagram of Localization techniques and process [3]

3.2 RF Signal Source Localization Platforms

RF signal emitter positioning problem continues in wireless radio communications and broadcasting systems. Radio services can be deployed in different environments: terrestrial (including Maritimes), air, and space. Beside deployment scenarios, propagation features of RF signal may be highly directional, omnidirectional, affected with interference, weak signal, and intermittent. Following these deployment scenarios and RF signal features, positioning problems can be categorized into: ground to ground, space to space, ground to space, or vice versa.

Following the features of radio waves, measurement techniques and localization platforms have to be tuned accordingly[19]. As shown in figure (3.3) radio spectrum monitoring platforms are categorized into mobile, portable, fixed, airborne, satellite, and integrated approaches. localization techniques such as TOA, AOA, TDOA, FDOA, and RSS are relied on these systems. Un op the complexity of enviroments and features of radio wave,it is possible to combine these techniques for more accurecy. The combination of these localization techniques is called hybryd method.

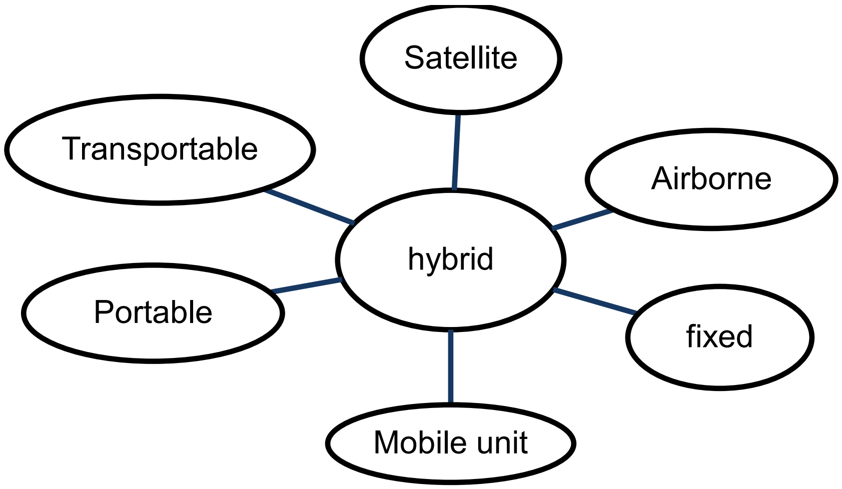


Figure 3.3 Illustration diagram for Radio spectrum monitoring platforms [18]

3.2.1 Uncooperative and Cooperative Localization

"Cooperative RF localization refers to localization schemes where there are some types of cooperation between the transmitter and the receiver. GPS is examples of cooperative RF localization, where there is coordination between the transmitters and the receivers. Timed signals are broadcast from the satellite-based transmitters in orbit, whereby a receiver can locate itself on earth using the time of arrival information. Uncooperative RF localization requires no coordination between the transmitter and the receivers, so it is useful in finding jammers and more benign interfering sources." [14][19]

"Locating an uncooperative RF emitter is significantly harder than locating an emitter that cooperates. In a scenario where the emitter wishes to be found, the emitter could simply broadcast GPS coordinates, making it trivial to find it. An uncooperative emitter may resist attempts to locate its position." [19]

3.2.2 Ground Based RF Signal Source Positioning

It is a process of positioning the object which placed in earth, air or space. By using radio spectrum monitoring system which deployed on the earth incorporated with localization techniques. It can measure the features of radio wave by being on the surface of the earth. Radio wave may be propagated from different environmental domain (on earth, in air or space). The limitation of this measurement type is, coverage. Which means many terrestrial radio spectrum monitoring systems are expected to be deployed in different geographical area to acquire the necessary data [17].

3.2.3 Satellite Approach RF Signal Source Positioning

It is the process of positioning the object which may be placed on earth, air, or space using satellite approach (it can be placed in lower orbit or geostationary orbit). The techniques are more or less the same with ground-based system.

3.3 Applications of RF Signal Emitter Localization

In broad concept, the applications of geolocating RF signal sources are: remote sensing, meteorological measurements, real-time monitoring, commercial application, RF interfere identifying, tracking, and emergence supports. As discussed in [15] in the arena of intelligence and military operation: time, distance, positioning, and related information are very critical factors. They are gathered through the RF based localization process. For example, as stated in[16] it is difficult to imagine modern military operations without electronic warfare and its components. This electronic warfare has three packages: electronic attack, electronic protection, and electronic warfare support. These military operation packages are highly relied on RF based localization techniques.

3.4 RF Signal Emitter Geolocation Techniques

As reviewed in previous section the well-known RF based localization techniques are: TOA, TDOA, AOA, and RSS. TOA applies to an active localization scenario. In this case, the time of the transmitted signal is known from the timestamp sent from the transmitter. A good example of TOA technique is GPS technology. But it cannot work for a non-cooperative or passive localization approach with a single receiver platform. For passive localization, TDOA technique can be used with at least three receivers. And they have to be synchronized with each other[20]. On the other hand, RSS-based approach relies on the accuracy of RF propagation environments. The other localization technique is AOA which requires at least two smart antennas or antenna arrays to draw the bearing line two ward the direction of the targeted transmitter and calculate the intersection of these bearing lines. The hybrid of these techniques also possible.

Table 3.1 Classification of localization techniques[4]

Techniques	Metrics to be measured	Characteristics	Associated algorithms
TOA	Signal propagation delay	• Time synchronization is needed • affected by NLOS conditions	ML, CWLS, LOCA
TDOA	Time difference of arrival	• Time synchronization among sensors	ML, LLS, WLS
RSS	Received power	• It requires an accurate propagation model	NLS, LLS, WLS
AOA	Direction of propagation	• Smart antennas are needed • affected by NLOS conditions	MUSIC/LLS
hybrid (AOA/ TDOA	time difference and angle	• Time synchronization among sensors • Antenna arrays	MUSIC/LLS

3.4.1 Hybrid Localization Techniques

According to [11] [12] most time the hybrid-based positioning uses the combination of TDOA and AOA techniques. It relies on the angle between the line of bearing from receiver to source and axis, and time difference among receivers. In hybrid method, two features of radio wave have to be captured. These features are time difference of arrival and angle of bearing. In order to collect the data, at least three receivers are needed to triangulate these lines of bearing to determine the position of the targeted object. As well these receivers must be time synchronized among each other. For this purpose, smart antennas (spatially separated antenna arrays and highly directional antennas) are needed. Steering these antennas toward the direction of peak signal to capture the bearing lines. The accuracy of this method is high when compared with other positioning techniques [12].

According to[21] hybrid localization approach also be the combination of AOA and RSS techniques. This is another alternative if time synchronization cannot be maintained among the receivers.as shown in figure (3.4) spatially distributed of RSS and AOA-based receivers are applied to evaluate the performance of this method and associated algorithms (least square and ML algorithms). For this evaluation purpose five RSS sensor are placed in the area of 800x800 meter square, whereas nine AOA sensor are also placed in the same area.

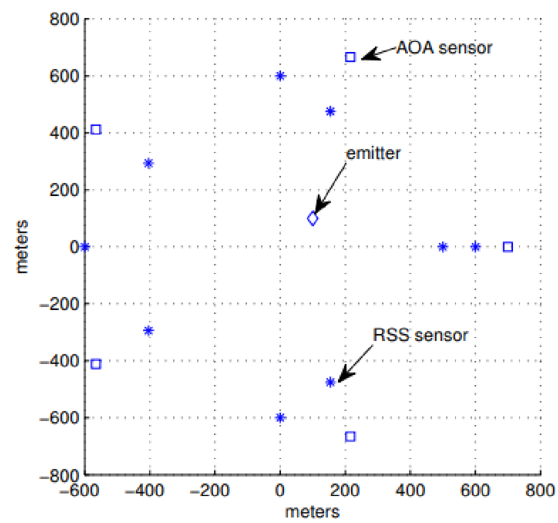


Figure 3.4 Receivers placement with hybrid technique [12]

These two algorithms are compared by performing computer simulation. And the simulation result is illustrated in figure 4.5, which their performance depends on factors such as: features of receivers, propagation environments, receiver-emitter geometry, etc. The comparison is done by tuning standard deviation of measurement power with different level of weight scale. Decreasing the weight scale and standard deviation can minimize position errors, but the error increase as weight scale and standard deviation are increased.

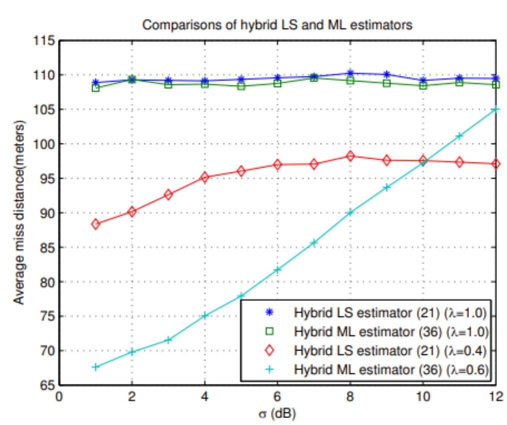


Figure 3.5 Position errors via standard deviation of RSS and AOA method[21]

In [22][23] 3D approach hybrid localization can be RSS-AOA or AOA.TDOA. Once the needed parameters are collected with these techniques, associated localization algorithms can be selected and compared. Figure (3.6) illustrates hybrid localization (TDOA, AOA) system deployment model, which can be used to collect radio wave features such as angle of arrival and propagation delay. But the emphasis point here is that coverage of this system. If the targeted object is not in the area of triangle as shown in figure 3.6, it is difficult to geolocate this object with this model scenario. So, many such system has to be deployed in the way to cover the intended area.

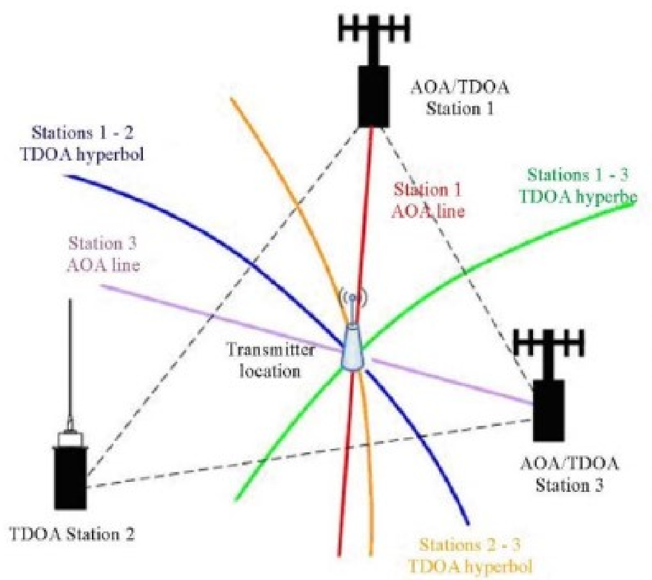


Figure 3.6 Hybrid localization system (TDOA, AOA)[23]

3.4.2 Angle of Arrival (AOA)

This technique deals with direction of signal propagation. It is typically achieved using an array of antennas. There is orientation between reference points or receivers and angle of signal. The spatial separation of antennas leads to differences in amplitudes, arrival time, and phases. But the placement of the receiver brings a negative or positive impact on the accuracy of locating the objects. For example, if jammers want to disturb RF system, they try to know our receiver placement. After they informed about receiver placement, they may set transmitter between receiver at an apart of 180 degrees. This is difficult to locate with this technique and current receiver topology unless receiver's placement is arranged. Mathematical model of AOA localization technique:

Let θ_i be the angle between bearing line from receiver i to source and axis (most probably x-axis)

$$\tan(\theta_i) = \frac{y - y_i}{x - x_i} \quad (3.1)$$

Whereas (x, y) coordinate of source and (x_i y_i), coordinate of receivers

3.4.3 Time of Arrival (TOA)

TOA technique relies on the measurement of propagation delay. The key variable, distance, is derived from RF propagation delay and velocity to perform localization. According to [24] the performance of TOA localization technique in line of sight(LOS) is high when compared with non-line of sight. As stated in [20][25] this technique works in the scenarios of:

- Highly accurate synchronization of source and receiver clocks
- Timestamps should be labeled with RF signal
- The position of receivers should be known (for dynamic it should be equipped with GPS)

Mathematical model of TOA localization technique:

- Let (x, y, z) the coordinate of the source and x_i, y_i, z_i (i=1,2,3……n) of receivers
- Distance d_i between the source and receivers i

$$di = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} \quad (3.2)$$

$$d_i = c\ t_i$$

Whereas

- d_i distance between the source and receivers i
- C speed of light (which propagation speed of RF signal assumed equal to it)
- t_i the propagation delay between source and receivers i

3.4.4 Time Difference of Arrival (TDOA)

This technique relies on the time difference of arrival of radio wave on each receiver and a network of receivers. At least three receivers are required to locate the source with high certainty. In fact, increasing the number of receivers increases the accuracy of the estimated location. In this technique time synchronization between receiver and transmitter is not required. But synchronization among the receivers is a must. Otherwise, errors lead to unrealistic location estimation[4] [26]. In [27] satellite system can also be used to geolocate an uncooperative or passive transmitter. Instead of considering the received time of arrival from the interested transmitter, which is unknown in this case, measuring the time at which that signal reaches each satellite, then considering the time difference arrival of signal among four satellites for localization purposes. For both terrestrial and satellite approach this technique mathematically expressed in equation (3.3).

$$D_{ij} = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} - \sqrt{(x - x_j)^2 + (y - y_j)^2 + (z - z_j)^2} \qquad (3.3)$$

$$d_{ij} = c\, t_{ij}$$

Whereas

- t_{ij} is time difference of arrival between receiver i and j
- d_{ij} the distance between receiver i and j

In [28] [29] this equation is tested with two localization estimators: Taylor series and Ezzat's method are discussed. Taylor series is based on range measurement, whereas Ezzat's method is based on the time dataset. Figure 3.7 illustrates the working principle of TDOA technique. The time arrival of RF signal at each receiver is different due to propagation environment or distance.

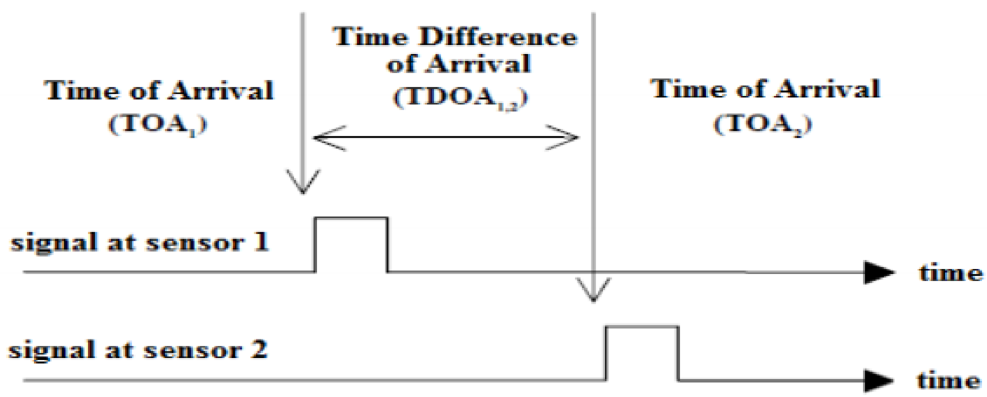


Figure 3.7 Technical illustrations of TDOA technique [30]

3.4.5 Received Signal Strength (RSS)

RSS based localization techniques rely on realistic RF propagation models [31]. The distances can be derived from these models. The models can consider priority information of transmitter power and reference distance. But for a noncooperative transmitter getting such information is a big problem. As discussed in [31] [32] such challenge can be overcome by applying RSSD method, which takes the ratios of signal power reach at the receiver point and then projecting these ratios to the receiver to emitter distance ratios. Still getting the best-fit propagation model in harsh environments is difficult. In these references the performance of four least square algorithms has been analyzed and compared with RSSD techniques and the result shows that the nonlinear least square algorithm performance best among others methods.

In[33] two thousand measurements were taken using twenty-five receivers within the area of 100m x 100m. The receiver's position is uniform within the range of distance of 25m both in x and y directions. Un on this dataset propagation model is built, and then distances are derived from it. Once the distance is estimated ML and least square algorithms are applied. The accuracy of the algorithms increases as the number of the receiver increase from four to eleven. This means position errors are correlated with the number of receivers and distance[34][35][36].

The localization accuracy depends on the accuracy of the estimated distance. For this analysis RSS based measurement techniques and algorithms (LLS, WLS, ML) are used. The performance evaluation criteria are the root mean square error (RMSE) and Cramer Rao lower bound (CRLB)[37] [38][39]. RSSD based localization technique is analyzed in IoT scenarios. This experiment was conducted by deploying different access points in the building with different power levels. According to the findings of the works, low power access points estimate better than higher power access points.

RSS based fingerprinting localization performance is tested for GSM and Wifi radio services with random decision forest (RDF) and K-nearest neighbors (K-NN) algorithms. For this purpose, data was collected using smartphones. RDF estimated a better position of the targeted emitter than K-NN algorithm. But RSS-based localization method is not effective in harsh environments due to: multipath propagation, shadowing, and fading effects. In such environments fingerprinting approach performs better by modeling long-distance path loss and applying generalized least square (GLS) algorithm [40][41][42][43].

3.5 Mathematical Model of Range-based Localization Algorithms

Distance between transmitter and receiver can be estimated using the measured propagation delay and received signal strength. The estimated distance using received signal strength is not straight forward, instead it is derived from pathloss models.

3.5.1 Nonlinear Least Square (NLS) Algorithm

The general 2D equation for RF emitter source localization using TOA, RSS, and TDOA measurement techniques is formulated in equation (3.4). whereas, x_n, y_n, and d_n represent the geographical coordinate of a receiver, and the estimated distance between the coordinate of the receiver and targeted emitter respectively. Whereas x and y represent as coordinate of targeted transmitter and N number of receives node: i=1,2,3…n

$$\begin{bmatrix} (x_1-x)^2+(y_1-y)^2 \\ (x_2-x)^2+(y_2-y)^2 \\ (x_3-x)^2+(y_3-y)^2 \\ . \\ . \\ (x_n-x)^2+(y_n-y)^2 \end{bmatrix} = \begin{bmatrix} {d_1}^2 \\ {d_2}^2 \\ {d_3}^2 \\ . \\ . \\ {d_n}^2 \end{bmatrix} \tag{3.4}$$

3.5.2 Linear Least Square Regression (LLS) Algorithm

Nonlinearity of the equation (3.4) make estimation of a source's location computational complex and expensive. Equation 3.5 is introduced to convert this nonlianarity it into linear equation form.

$$A = \begin{bmatrix} 2(x_n - x_1) & 2(y_n - y_1) \\ 2(x_n - x_2) & 2(y_n - y_2) \\ 2(x_n - x_3) & 2(y_n - y_3) \\ . & . \\ . & . \\ . & . \\ 2(x_n - x_{n-1}) & 2(y_n - y_{n-1}) \end{bmatrix} \tag{3.5}$$

$$b = \begin{bmatrix} {d_1}^2 - {d_n}^2 - {x_1}^2 - {y_1}^2 + {x_n}^2 + {y_n}^2 \\ {d_2}^2 - {d_n}^2 - {x_2}^2 - {y_2}^2 + {x_n}^2 + {y_n}^2 \\ {d_3}^2 - {d_n}^2 - {x_3}^2 - {y_3}^2 + {x_n}^2 + {y_n}^2 \\ . \\ . \\ . \\ {d_{n-1}}^2 - {d_n}^2 - {x_{n-1}}^2 - {y_{n-1}}^2 + {x_n}^2 + {y_n}^2 \end{bmatrix} \tag{3.6}$$

This matrix can be expressed as AX=b

$$X = (A^T A)^{-1} A^T b$$

where A is n x 2 matrix, b is n x 1 matrix, d_n is represent the distance from receiver to the targeted transmitter, and N is the number of receivers. The terms x_n , y_n are represent the coordinate of the receiver n.

3.5.3 Weighted Least Square Algorithm

Ordinary least squares (OSL) assumes that there is constant variance in the errors. But this is always not true due different factors such as environmental effects. Instead weighted least squares can be used when the rule of constant variance is violated. These weights can be calculated by inverting each variance.

$$w_i = \frac{1}{\sqrt{(\sigma_{d_i})^2 + (\sigma_{p_i})^2}}$$

$$(\sigma_{p_i})^2 = (\sigma_{xi})^2 + (\sigma_{yi})^2 \tag{3.7}$$

$$w = \begin{bmatrix} w_1 & 0 \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_n \end{bmatrix}$$

where w_i is the diagonal matrix, σ_{d_i} is the standard deviation of receiver i, and σ_{p_i} is the standard deviation of receiver i position. The terms σ_{xi} and σ_{yi} represent the standard deviation of position of receiver i, and n is the number of receivers.

$$A = \begin{bmatrix} 2(x_n - x_1) * w_1 & 2(y_n - y_1) * w_1 \\ 2(x_n - x_2) * w_2 & 2(y_n - y_2) * w_2 \\ 2(x_n - x_3) * w_3 & 2(y_n - y_3) * w_3 \\ . & . \\ . & . \\ . & . \\ 2(x_n - x_{n-1}) * w_{n-1} & 2(y_n - y_{n-1}) * w_{n-1} \end{bmatrix} \tag{3.8}$$

$$
b = \begin{bmatrix} (d_1{}^2 - d_n{}^2 - x_1{}^2 - y_1{}^2 + x_n{}^2 + y_n{}^2) * w_1 \\ (d_2{}^2 - d_n{}^2 - x_2{}^2 - y_2{}^2 + x_n{}^2 + y_n{}^2) * w_2 \\ (d_3{}^2 - d_n{}^2 - x_3{}^2 - y_3{}^2 + x_n{}^2 + y_n{}^2) * w_3 \\ . \\ . \\ . \\ (d_{n-1}{}^2 - d_n{}^2 - x_{n-1}{}^2 - y_{n-1}{}^2 + x_n{}^2 + y_n{}^2) * w_{n-1} \end{bmatrix}
$$

$$
x = (A^T W A)^{-1} A^T W b \tag{3.9}
$$

where A is n x 2 matrix, b is n x 1 matrix, d_n is represent the distance from receiver to the targeted transmitter, and N is the number of receivers. The terms x_n , y_n are represent the coordinate of the receiver n.

3.6 Localization System in Mobile Networks

"Enabling the positioning and tracking of mobile phones has emerged as a key facility of existing and future generation mobile communication systems. This feature provides opportunities for many values added location-based services and systems. For instance, mobile phones are increasingly employed in traffic information systems and present several advantages over traditional sensor-based traffic systems [44]". The main components of the traffic estimation system using mobile phone include central server or location data processing, traffic state estimation, location of satellites and the cellular network. The mobile phone's location is calculated using the embedded GPS receiver and the network-assisted information. The mobile application sends location updates to the server. The communication between server and client is implemented through the cellular network. The server collects locations and then estimate the traffic to send to each client the dynamic information. As shown in Figure (3.7), the information presented on mobile phone display consists of an area map with the user's location and colored road segments showing traffic conditions [44].

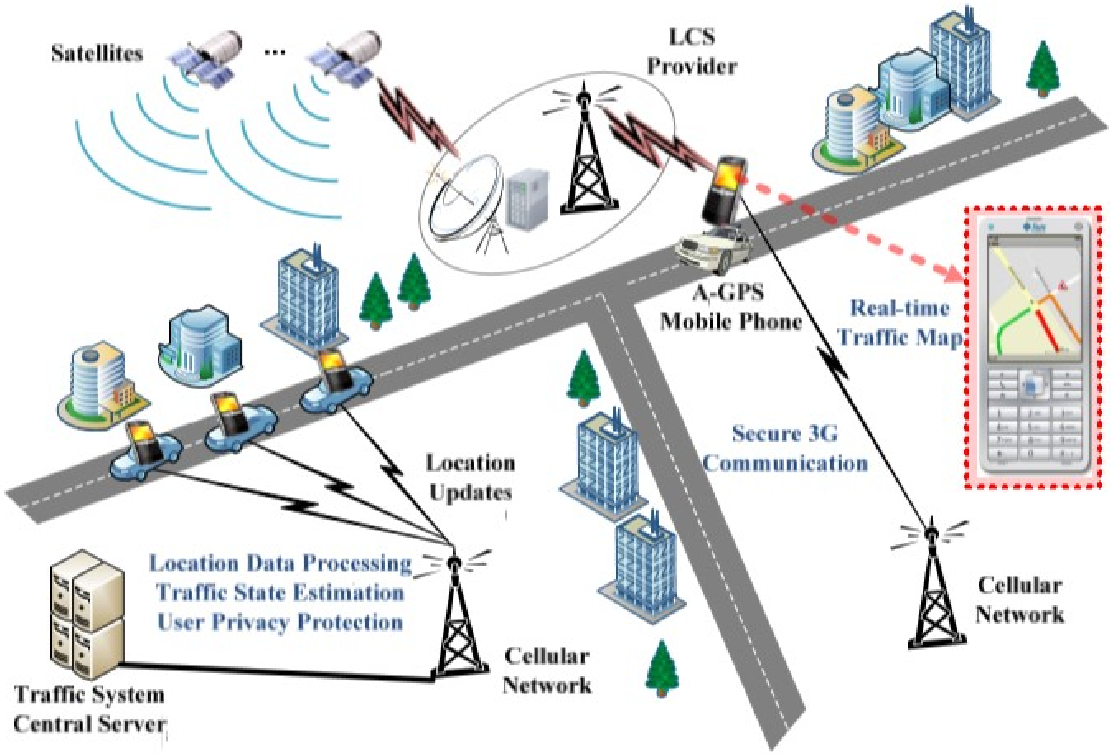


Figure 3.8 Mobile Phone-based Smart Traffic Information System [44]

As illustrated in table 3.2 the supported methods and features for localization purpose in mobile networks are different from technology to technology.

Table 3.2 Localization in mobile networks [44]

RAN Technologies	Supported methods	Features
GSM/EDGE	Assisted GPS	• MS with GPS receiver • Information from RF signal transmitted by satellite
	Enhanced Observed Time Difference (E-OTD)	• Location is estimated by MS • BTS serve as reference points
	Time advance (TA)	• Cell ID technology • Propagation delay
	Uplink Time Difference of Arrival (U-TDOA)	• Location is estimated by the network of infrastructures

UTRAN	Observed Time Difference of Arrival (OTDOA)	• Intersection of node Bs • Use TDOA techniques
	Cell ID technology	• Round-trip-time (RTT)
	Uplink Time Difference of Arrival (U-TDOA)	• Location is estimated by the network of infrastructures
	Assisted GPS	• UE with GPS receiver • Information from RF signal transmitted by satellite
E-UTRAN (Release 10)	Enhanced Cell ID (E-CID)	• UE position from E-Node B and cell, and E-UTRAN resources
	Downlink positioning	• TDOA observed by the UE
	A-GPS	• UE with GPS receiver • Information from RF signal transmitted by satellite

3.7 Host Localization with IP Geolocation Approach in Cyberspace

"IP geolocation is used to determine the exact geographic address of a target device by its IP address. It is an important technique to achieve network attack traceability, network security early warning, and improve the ability of cyberspace governance. For examples, it is used for content positioning, targeted advertisements, identity authentication, the continuity and supervision of cloud service, screening of sensitive network entity, network forensics of illegal acts like Internet fraud and attack, develop the deployment strategy of the network infrastructure and discover fault nodes, network performance optimization and so on. Because of these wide range of applications and important value, it has been highly concerned by the academic and industrial circles. At present, there are many commercial and academic IP location databases on the Internet, such as IP2location, Maxmind, Geobytes, Netacuity, IPIP.net, Chunzhen, Sina, Taobao, Baidu, etc." [45][46]

For the transmitters that do not use an electromagnetic wave as media, IP-based localization is another approach for such cases. It is the means to locate the targeted device in cyberspace by using the device's IP address. This technology can be active or passive localization. For a collaborative approach, information can be gathered from entities such as the DNS database, database, and ISP carriers. But for a noncooperative, the targeted IP host location is estimated through measuring parameters such as delay and topology discovery[45]. Multilateration methods were applied to formulate the distance as a function of propagation delay. As shown in figure (3.10) the targeted device location is estimated using the nearest common router**.** In real-time, the location of hosts is usually close to the last hop router.

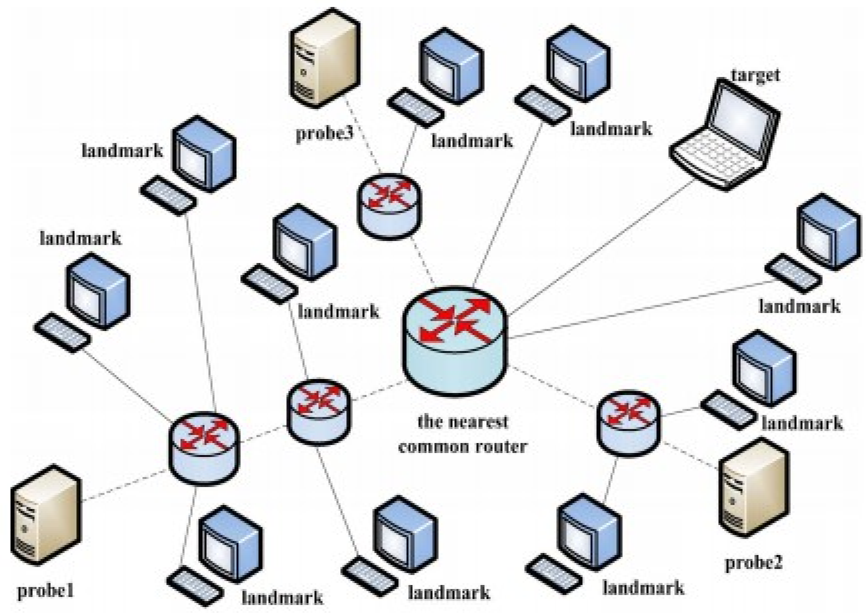


Figure 3.9 Topology of IP geolocation[45]

The correlation between physical distance and latency of the network is analyzed with delay techniques by ping the targeted Ip address and measuring RTT.

The currency IP geolocation measurements rely on the distribution of landmarks. For optimal placement of these landmarks, a Linear programming model and Euclidean metrics were applied. The distance is derived as a function of hop count and RTT. These two known parameters: estimated distance and coordinates of landmarks to estimate the physical location of the targeted host[47] [48][49]. “Based on shortest relative delay in the real Internet, IP geolocation algorithm to estimate the geographic location of internet host using the nearest common router between the target host and landmarks. This algorithm finds the nearest common router between the target host and landmarks through topology discovery and takes the network entity with known location as passive landmark; estimates the delay between nearest common router and landmark, determines the geographic location of this router, then mapping the target host to this location.” [45].

Figure 3.10 Measurement of RTT for IP based localization [47]

Before calculating the conversion of delay and distance between nearest common routers and landmarks, it is need to find out the nearest common router between target IP and landmarks. For instance, for target IP 120.194.19.227 and 120.194.19.229, the nearest common router 120.194.30.42 is selected and combined with 12 landmarks connected to 120.194.30.42, as shown in table (3.4).

Table 3.3 The nearest common router and related landmarks of targeted hosts [45]

Target host IP	Nearest common router IP	Landmark IP	Latitude	longitude
120.194.19.227 120.194.19.229	120.194.30.42	120.194.19.251 120.194.21.99 120.194.21.109 120.194.21.110 120.194.24.113 120.194.24.137 120.194.24.142 120.194.24.153 120.194.24.160 120.194.24.168 120.194.24.174 120.194.24.182	34.31920442 34.4617359 34.41836217 34.46383206 34.44353613 34.33220076 34.33220076 34.37341641 34.41911437 34.31920442 34.40685687 34.37146776	112.90632 113.12939 113.41749 113.50942 113.26704 113.82434 113.82434 113.27229 112.76502 112.90632 113.15662 113.27132

4 System Modeling and Data Analysis Approaches

In this section, methods of data acquiring, measurement tools and the statistical analyses of the field measurements data are presented. The main ideas of the statistical analyses are to understand the radio wave propagation features for two FM stations which operate at 97.1 and 101.1MHz, comparing and analyzing propagation models. And also comparing and analyzing range-based localization algorithms. This thesis utilized empirical data to achieve the objective. The objective was to compare the performance of RSS-based geolocation techniques and algorithms in the context of Addis Ababa city (from the perspective of environmental effects). Two main activities were performed to achieve this objective: the first task is to model RF propagation path loss, in which distance is deriving from it, and the second is to compare the performance of RSS based geolocation algorithms using RMSE based evaluation metrics.

Assumptions

- Transmitter is not implementing power saving schemes (power is not varying)
- Transmitter is stationary
- 2D (latitude and longitude grid)
- Antenna of transmitter is omnidirectional
- Transmitter is assumed broadcasting continuously at a known center frequency
- The emitter is within the range of the receivers

4.1 Data Collection and Analysis Methods

The primary data was collected through field measurement using a single radio monitoring unit. This monitoring equipment has the capability of measuring: frequency range up to 3GHz, power of the received signal in dBm, its position (latitude, longitude) using GPS, the band width of different modulation types. As shown in figure (4.1), there are many modules installed in the car: spectrum monitoring unit, nine antenna arrays (with vertical and horizontal polarization, direction-finding antennas), Ethernet LAN, air compressor for lifting antenna, compass, GPS, power modules, and PCs. In addition to this equipment, software tools such as python and excel were also used to analyze data.

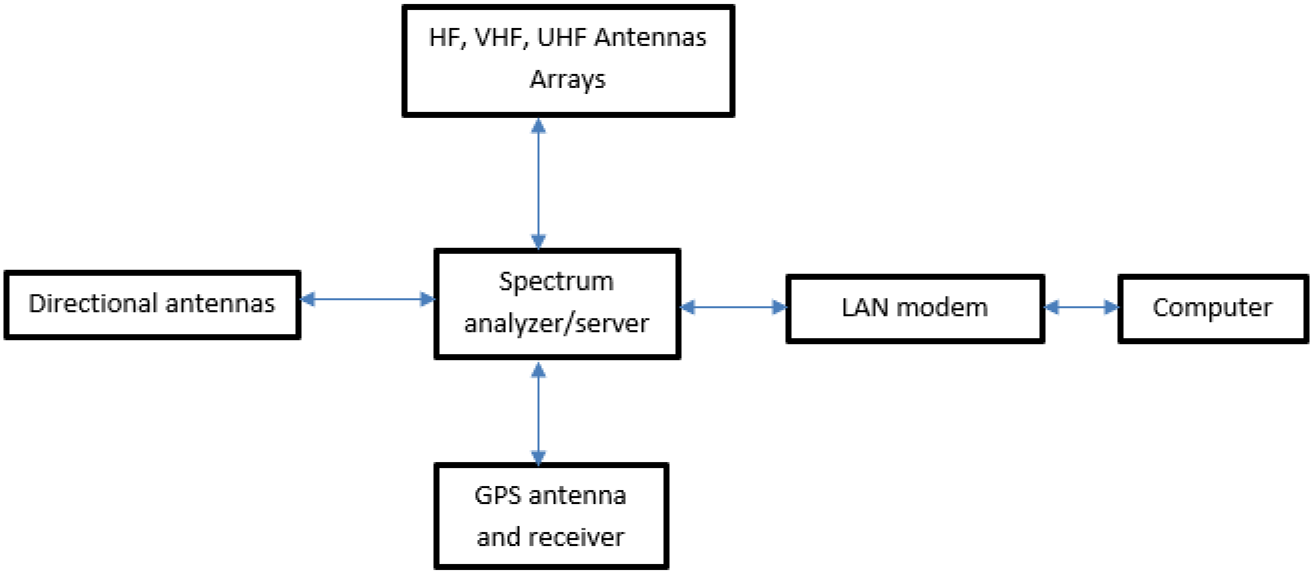


Figure 4.1 Illustration diagram of integration of measurement tools

The measurement equipment shown in figure 4.2 and 4.3 and are integrated within mobile monitoring unit for data collection. The collected parameters with this equipment were: average power, distance, geographical coordinate (latitude, longitude) of the monitoring unit at each measurement. Spectrum analyzer, which is shown in figure 4.2 is used to collect RF signal from frequency range from 9KHz up to 3GHz. It has many RF signal input and output ports with different cable connectors types. Ethernet connection and USB port are also available.

Figure 4.2 Spectrum analyzer (ECA's property)

Figure 4.3 Ford F350 Van: integrated mobile spectrum monitoring unit and car (ECA's property)

The antenna types and specifications of mobile monitoring unit shown in figure 4.3 are; single direction finding and monitor antenna for full VHF/UHF Coverage, wideband spectrum monitoring system (20/2 MHz), dual polarized (H/V), single-band direction finding and monitor antenna for full VHF/UHF coverage, VHF/UHF DF and monitor antenna up to 3000 MHz, VHF/UHF vertical direction finding and monitor antenna and VHF/UHF horizontal direction finding and monitor antenna up to 3000 MHz, but current directional and polarizations antennas are not working properly. The measurement strategy is driving a car on different routes and collects the data according to the sheet shown in table (4.1).

Table 4.1 Data collection approach

Information from receiver (measurement tool)				Location of Transmitters	
Coordinate of receiver (N, E)	Coordinate of receiver (UTM)	Received power (dBm)	Distance (m)	Tx1	Tx2
(N_1, E_1)	(x_1, y_1)	p_1	d_1	(x_{01}, y_{01})	(x_{02}, y_{02})
(N_2, E_2)	(x_2, y_2)	p_2	d_2		
(N_3, E_3)	(x_3, y_3)	p_3	d_3		
(N_n, E_n)	(x_n, y_n)	p_n	d_n		

The strategy used for fieldwork was taking measurements of received signal power (dBm) and corresponding coordinates at each measurement position, using a single mobile radio spectrum monitoring unit. The average power is taken at each specific coordinate because the power of the transmitted signal fluctuates with the variation of distance and environment. Due to these reasons, an average of ten measurements was taken at each specific physical coordinate. Following this approach, 120 average values of received powers and associated coordinates were collected from two FM transmitters.

Data preparation was done using statistical data analysis methods. Manipulating data by: checking outliers, data distribution, and cleaning. The prepared and structured dataset were analyzed using python and excel tools with statistical methods. These statistical methods are means, standard deviation, regressions, mathematical equation derivations (Algorithms). In addition, representative visualizations: plots, diagrams, figures, and tables were used. Prior to data preparation, radio wave propagation models training was done, then testing the models. Since data was randomly collected in selected area, rather than building an inclusive model for whole selected area, it is better to model the radio wave propagation by clustering the selected area or environment. The selected propagation model are lognormal shadowing model and linear regression methods.

4.2 Lognormal Shadowing Pathloss Model

The Lognormal propagation model can be formulated with; distance between the transmitter and the receiver, and propagation environments. As formulate in equation 4.1 average received power at distance di is written as function of four variables; path loss exponent, power at reference distance, distance from receiver to transmitter, gaussian distribution, and reference distance.

$$\mathrm{P}(d_i) = p_0 - 10\alpha\log\left(\frac{d_i}{d_0}\right) + \mathrm{F}(\sigma) \tag{4.1}$$

Parameters defined as:

- $\mathrm{P}(d_i)$: average received power at distance di
- d_i: distance from receiver to transmitter
- d_0: reference distance
- p_0: power at reference distance
- α: path loss exponent (decaying exponent)

- σ: standard deviation of zero mean gaussian distribution of measured power
- F (σ) Gaussian distribution function

4.3 Linear Regression Pathloss Estimation Methods

Modeling the distance as the function of power and environmental factors using ordinary least square (OSL) method, which is built in function in python. Where b_0 and b_1 are variables that to be calculated using ordinary least square method. Once these variables are determined, it is straightforward to get the distance as shown in equation 4.2.

$$\log(d) = b_0 + b_1 * P(d_i)$$

$$d_i = 10^{(b_0 + b_1 * P(d_i))} \tag{4.2}$$

Once these models were evaluated and optimized by minimizing the error of distance, it was necessary to derive the distance from these models. In fact, exploring distance from these propagation models may has accuracy problem due to environmental effects and used measurement techniques. The evaluation metric used for these models is RMSE. It is one of the most commonly-used performance evaluation metrics used for evaluating the accuracy of estimated or predicted parameters. The final stage of the method was comparing the location estimation performance of range-based geolocation algorithms (LLS, WLS). RMSE also used for algorithms comparison. As shown in figure 4.4 the covered area was roughly 193 kilo meters squares

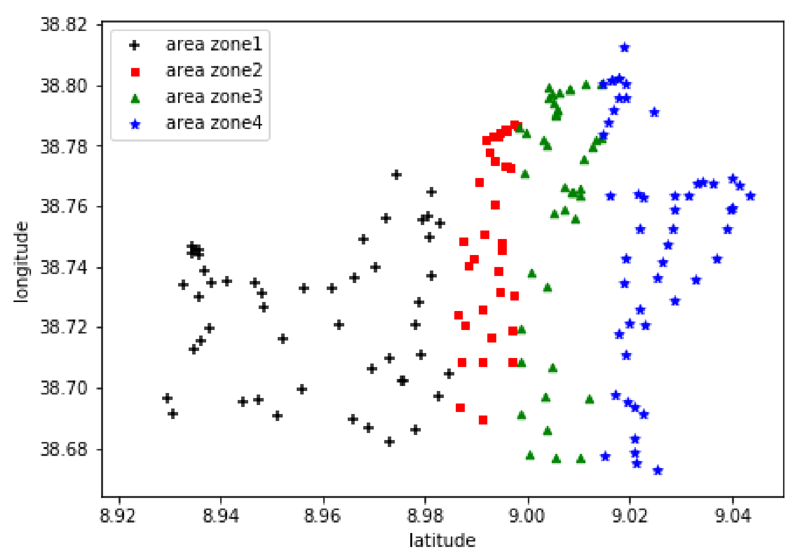


Figure 4.4 Receiver coordinate points at measurements were taken (latitude and longitude)

Clustering this area was needed due to: uncovered areas in total area, the distribution of distance, and the distribution of received power. As well, the distance between each receiver's coordinate is not the same because it was randomly captured. Also, environment and distance effect are different for each coordinate. Due to these reasons the total area was clustered into four groups of area to minimize the errors of estimated distance or location.

Figure 4.5 illustrate the area in terms of UTM (northing and easting). It is nothing but the conversion f latitude and longitude into UTM form. This conversion is needed because of computational simplicity with UTM. It is difficult to deal with latitude and longitude during distance calculation. Converting degrees to UTM is straight forward and easy to calculate the distance between receiver and transmitter from measurements data during training the model. But for testing purpose, this distance is to be estimated.

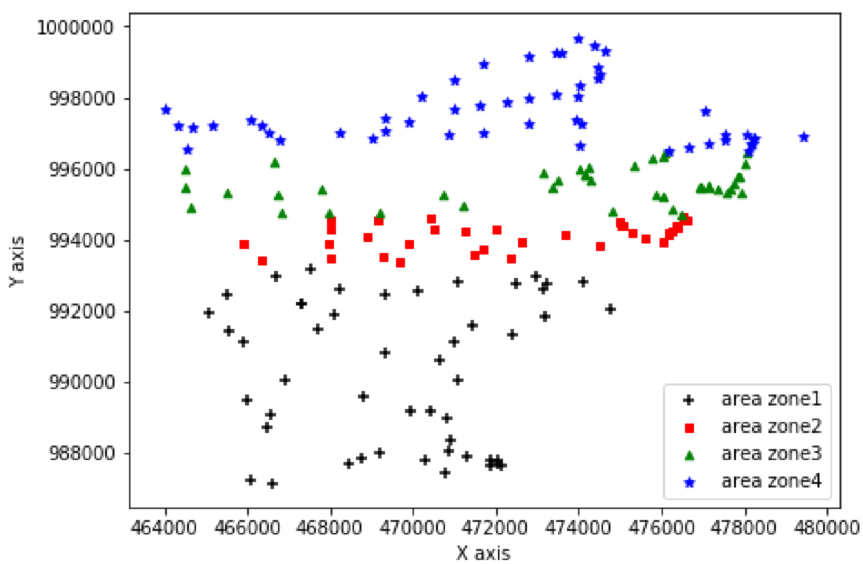


Figure 4.5 Receiver coordinate points at measurements were taken (UTM)

Figure 4.6 shows the distribution of the measured signal power of 101.1FM transmitter. The minimum and maximum measured value is -68dBm and -58dBm respectively. The mean of the data is around -64dBm and it is the skewed gaussian distribution.

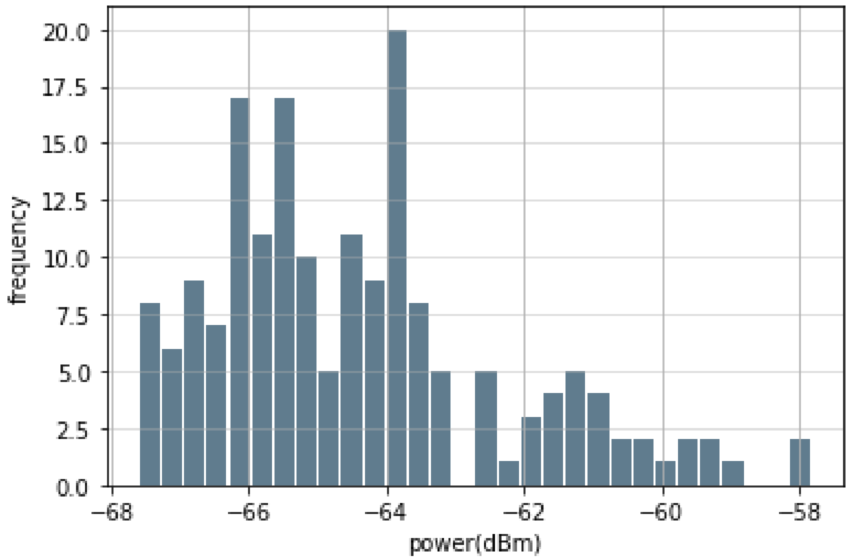


Figure 4.6 Histogram of power distribution for 101.1FM transmitter

Figure 4.7 shows the distribution of the measured signal power of 97.1FM transmitter. The minimum and maximum measured value is -63dBm and -56dBm respectively. The mean of the data is -59dBm and it is the skewed gaussian distribution.

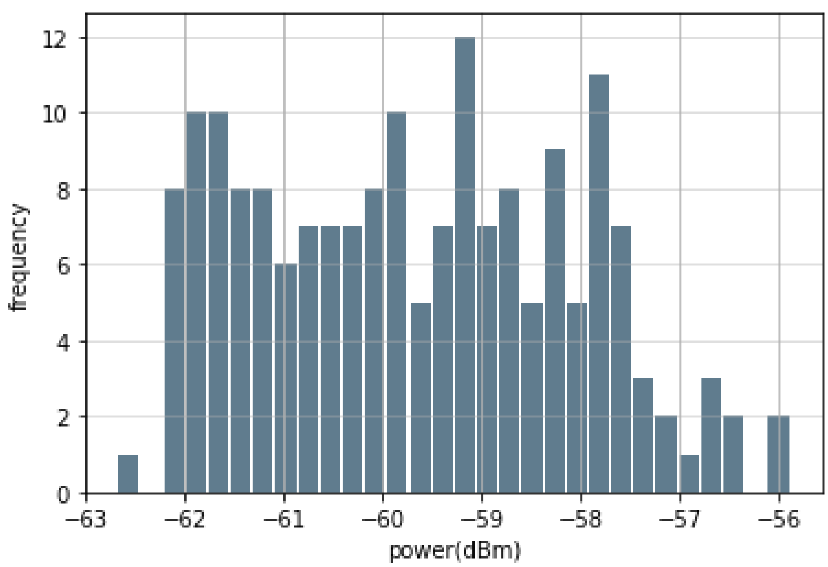


Figure 4.7 Histogram of power distribution for 97.1FM transmitter

Figure 4.8 illustrate the histogram distribution of measured distance. The minimum and maximum distance is 6000m and 20000m respectively.

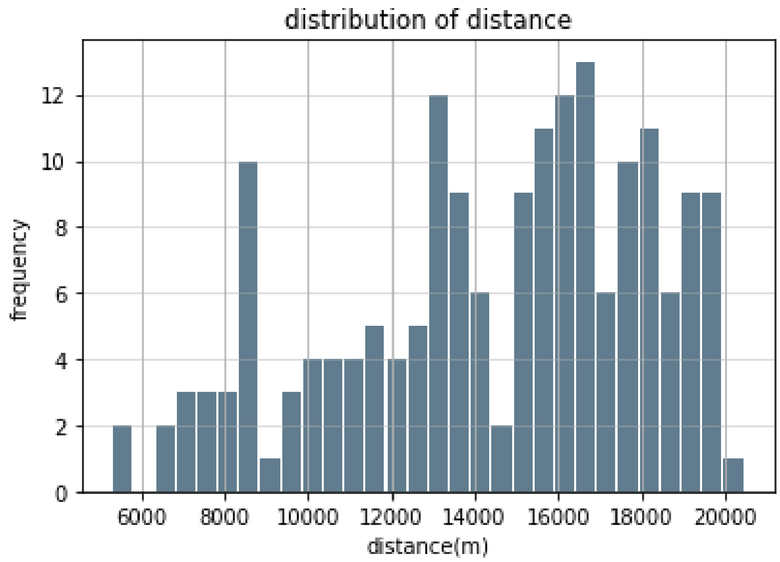


Figure 4.8 Histogram distribution of measured distance

RSS-based localization technique is chosen among other geolocation techniques such as TOA, FDOA, AOA, and TDOA. The justification for selecting this technique is: time synchronization between transmitter and receiver is not needed, simple to measure the required parameters, no need for a line of sight, smarts (antenna array) are not needed, and the computational aspect is not expensive. But the other techniques have the challenge of complexity and expense, assume the line of sight, and need time synchronization. The limitation of RSS-based localization techniques and algorithms is accuracy, which compromises the accuracy of targeted parameters.

5 Results and Discussions

5.1 Results

To compare the performance of RSS based geolocation algorithms, pathloss models were first trained and tested with primary data. And then, RMSE was used for performance evaluation for both pathloss models and algorithms.

5.1.1 Propagation Pathloss Models

The results of 101.1 FM propagation models (regressive method and lognormal shadowing model) are shown in figure (5.1). From these models' every distance between receiver position and targeted transmitter position has been estimated. Upon these distances, the geolocation algorithms estimate the location of the targeted object, the transmitter. The geolocation algorithm applied in this thesis is least-square linear regression and weighted least-squares linear regression.

```
The output model of linear regressive method for 101.1 FM is:

               log(d) = b0+b1*power(p)

               Intercept(b0) = 0.33669319843057854

               Coefficient(b1) = [-0.05902653]

               log(d)= 0.336693 - 0.0590265*p

 lognormal shadowing model for 101.1FM
```

Area zone 1: $p_r(d) = 20 - 20.655 * \log(d)$

Area zone 2: $p_r(d) = 20 - 20.442 * \log(d)$

Area zone 3: $p_r(d) = 20 - 20.283 * \log(d)$

Area zone 4: $p_r(d) = 20 - 20.226 * \log(d)$

As can be seen from figure (5.1) the distance and power measurement started at six kilometers away from the targeted transmitter, but data density is high between ten and twenty kilometers. The estimated distances with both propagation models are crowded at nearest to the points of the measured distance. OSL based distance estimation is better closer to the true distance.

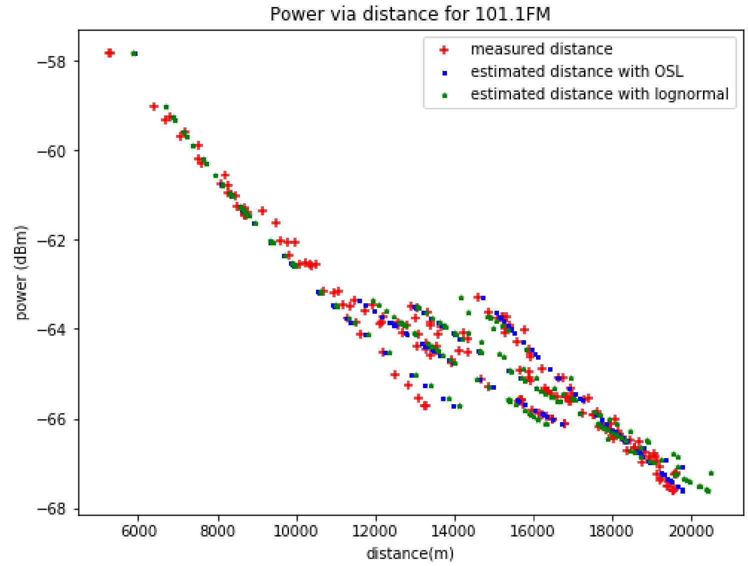


Figure 5.1 Estimated and true distance via power for 101.1FM

The estimation performance of these algorithms varies with many parameters such as the number of receivers and placement, propagation effects, measurement quality, and sample size. As shown in figures (5.2) there is a significant difference between the two models during estimation of the distance and the error is less for the regressive method.

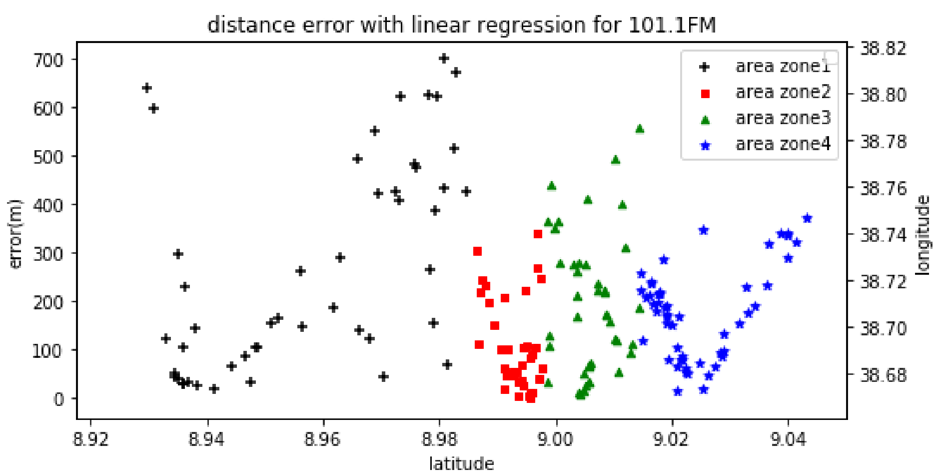


Figure 5.2 Distance error with linear regressive method (101.1FM)

As illustrate in figure (5.3) the error is high with the lognormal shadowing model. Their comparison depends on the standard deviation of the measured power. The result indicates that lognormal estimation is better for less than 2dB of standard deviation, linear regression is better for greater than 2dB. The estimated location is affected by distance errors. The low error of estimated distance means a better estimation of the location of the targeted object. There is a high positive correlation between the distance and position of the targeted object. This means as the errors of the distance increase the errors of location also increase. On the other hand, as errors of distance decrease, the errors of location also decrease. The distance errors levels, at each measurement position, are different for each cluster. The error level is high for areas zone 1 and 4. But for areas zone 2 and 3 the error is lower. This is due to environmental and measurement effects. During data collection, receive can pick up the RF signal in line of sight since it is mobile monitoring unit and driven on the streets.

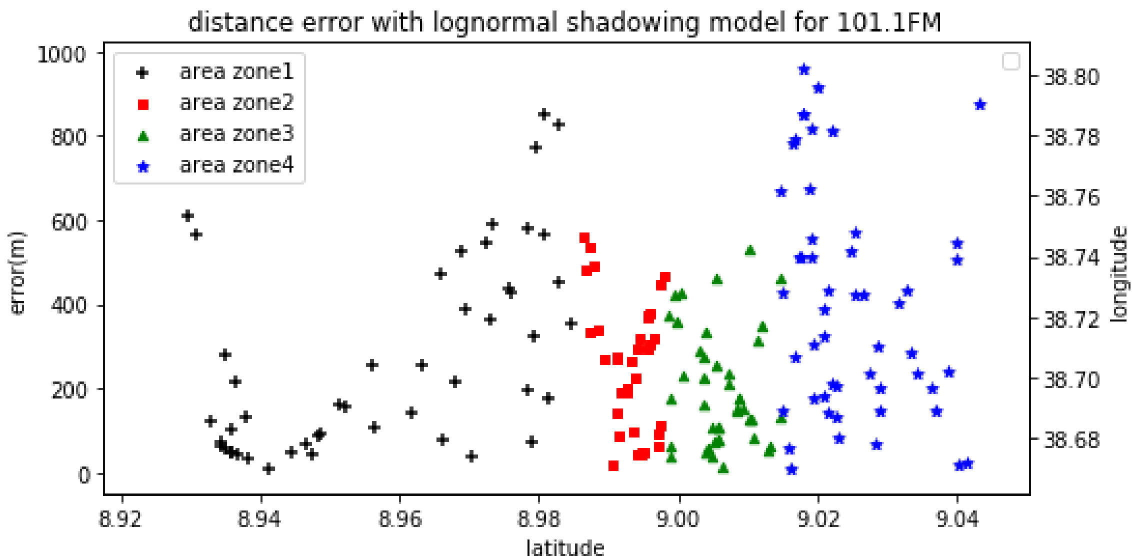


Figure 5.3 Distance error with lognormal shadowing model (101.1FM)

For 101.1FM, the error of estimated locations with lognormal shadowing and least linear regression is less with the OSL method and weighted least square algorithm. This result shows that OSL and weighted least square algorithm estimated better than lognormal shadowing model. The performance of the two models depends on the standard deviation of the measured power. For 101.1FM a lower error of 170m was found with the OSL method and weighted least square algorithm.

The selected measurement area was divided into four clusters. This is because of the propagation effects which, are different in each environment due to physical obstructions. The characteristics of one propagation environment are not the same as other environments. So, merging such environments can affect the localization estimation problem. As shown in figure (5.4) the errors with non-clustered areas are very high than that of the clustered. So, rather than modeling whole areas at once using both the lognormal shadowing model and regressive method, it is better to model by clustering the area using both these modeling methods.

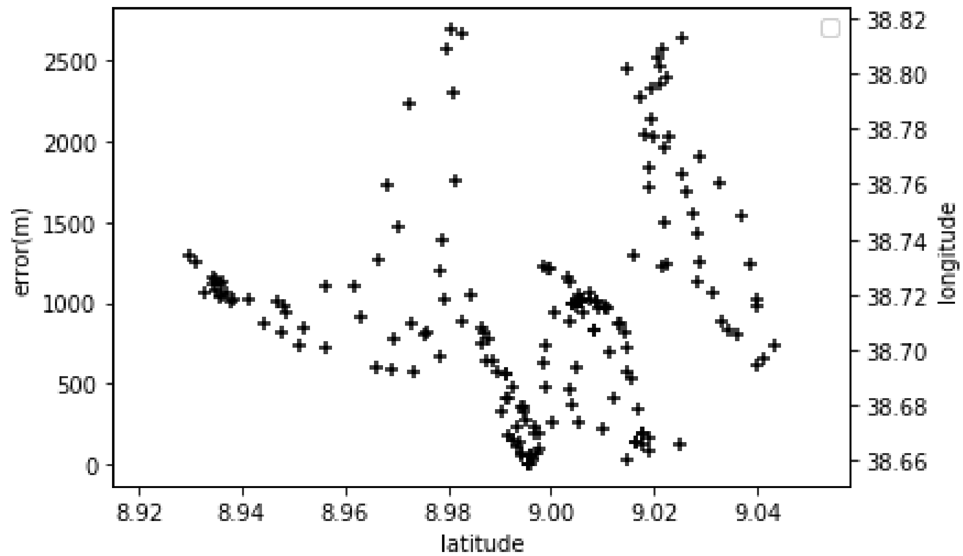


Figure 5.4 Distance errors with no clustering of area for 101.1FM

The clustering of the area can consider power and distance probability distributions function (pdf). As we can see from figure (5.2,5.4) there is a significant difference between clustering and non-clustering in the case of distance estimation.

The path loss exponent is the approach to free space loss. It is due to three reasons: the first reason is the location of the transmitter, which is placed at a high mountain with an antenna height of 80m. The second reason is the receiver antenna high 8m from the ground. The third reason is the way data is collected which means using mobile monitoring unit and driving the car on the street which most signals picked up in line of sight.

```
The output of linear regressive method for 97.1 FM

          log(d) = b0+b1*power(p)

          Intercept(b0) = -0.33796136715359815

          Coefficient(b1) = [-0.07507483]

          log(d)= -0.33796 - 0.07507483*p
```

lognormal shadowing model for 97.1FM

Area zone 1: $p_r(d) = 28 - 21.606 * \log(d)$

Area zone 2: $p_r(d) = 28 - 21 * \log(d)$

Area zone 3: $p_r(d) = 28 - 21.104 * \log(d)$

Area zone 4: $p_r(d) = 28 - 20.907 * \log(d)$

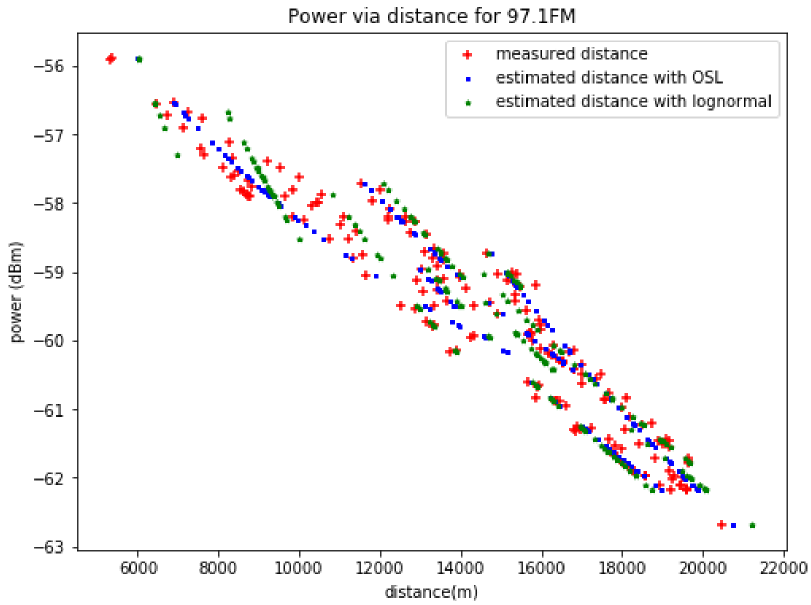


Figure 5.5 Estimated and true distance via power (dBm) for 97.1FM

As shown in figure 5.6 and 5.7 the estimated distance error for 97.1FM lognormal shadowing model is lower than linear regression method. This mean the standard deviation of the measured power is less than 2dB. For 101.1FM case the error level of OSL method is lower than lognormal shadowing model, this is the matter of measurement conditions and environments effects.

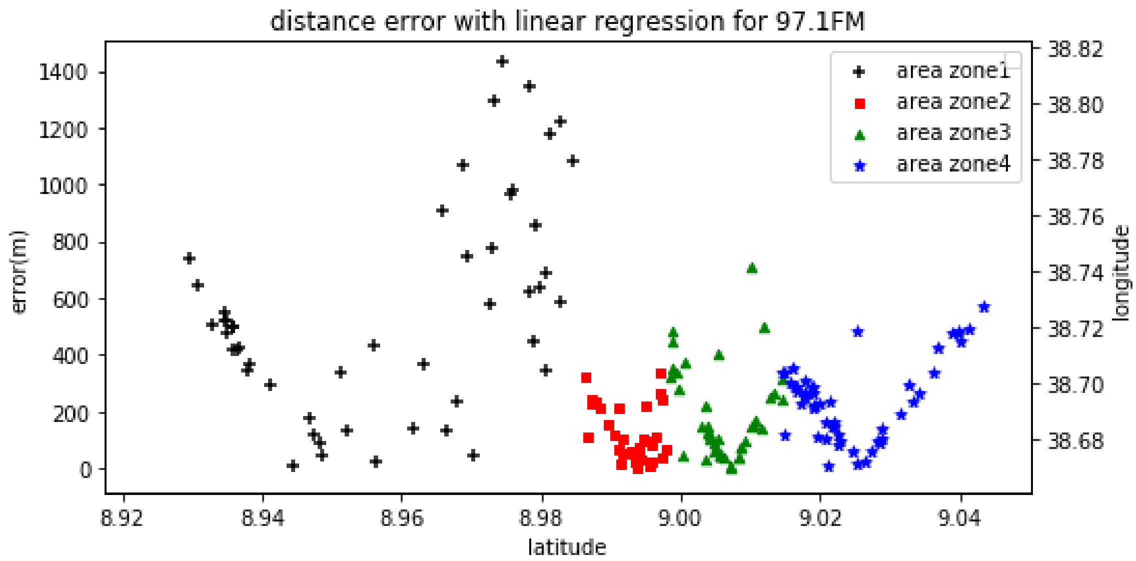


Figure 5.6 Distance error with linear regressive method (97.1FM)

The other significance changes for 97.1FM regarding distance estimation was, the error of area zone 1 became higher than of 101.1FM. The reason for this big difference is that the effects of environments and measurement conditions.

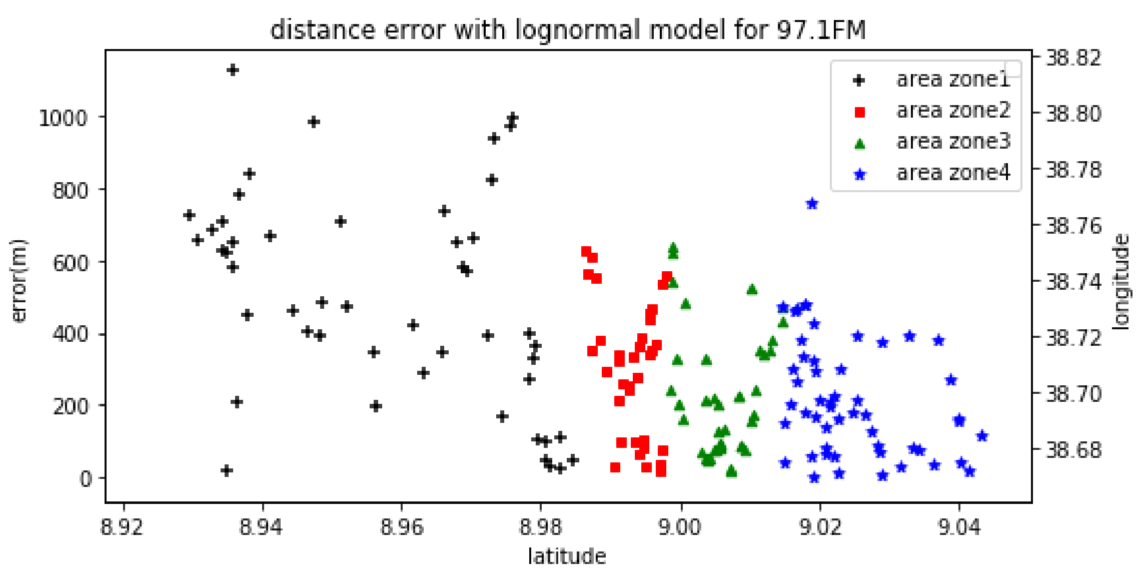


Figure 5.7 Distance error with lognormal shadowing model (97.1FM)

5.1.2 Estimated Location of Targeted Emitter

The object of thesis was to compare RSS based localization techniques for a passive and uncooperative RF emitter that is located on the surface of the earth. This is based on geometric principle, to determine the distance between receiver and fixed ground stations. This distance is expressed as a function of the propagation loss. The mathematical models that express the propagation loss as a function of distance is required. These models are lognormal and least linear square method. Once this function is defined, and the distance between the receiving and emitting stations is estimated. The next step is to estimate the location of targeted emitter using the selected geolocation algorithm. In this case weighted least square regression and linear least square regression algorithms are compared and analyzed. Table 5.1 illustrate the summery of estimated coordinates of two FM transmitters.

Table 5.1 Estimated location of two FM transmitters

101.1FM transmitter				
Propagation models	Algorithms	Estimated location		Position Errors(m)
		UTM(X)	UTM(Y)	
OSL	LLS	465359.87	981830.36	206
	WLS	465142.6	981814.8	170
Lognormal model	LLS	465145.22	982659.42	799
	WLS	465485.9	981983.3	660
97.1FM transmitter				
Propagation	Algorithms	UTM(X)	UTM(Y)	
OSL	LLS	465069.47	981780.64	476
	WLS	465142.6	981814.8	397
Lognormal model	LLS	465467.1	981976.18	95
	WLS	465485.9	981983.3	90

Figure 5.8 shows the estimated coordinate of 101.1FM transmitter with two propagation pathloss and algorithms. As indicated in this figure the error is high (799m) with lognormal shadowing pathloss model (Log:). But with regressive method (OSL:) the error is comparable less (170m). Weighted least square regression estimate with better accuracy than linear least square regression algorithms.

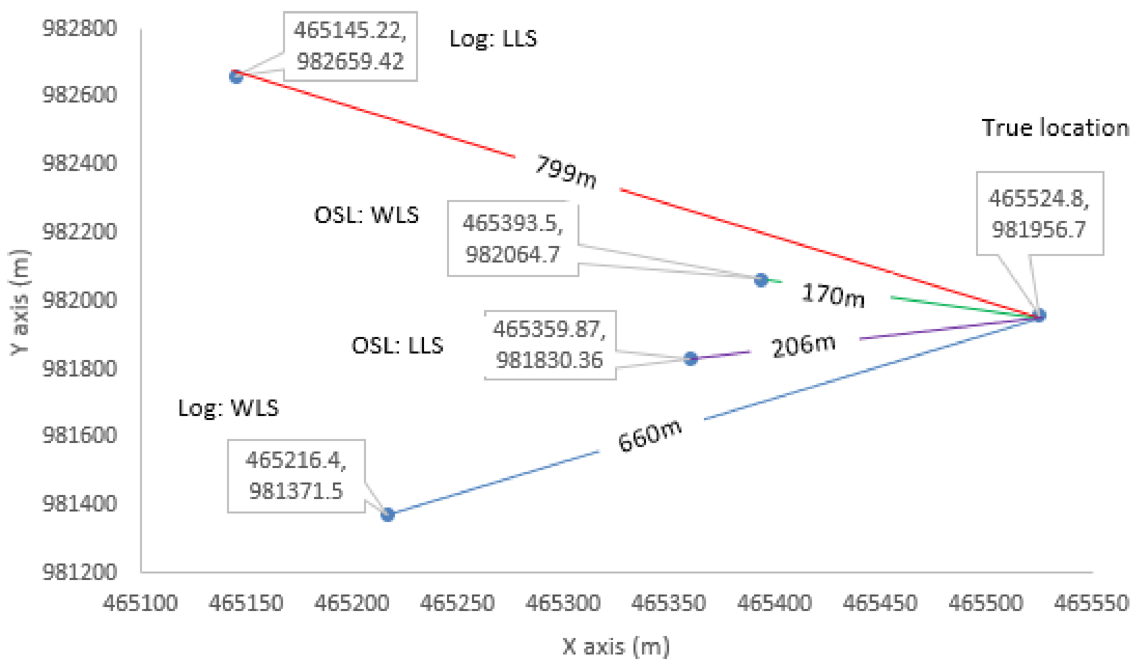


Figure 5.8 Estimated location for 101.1FM transmitter

Root Mean Square Error (RMSE): compute localization error for both coordinates, so RMSE for both coordinates can be calculated as:

$$\mathrm{RMSE_X} = \sqrt{\frac{\sum(\mathrm{Est_x} - \mathrm{Actual_x})^2}{\text{number of estimates}}}$$

$$\mathrm{RMSE_y} = \sqrt{\frac{\sum(\mathrm{Est_y} - \mathrm{Actual_y})^2}{\text{number of estimates}}} \tag{5.1}$$

$$\text{net RMSE} = \sqrt{\mathrm{RMSE_X}^2 + \mathrm{RMSE_y}^2}$$

In equation (5.1) $\mathrm{Est_x}$ and $\mathrm{Actual_x}$ represent estimated coordinate of emitter and true position in x axis respectively. Also $\mathrm{Est_y}$ and $\mathrm{Actual_y}$ represent estimated coordinate of emitter and true position in y axis respectively. In addition, $\mathrm{RMSE_X}$ and $\mathrm{RMSE_y}$ represent the root mean square error in x axis and y axis. In addition, accuracy also calculated, which represents the difference between the exact position and the estimated position, and its performance evaluation based on the Euclidean distance, which described in equation (5.2).

Whereas, x_{est} and x_{actual} represent estimated coordinate and true position of emitter in x-axis respectively. And y_{est} and y_{actual} represent estimated coordinate and true position of emitter in y-axis respectively.

$$d_{accuracy} = \sqrt{(x_{est} - x_{actual})^2 + (y_{est} - y_{actual})^2} \tag{5.2}$$

As indicated in figure 5.9 Lognormal model perform better than regressive method estimates better. This is because the measured power of 101.1FM has higher standard deviation when compared with that of 97.1FM.

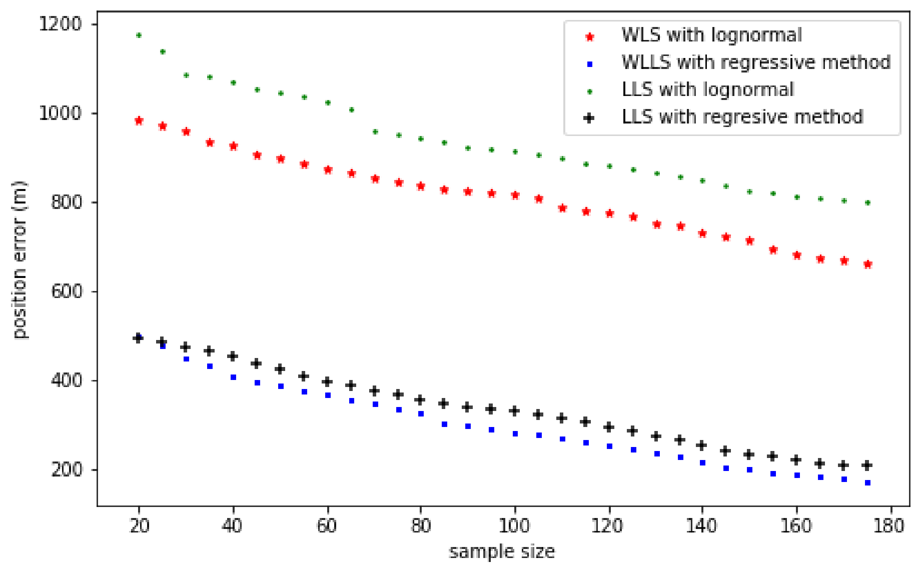


Figure 5.9 Error of estimated location via sample size for 101.1FM transmitter

Figure 5.10 shows the estimated coordinate of 97.1FM transmitter with two propagation pathloss and algorithms. As indicated in this figure the error is high (476m) with regressive method (OSL:), but with lognormal shadowing pathloss model (Log:) it is less (90m). For both propagation pathloss weighted least square regression estimate with better accuracy than linear least square regression algorithms.

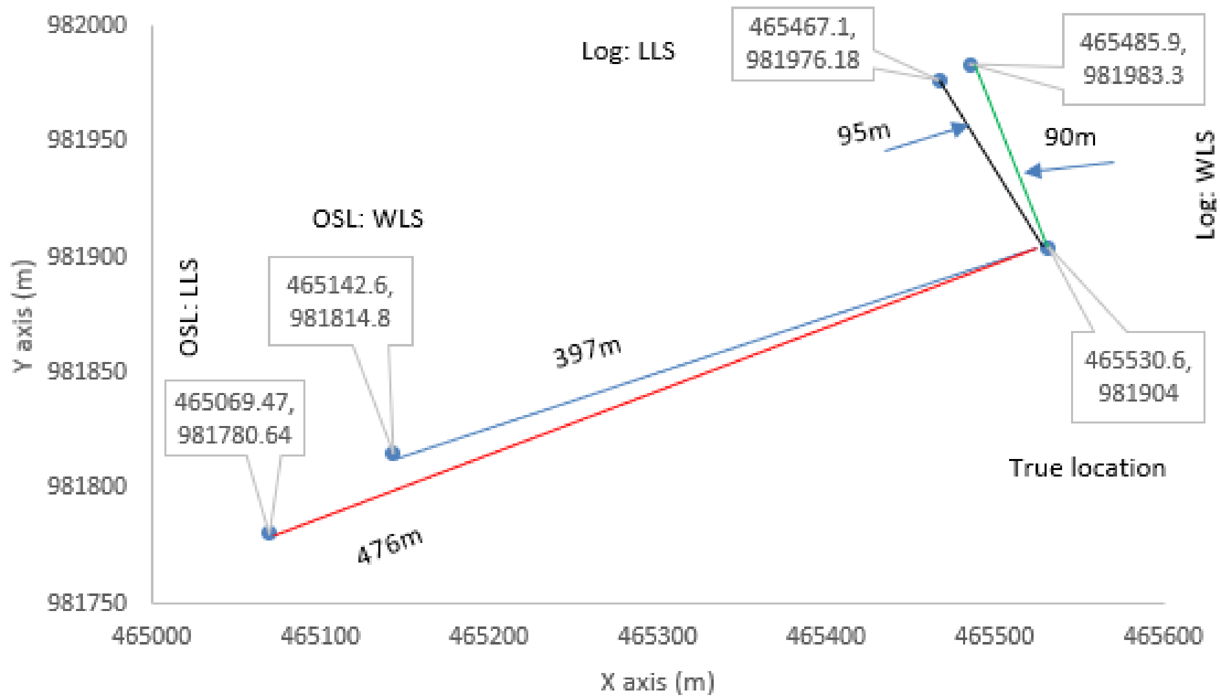


Figure 5.10 Estimated location for 97.1FM transmitter

As shown in figure (5.11) with lognormal model for 97.1FM the position error is minimized, but for 101.1FM transmitter it is high due to the standard deviation of the measured power. If the standard deviation of power is relatively low lognormal shadowing model perform better. As indicate in the figure as the size of sample increase the error decrease.

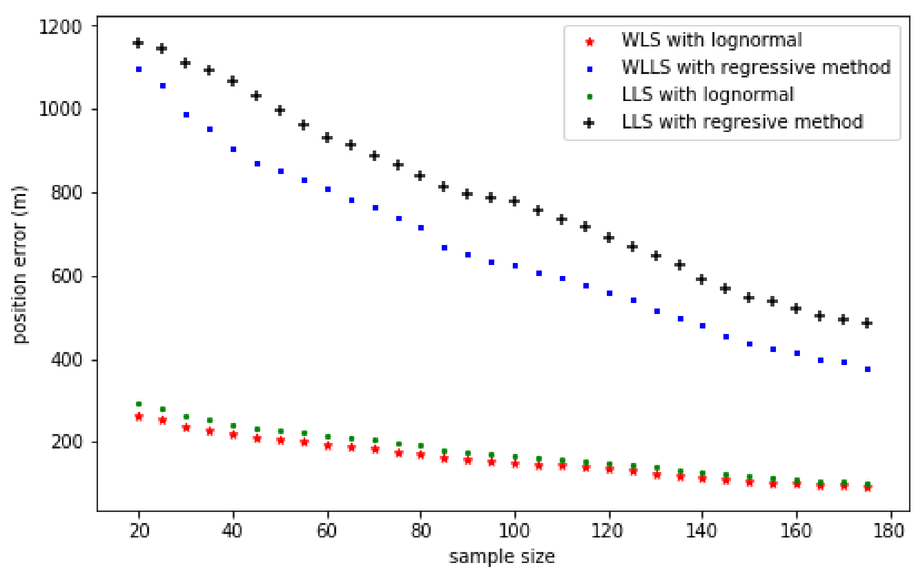


Figure 5.11 Errors of estimated location via sample size for 97.1FM transmitter

5.2 Discussion

This thesis setout with the objective of comparing and analyzing RSS based geolocation techniques and algorithms. The most significant findings are:

5.2.1 Estimated Distance from Propagation Pathloss Models

As stated in [50] the characteristics of a radio wave can be influenced by factors such as distance, atmosphere conditions, frequency range, and propagation environments. Due to these factors, RF signal strength degraded, theoretically the expected coverage area is missed and creating different delay profiles for the same signal. So, mathematically modeling radio wave propagation as a function of these factors is very important for radio planning, regulatory activities, etc.

These factors also remain the main challenge to the localization of the objects of interest. As discussed in [50]the localization problem has been solved mainly by two approach range and angles. This distance can derive from radio propagation features such as received signal power and propagation delay, whereas the angle of arrival can derive from antenna arrays at receiver ends. If the measurements don't consider the factors that affect the behaviors of radio wave propagation, the localization problem can be highly biased. Small changes in transmission time can bring high errors during the estimation of the distance.

RSS-based emitter localization technique is highly reliant on the realistic radio propagation model. Because the estimated distance is formulated as a function of received power and propagation environment, multipath and shadow fading, which is random and leads to high distance error. To solve localization problems propagation environments should be taken into account. This consideration may include receiver placements, number of needed receivers, integration of receivers, the capacity of receivers, etc.

In this thesis, two RF propagation models are analyzed and compared. These models are lognormal shadowing and regressive method. They are statistically derived by collecting data through field measurements with a single mobile radio monitoring unit and analyzed with software tools such as excel and python. The dataset variables are the average power, which is broadcasted from two FM transmitters, and the geographical coordinates of the receiver at measurement points.

As expected, the result shows that the accuracy of the estimated distance highly depends on the performance of the model. As expected the relation between power and distance inversely proportional as expected. As the distance increase the power decrease, but this is not as smooth as that of the free space scenario due to environmental effects. This result is roughly consistent with[51] even if the effects of environments types and the context is different. In this work, two methods are used to estimate the distance these are: lognormal and regressive methods. their estimation accuracy depends on the standard deviation of the power.

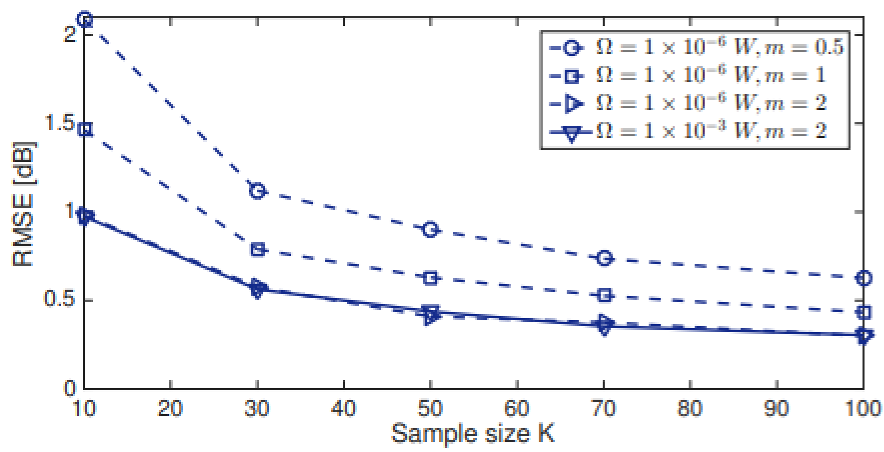


Figure 5.12 RMSE of power via sample size (where m is fading parameter) [51]

RSS-based localization technique can offer information for fingerprinting-based localization to build radio maps. Due to the randomness of propagation environments, it is difficult to get the dominant model for distance estimation. This is one limitation of the research. The other limitation is the data measurement approach, which is collected using a single mobile monitoring unit by driving only on the street which excluded many spot areas.

5.2.2 Performance of Algorithms

Locating the object of interest using radio wave propagation properties still not get a unique solution due to the variation of propagation environments and intentional radio jammers. Specially RSS-based localization technique is highly dependent on propagation environments. RSS-based technique, variables are formulated as a function of radio wave propagation models. These variables can be known by modeling the radio wave propagation and estimating the distance based on field measurement data. The accuracy of the estimated distance depends on the performance of propagation models. As stated in[18] the precision of the RSS-based localization technique mainly depends on distance and propagation environments, which determines the accuracy of localization.

In this thesis, distance-based localization algorithms; linear least square and weighted least square regression algorithms are analyzed and compared. The locations are estimated with a minimum error of 170m and a maximum error of 800m. The estimated distance errors of these two models; regressive method and lognormal model vary with the standard deviation of measured power. The standard deviation of measured power for 101.1FM is 2.12dB and for 97.1FM is 1.59dB. As indicated in the result for standard deviation less than 2dB lognormal model estimate better. But for the value greater than 2dB, the regressive method estimates better for this specific data. weighted least square regression algorithm estimation is better than linear least square regression algorithm. Theoretically, these results consistent with that analyzed in [37] even if the dataset type and size are different. As shown in figure (5.13) positioning error is proportional to distance error. The distance and positioning errors are positively correlated. As the error increase for distance, the error of positioning also increases the theoretical concept is also the same in this paperwork. With field measurement datasets or simulation, it can be possible to analyze and compare techniques and algorithms, even possible to optimize them since we know the position of the targeted emitter, but for real-time case, or for unknown position of transmitter, how can we optimize the predicted distance or location? This question could not be answered in this thesis because it is beyond the scope of this research.

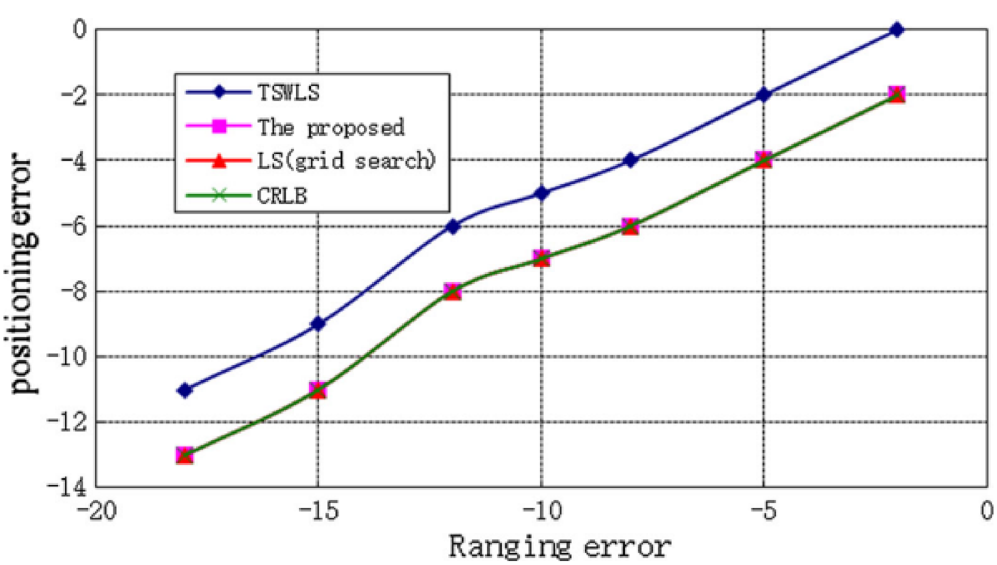


Figure 5.13 Positioning error via ranging error [37]

6 Conclusion and Future Works

6.1 Conclusion

This thesis studies path loss models (lognormal model and least square method) and RSS based localization algorithms (weighted least square regression and linear least square regression). Although these two concepts seem unrelated they are marching towards the same aim. To solve RSS based localization problem propagation model is required, which the distance from transmitter to receiver is estimated. For these comparisons the field measurements were taken in Addis Ababa city using a mobile radio spectrum monitoring unit. The comparison of these propagation models has been conducted to select the one, which estimate distance with minimum error. And then the comparison of two algorithms was conducted upon the distance information, which is estimated from propagation pathloss models.

There are many variables bias the performance of localization, among these variables; environment effects, receiver position, and receiver measurement quality. It is impossible to avoid the negative impacts of environment-dependent variables during the localization process with the RSS approach because of signal strength variation with the environments. Distance to be expressed as a function of power to estimate the position of the emitter. But uncertainty is high due to environmental effects such as multipath fading, shadowing effects, and errors from propagations models. The performance of estimation of the distance with regressive and lognormal shadowing models depends on the standard deviation of received signal power. If the standard deviation is less than 2dB lognormal performs better than the regressive method, while the standard deviation of the received signal power is greater than 2dB regressive methods perform better. Results from the analysis and measurements lead to the conclusion that the performance of the weighted least square regression algorithm estimates better when compared with the linear least square regression algorithm. Generally, it is possible to conclude that the accuracy of RSS-based emitter localization depends on the accuracy of the radio wave propagation model, the number of spatially separated receivers for data collection, and data analysis tools.

6.2 Future Works

Future work may include:

- Optimizing the predicted distance and localization in real time measurement scenarios (without a priority information of distance or position)
- Analyzing and comparing RSS based localization techniques with TDOA and AOA techniques
- Comparing and analyzing range-based algorithm by assuming the transmitter is in motion

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Geolocation of Narrow Band Radio Frequency Emitter Using RSS based Localization Techniques: The Case of Addis Ababa

Murad Ridwan, Kebe Adugna Gelmecha

Addis Ababa Institution of Technology, Addis Ababa University, Ethiopia

muradridwan@gmail.com, kebelenchoadugna@gmail.com

Abstract—Conventional received signal strength (RSS) based localization techniques rely on the lognormal shadowing path loss model to calculate the distance between receiver and transmitter. But the error of estimated distance is high with this approach. In this paper, the potential gain is offed by a regressive method with a cluster approach for distance estimation. Two location estimation algorithms are considered: linear least square and weighted least square regression algorithms. Data were collected by performing field measurements using a mobile radio monitoring unit in Addis Ababa city from two frequency modulation (FM) transmitters. And it was analyzed using python and excel tools. The results indicate that the error of estimated distance decrease on average by 96% over the non-clustered approach. With this approach, weighted least square (WLS) estimates location with the error of 170 meters, whereas linear least-squares (LLS) estimate with the error of 206 meters. The lognormal model predicts distance with a minimum error than the regressive method only when the standard deviation of data is less than 2dB. There is a positive correlation between estimated distance and location, which means the error of estimated location increases, as the error of estimated distance increases

Keywords: *WLS and LLS algorithms, RSS-based geolocation techniques, clustering, Lognormal shadowing model and regressive method*

I. Introduction

Determining the coordinate of fixed or moving objects using propagation features of radio waves have been a subject of interest in radio determination. These features are signal strength, propagation delay, signal phase, and angle of arrival. Radio determination can be categorized into radiolocation, ranging, and radio navigation. Radiolocation (geolocation for an object on the surface of the earth) is the process of locating the physical position of an object. Ranging is the process estimate the distance between receiver and transmitter. Radio navigation encompasses ranging and radiolocation. Measurement systems can be deployed on the ground (including movables) or aircraft to measure the features of any radio wave. The deployment may consider the properties of radio wave propagation and applied technology. Upon measured data, appropriate or one-step approach positioning algorithms to be used[1][2].

The accuracy of determining the positioning of object of interest may affected by different factors. The main factors that affect the radio wave and its propagation are Propagation environments and distance between transmitter and receiver (measurement device) [3]. As discussed in [4][5] physical environment is where radio waves propagate from transmitter to a receiver. This environment may contain only free space, free space with oxygen and water absorption, and blocking objects in the middle of the propagation paths.

Free space propagation of radio waves propagates without encounter of the object in the middle, and the attenuation of signals is in the function of frequency and distance (path loss). But if the propagation environment is none of line of sight, radio wave impinges upon the object encounters in between transmitter and receiver. This causes multipath and shadowing fading phenomenon. Modeling such environment with empirical model to find the optimum function that fit the measurement dataset[6][7]. The problem of estimating location of transmitter based on RSSI measurements is considered, in which it is formulated received signal strength as the function of distance. The power of the signal is received from the with N receiver[8][9].

RSS measurements-based localization need signal attenuation model to estimate the distance. But due to multipath and shadow fading this model has accuracy, this is the disadvantage of the method[10][11]. When an RF signal encounters an object, it may diffract, reflect, absorbed, refract, and scatter. These behaviors can bring the sequences of different delay profiles for the same signal, attenuated signal, and bias geolocation problem. Especially for propagation model-based (RSS approach), the RF emitter geolocation process is highly biased. The performance of RSS-based geolocating depends on the distance, path loss model from the distance from the receiver to emitter is determined, so as much as possible, this model should be optimally modeled to geolocate targeted objects with minimum errors[12][13].

In this paper RSS based localization techniques and algorithms were analyzed. Performance was evaluated using RMSE for both pathloss models and algorithms. Using regressive method with a cluster approach the error of location estimation minimized from 799meters (with conventional lognormal model) to 170 meters.

The rest of the paper is organized as follows. Section II provides the system model. Section III elaborates on data collection and analysis methods. While section IV presents the result and performance analysis. Finally, section V concludes the paper work.

II. System model

There are two stages to be followed in the localization process with RSS-based techniques. The first stage is to calculate the distance from propagation path loss models. The second stage is to determine the location of the transmitter based on the estimated distance. The general 2D equation for RF emitter source localization using RSS measurement techniques is formulated as shown in equation (1). Where (x_n, y_n), and d_n represent the geographical coordinate of a receiver, and the estimated distance between the coordinate of the receiver and targeted emitter respectively. Where N is the number of receives node i=1,2,3…n and (x, y) represent as coordinate of targeted transmitter.

$$\begin{bmatrix} (x_1-x)^2 + (y_1-y)^2 \\ (x_2-x)^2 + (y_2-y)^2 \\ (x_3-x)^2 + (y_3-y)^2 \\ . \\ . \\ (x_n-x)^2 + (y_n-y)^2 \end{bmatrix} = \begin{bmatrix} {d_1}^2 \\ {d_2}^2 \\ {d_3}^2 \\ . \\ . \\ {d_n}^2 \end{bmatrix} \tag{1}$$

Nonlinearity of the equation (1) make estimation of a source's location computational complex and expensive. Equation 2 is introduced to convert this nonlianarity it into linear equation form. And it can be expressed as

$$X= (A^TA)^{-1} A^Tb) \tag{2}$$

Where A and b are matrix formulated as follow

$$A = \begin{bmatrix} 2(x_n-x_1) & 2(y_n-y_1) \\ 2(x_n-x_2) & 2(y_n-y_2) \\ 2(x_n-x_3) & 2(y_n-y_3) \\ . & . \\ . & . \\ . & . \\ 2(x_n-x_{n-1}) & 2(y_n-y_{n-1}) \end{bmatrix}$$

$$b = \begin{bmatrix} {d_1}^2-{d_n}^2-{x_1}^2-{y_1}^2 + {x_n}^2 + {y_n}^2 \\ {d_2}^2-{d_n}^2-{x_2}^2-{y_2}^2 + {x_n}^2 + {y_n}^2 \\ {d_3}^2-{d_n}^2-{x_3}^2-{y_3}^2 + {x_n}^2 + {y_n}^2 \\ . \\ . \\ . \\ {d_{n-1}}^2-{d_n}^2-{x_{n-1}}^2-{y_{n-1}}^2 + {x_n}^2 + {y_n}^2 \end{bmatrix}$$

A. **lognormal shadowing model**

The Lognormal propagation model can formulate with the distance between the transmitter and the receiver and propagation environments. As driven in equation 3, the average received power at distance di is written as a function of four variables; path loss exponent, power at reference distance, distance from the receiver to the transmitter, gaussian distribution, and reference distance.

$$P(d_i) = p_0-10\alpha\log\left(\frac{d_i}{d_0}\right) + F(\sigma) \tag{3}$$

Parameters defined as:

$P(d_i)$: average received power at distance di
d_i: distance from receiver to transmitter
d_0: reference distance
p_0: power at reference distance
α: path loss exponent (decaying exponent)
σ: standard deviation of zero mean gaussian distribution of measured power
F (σ): Gaussian distribution function

B. **Linear regression method**

Driving linear equation for distance using ordinary least square as follow

$$\log(d_i) = b_0 + b_1 * P(d_i) \tag{4}$$

Where b_0 and b_1 are variables that to be calculated using ordinary least square method. Once these variables are determined, it is straightforward to get the distance as shown in (4)

$$d_i = 10^{(b_0+b_1*P(d_i))} \tag{5}$$

C. **Performance evaluation metric**

Root Mean Square Error (RMSE) compute localization error for both coordinates, so RMSE for both coordinates can be calculated as:

$$\mathrm{RMSE_X} = \sqrt{\frac{\sum(\mathrm{Est_x}\text{-}\mathrm{Actual_x})^2}{\text{number of estimates}}}$$
$$\mathrm{RMSE_y} = \sqrt{\frac{\sum(\mathrm{Est_y}\text{-}\mathrm{Actual_y})^2}{\text{number of estimates}}} \qquad (6)$$
$$\text{Net RMSE} = \sqrt{\mathrm{RMSE_X}^2 + \mathrm{RMSE_y}^2}$$

In equation (6) $\mathrm{Est_x}$ and $\mathrm{Actual_x}$ represent estimated coordinate of emitter and true position in x axis respectively. Also $\mathrm{Est_y}$ and $\mathrm{Actual_y}$ represent estimated coordinate of emitter and true position in y axis respectively. $\mathrm{RMSE_X}$ and $\mathrm{RMSE_y}$ represent the root mean square error in x axis and y axis

III. Data Collection and Analysis Methods

The primary data were obtained through field measurement by using a single mobile radio monitoring unit. Dataset variables are signal power, distance, coordinates (latitude, longitude) of the monitoring unit at each measurement point. Fig.1 illustrates the coordinate at measurements were taken.

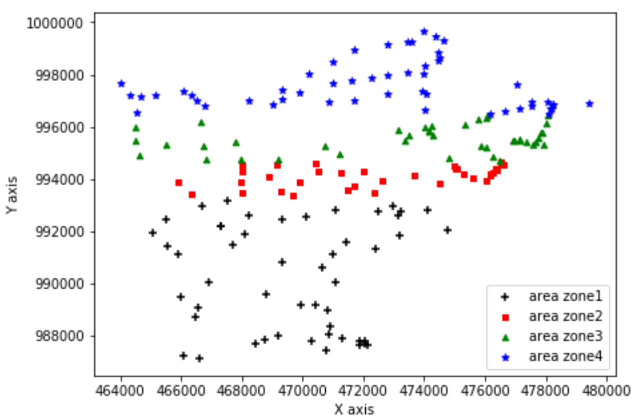

Figure 1 Coordinates of the receiver (UTM)

The prepared and structured datasets were analyzed using python and excel tools with statistical methods. These statistical methods are means, standard deviation, regressions, mathematical equation derivations (Algorithms). The distance between each receiver's coordinate is not the same because data was collected randomly. To minimize the errors of distance or location to be estimated, area was divided into four subareas by considering power and distance probability distributions function. As seen in fig.3 and fig.5 there is a significant difference between the clustering and non-clustering approaches.

IV. Results and performance analysis

A. Estimated distances

The object of the paper is to compare the performance of RSS based localization techniques. To this end, distance was obtained from propagation pathloss models, and based on this distance the coordinate of transmitter also estimated by considering linear least square and weighted least square regression algorithms. As can be seen from fig.2 the estimated distances with both propagation models are crowded at nearest to the measured distance.

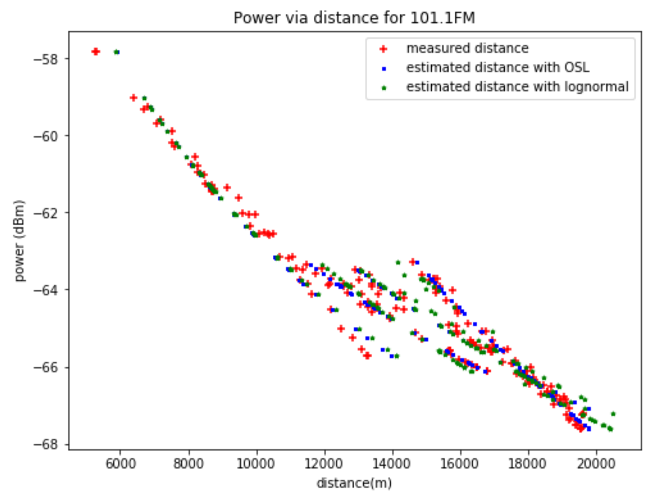

Figure 2 Estimated and true distance via power

As shown in fig.3 and fig.4 regressive method estimation distance with less error than lognormal shadowing model.

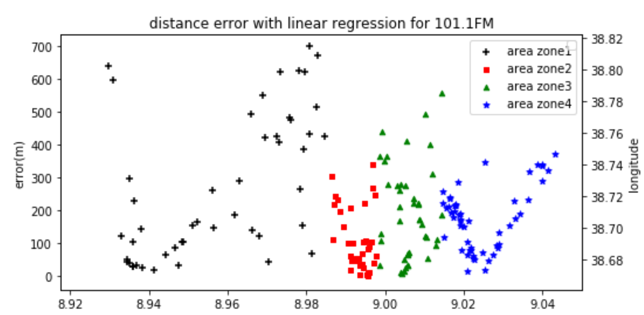

Figure 3 Distance error with linear regressive method

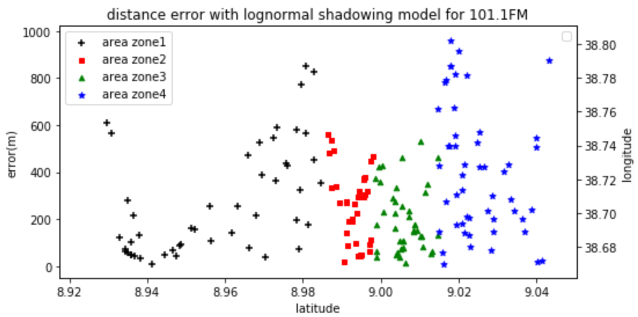

Figure 4 Distance error with lognormal shadowing model

As shown in fig.5 the errors with non-clustered area is higher than that of the clustered one. So, rather than modeling total areas of measurement it is better to estimate the distance from the model built by considering clustering approaches. And tuning the model to minimize the errors and then apply location estimation algorithms.

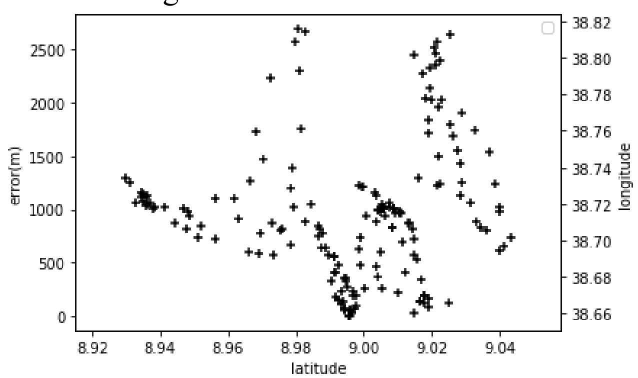

Figure 5 Distance errors without clustering the area

B. Estimated location of targeted emitter

Figure 6 shows the estimated coordinate of the 101.1FM transmitter with two propagation path loss and algorithms. As indicated in this figure the error of estimated location is high (799m) with the lognormal shadowing path loss model (Log:) and LLS algorithm. But with the regressive method (OSL:) and WLS the error is (170m). This result indicate that weighted least square regression estimate with better accuracy than linear least square regression algorithms.

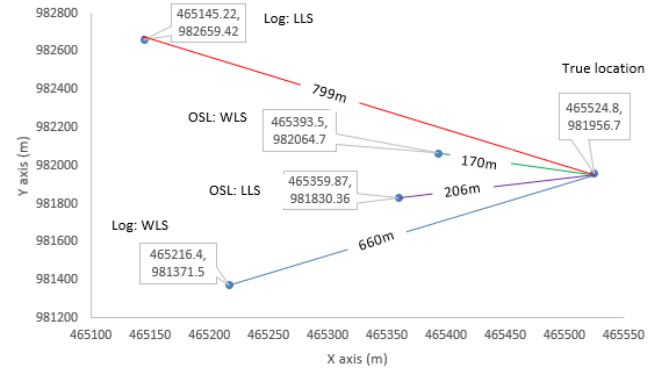

Figure 6 Estimated location of transmitter

V. Conclusion

Determining the physical coordinate of fixed or moving objects using propagation features of radio waves has been a subject of interest in radio determination. For that, many pieces of literature have proposed RSS-based localization techniques, which rely on the accuracy of the propagation path loss model to calculate the distance between receiver and transmitter. In this paper, a regressive method with an area clustering approach is proposed for distance estimation. The errors of estimated distance are minimized with this method than lognormal shadowing path loss model. Based on the estimated distance WLS estimate location of transmitter with better accuracy than LLS algorithm. RSS based localization techniques have the limitation of real-time application and accuracy. For unknown emitter, it is difficult to know whether it is in our distance estimation model or not. Maybe pattern matching (fingerprinting) can be followed by building a radio map. But practically, it is impossible to build radio maps for all radio services types and large geographical areas. Therefore, future work will consider others geolocation techniques (e.g., TDOA, AOA) to compare their performance with RSS-based localization techniques.

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