

**Addis Ababa University  
School of Graduate Studies  
Faculty of Informatics**

**IMPACT OF FACE IMAGE CURRENCY  
ON RECONGITION RATES OF  
THE EIGENFACE ALGORITHM**

**BY**

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**JUNE 2005**

**A Thesis submitted to the School of Graduates Studies of Addis Ababa  
University in partial fulfillment of the requirements for the degree of  
Master of Science in Computer Science**

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# Acknowledgement

I would like to thank Dr. Karl Ricanek, Jr. who enforces me to see the beauty and challenges of computer vision research and for his trust in my capability. I am grateful for his motivation, guidance, suggestions, and support anytime in my study. He is a gift given by God to me.

My appreciation also goes to Dr. Mulugeta Libsie for his support, guidance and encouragement in the process of the study. In addition to his advice, I found him as one of my best English teachers in my educational experience.

I would like to thank the Department of Computer Science for allowing me to work with external advisor, especially to Dr. Solomon Atanfu for redirecting me to Dr. Mulugeta.

My Sincere appreciation also goes to Ms. Shalon Simmons, President of Global Internet Studios for establishing contact with Dr. Karl Ricanek.

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# ACRONYMS AND ABBREVIATIONS

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<b>AA:</b>	<b>African-American</b>
<b>AAM:</b>	<b>Active Appearance Model</b>
<b>ASM:</b>	<b>Active Shape Model</b>
<b>CMC:</b>	<b>Cumulative Match Characteristics</b>
<b>DLA:</b>	<b>Dynamic Link Architecture</b>
<b>CSU FIES:</b>	<b>Colorado State University Face Identification and Evaluation System</b>
<b>EBGM:</b>	<b>Elastic Bunch Graph Matching</b>
<b>FERET:</b>	<b>Face REcognition Technology</b>
<b>FG-NET:</b>	<b>Face and Gesture Recognition Research Network</b>
<b>FR:</b>	<b>Face Recognition</b>
<b>FRVT:</b>	<b>Facial Recognition Vendor Test</b>
<b>HCInt:</b>	<b>High Computational Intensity</b>
<b>HyperBF:</b>	<b>Hyper Basis Function</b>
<b>JEPG:</b>	<b>Joint Photographic Expert Group</b>
<b>ICA:</b>	<b>Independent Component Analysis</b>
<b>LDA:</b>	<b>Linear Discriminant Analysis</b>
<b>MCInt:</b>	<b>Medium Computational Intensity</b>
<b>NIST:</b>	<b>National Institute of Standards and Technology (USA)</b>
<b>PCA:</b>	<b>Principal Component Analysis</b>
<b>PGM:</b>	<b>Portable Gray Map</b>
<b>PIE:</b>	<b>Pose, Illumination, and Expression</b>
<b>POWL:</b>	<b>Person On Watch List</b>

# Abstract

A technology evaluation is administered to assess the impact of face image currency on the recognition rates of the Eigenface algorithm. Several experiments have been carried out to highlight the challenging problem in Face Recognition, -- ageing or aging. The MORPH database is used as a data source since it contains long-term data that spans from few days up to 29 years, between the acquisition of the first (gallery) and the subsequent (probe) image sets. The Identification test indicates that 1) the performance of the Eigenface algorithm decreased linearly (in general) with age-progression. 2) The Eigenface algorithm performed better in identifying older people than younger people. 3) The algorithm performed better in identifying males at younger age than females. 4) The algorithm achieved more or less similar results for the African-American and the Caucasian ethnic origin. In general, the overall performance evaluation test on the Eigenface algorithm indicates that the performance of the Eigenface approach is very sensitive to age-progression.

**Keywords:** *Eigenface, age-progression, MORPH, FERET, FRVT, PCA*

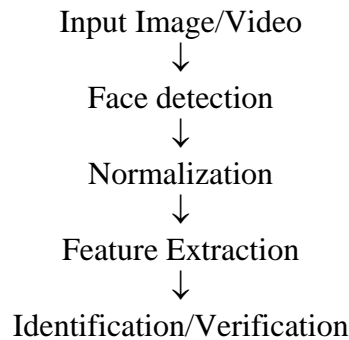
### 1. Introduction

The term biometrics refers to measuring and analyzing both the physiological (such as face, eyes, and ear) and behavioral (like voice and expression) characteristics for identification and/or verification purposes. The mechanism of selecting methods of acquisition of a biometric characteristic varies from application to application and must not put the health, safety, or welfare of individuals in danger. Furthermore, the ease with which a given biometric feature can be updated over a certain period of time also impacts one's selection. A variety of methods and techniques are available to be used to automatically identify or verify the claimed identity of individuals such as fingerprint, hand geometry, voice, face, retina scans, iris scans, bio-signatures, etc. Among these diverse types of biometrics, the most promising is face recognition.

#### 1.1 Face Recognition (FR)

The human face, which possesses both the physiological and behavioral characteristics, is an extremely complex visual stimulus that articulates identity, emotion, race/ethnicity, age, and gender of an individual. Facial recognition (FR) is one of the most natural means of biometric techniques. Humans are pre-wired from birth for FR [49, 50]. The human brain is highly adapted for recognizing faces. It is also far better than computers at compensating for changes in lighting, facial hair growth, weight changes, and ageing. It is, therefore, natural that humans would develop techniques for FR, which can be traced back to Francis Galton circa 1888 [50]. Modern FR techniques are applications of computer vision, which employs pattern recognition and image processing to identify subjects based on features present in the human face. Although humans perform the tasks of FR in an effortless manner, the automation of this task has been a difficult problem and required a wide area of diverse fields of study from cognitive psychology to psychophysical psychology to pattern recognition. Automating the FR task will be useful for several application areas such as passport verification, entrance control, criminal investigation, and surveillance to name a few.

As shown in Fig. 1.1, FR can be generalized as a five-step process regardless of the specific approach employed.



**Figure 1-1: Generalized steps for FR.**

- **Input Image/Video:** A face image is acquired from an existing photograph, digital still images, or video of individuals.
- **Face Detection:** The detection process is performed to locate a face in the acquired image. A good face detection algorithm is paramount to a successful FR system. Although, this work does not focus on detection, the interested reader can review [41, 42, 48] for robust detection in still and video images.
- **Normalization:** The detected faces may vary in size, colors, pose, etc. Normalization is used to homogenize these variations.
- **Feature Extraction:** The feature extraction process is used to extract a recognizable pattern for comparison purposes.
- **Identification/Verification:** In this step, the determination and classification of a match is performed based on the user requirement of a specific application.

To explain the applications of FR technology, we need to categorize the real world applications as *Identification*, *Verification*, and *Watch list*. *Identification* is a closed universe application that ranks the gallery by similarity to the probe (query image). A gallery is the known image in the face database whereas the probe image is the face image to be classified. It can be used for criminal identification. *Verification* is a one-to-one process and open universe application where a person presents his/her identity like badge or passport. The system determines if the claimed identity is correct. It can be used for immigration control and airport/seaport security. A *Watch list* based application is an open universe; one-to-many application where a person's live image is compared to each face image in the list. It is of

importance for intelligence agencies and police departments like searching for known terrorists.

FR has a number of benefits over other biometric methods such as fingerprint, retina, and iris recognition due to its natural passive recognition. Almost all of the other biometric techniques require some voluntary, invasive actions. FR has tremendous benefits for covert use such as surveillance for intelligence agencies, military and police departments. In addition, it is non-intrusive which means, it doesn't require physical interaction of the user.

## 1.2 Overview of FR Algorithms

Face recognition, in general can be performed in either frontal or profile view. There are several algorithms claiming to be the best in the face recognition arena. Almost all of them fall in the categories of **holistic**, **part-based**, and the **synthesis** techniques [16, 17, 28, 30, 33]. A part-based algorithm (also known as **parameter** or **feature-based algorithm**) actually focuses on an element/feature of a face such as the eye region, jaw, nose, or a combination of features like the eye-nose-mouth. Holistic techniques for FR make use of different approaches for recognition purpose. Almost all of them treat the face image as a whole and do not destroy information by exclusively processing only a specific part of a face. Synthesized models like Cootes "Active Shape and Appearance" models and Vetter "Morpable Models" are making a huge push in the research and commercial sectors [27, 28, 36]. Although there are many additional approaches for FR, which are covered in detail in Chapter 2, the most widely used techniques generally consist of appearance-based methods.

**Appearance-based** methods are holistic techniques that use information theory in which relevant information for a face image will be extracted and encoded as efficiently as possible. The picture elements, known as **pixels**, are used as information for the face. **Neural network** [35,49] and **Statistical analysis** [18] can in general be considered as appearance-based approaches. As indicated above, appearance-based methods utilize the idea of using pixel values for encoding face information. In order to encode the pixel values, appearance-based methods start with the concept of a vector space known as **image space**. The image space representation is used to explain the relationships among the collection of images. In these methods, a face image is considered as a matrix of  $N_x \times N_y$  pixels that is vectorized, dimensionally reduced, and projected into a space defined by the set of known images as "face space". Detailed description of this approach is provided in Chapters 2 and 4. Statistical

analysis is one of the most widely used appearance-based techniques to employ dimensionality reduction.

As the name indicates, statistical analysis makes use of statistical concepts to simplify a data set by taking a sample representation of the entire data set. There exist a number of well-known statistical methods used for dimensionality reduction. **Principal Component Analysis** (PCA) is one of the most popular ones [11]. Among the known appearance-based methods, the **Eigenface** approach is widely used. The Eigenface (developed by Turk and Pentland in 1991 [2]), which utilizes the PCA technique, is considered as the baseline for most FR algorithms. It employs dimensionality reduction by considering a small subspace from the entire image space.

### 1.3 Research Objective

The performance of FR algorithms generally depends on many factors. Template<sup>1</sup> ageing, in which the time elapsed between the creation of the enrolment template and the verification or identification attempt, is a case in point. Generally, a shorter elapsed time between probe and gallery creation wherein the user appearance has changed very little is by far better in performance than probe images obtained several months or years later. The motivation of this thesis is to study the impact that natural human face age-progression has on the Eigenface FR algorithm. This algorithm has been used as an accepted benchmark for evaluating performance in the face recognition community. It is stated in [11, 13, 14] that the process of ageing causes significant alterations in the appearance and anatomy of human face. The question that this work will address directly is “what quantifiable impact will natural human age-progression have on appearance-based FR algorithms?” Again, the baseline appearance-based FR algorithm, viz., Eigenface, will be considered for this research. Further, this work will quantify the performance impact of ageing and provide some understanding of the effectiveness of this technique for handling the problem of facial age-progression.

The performance evaluation was made on impact of image currency on recognition attempt. FERET and FRVT 2000 indicated that as the elapsed time between the enrolled image and the new image of a person increases, the recognition rate decreases. However, the rate at which performance declines had not been thoroughly investigated. In FRVT 2002, the second FRVT evaluation, the temporal effect was considered systematically with the available data set with

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<sup>1</sup> The template is the reduced set of data to represent biometric characteristics.

the interval of 60 days [1]. It was concluded that, face recognition performance decreases approximately linearly with elapsed time gallery and probe images. However, it is known that since the process of ageing is slow, the collection of suitable data for performance analysis is difficult. Further details about evaluations methods are given in Section 2.2.

Hence, the objectives of the research are:

- to assess the impact of face image currency on recognition rates of the Eigenface FR algorithm,
- to analyze the algorithm for its effectiveness in identifying subjects with large time span, (i.e., between a subject's image within the known dataset and the test image of the subject), and
- to quantify the performance impact of the natural ageing process.

#### **1.4 Overview of the Methodology**

From statistical point of view, one can ask about the impact of covariate in the performance of an algorithm. For a given category of images, how does performance change if the algorithm is given a different gallery and probe set? In face recognition technology, there are many performance evaluation methodologies for FR. Among them, the most widely used are FERET and FRVT. These methodologies are based on the biometric evaluation proposed by [12]. Both FERET and FRVT contain a face database together with the evaluation methods. However, apart from the methodology, the databases are not used for this research. The reason is that the time span of the individual face images in the databases is less than five years. So a more reasonable dataset is required to evaluate the impact of facial image currency on recognition rate. Instead, the MORPH [54] is suitable for this purpose.

The MORPH database consists of images that have a time span of more than a decade. The images have been collected by law enforcement officials in the southeastern part of the United States. The database contains 1,724 facial images of individuals that vary in age, gender, and ethnicity. Since the MORPH database has taken into consideration the age parameter, which is the important attribute for this research, it will be used as a primary data source.

Towards this end, a technology evaluation is employed to assess the performance of FR algorithms. The goal of the technology evaluation is to determine a particular technology, in this case face recognition technology. It provides performance information that can be used to

select algorithms for scenario evaluation [3]. Technology evaluation was performed in the Face REcognition Technology (FERET) series and Facial Recognition Vendor Test (FRVT). Matlab development environment is used for realization of the performance of the Eigenface algorithm. In addition, the preprocessing of the face images will be performed automatically by the preprocessing tool provided by the Colorado State University Face Identification and Evaluation System (CSU FIES). Please see the Methodology section for a detailed description of the MORPH database and the reason for the choice of the Matlab development tool.

## **1.5 Thesis Outline**

The rest of the thesis is organized as follows:

In Chapter 2, FR technology issues together with works that are related to the work in this thesis will be assessed. It begins with earlier developments of face recognition and an overview of FR algorithms. After that, FR evaluation methodologies will be discussed in detail. Finally, the databases available in the face recognition community will be described in relation to the temporal variability, which is the core for this research.

In Chapter 3, a detailed description of the MORPH database is given, which will be used as a primary data source for the experiment. In addition, the preprocessing stage in FR and the reason for the realization of the algorithm using the Matlab development environment will be discussed.

In Chapter 4, the implementation of the algorithm is reported. A detailed description of each step of the algorithm will be discussed with reference to the performance evaluation methods.

In Chapter 5, experimental results of the algorithm, specifically on the MORPH database will be analyzed. The performance evaluation on the Eigenface algorithm will be made based on FERET and FRVT methodology. The impact of image currency on the recognition rate of the algorithm will be reported.

In Chapter 6, a summary of the results obtained on the performance evaluation of the algorithms is presented. Finally, an insight into future work will be provided.

# CHAPTER 2

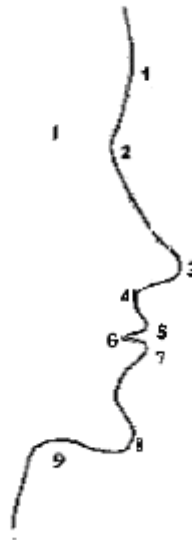
## FR TECHNOLOGY AND RELATED WORKS

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### 2. FR Technology and Related Works

There are several fields that have dealt with face recognition and biometrics in general. Cognitive Psychology and NeuroPhysiology are examples of disciplines that have dealt with the empirical and theoretical development of the cognitive process that enable the conceptual understanding of how the human brain recognizes a face [49]. However, since we are interested in constructing the computational models, we don't deal with the empirical and theoretical background of the human cognition process in detail.

There are a number of FR algorithms developed by researchers in computer vision that utilize frontal, profile or both frontal and profile views of face images. In full frontal view as described in [20], the nose doesn't play a significant role as compared to eyes and mouth for example. In dealing with the profile view however, the nose is one of the fudicial points that require extreme interest. The shape and length of the nose are some of the features that are explored for profile based FR. As can be seen from Fig 2.1, the fudicial points used correspond to the forehead, nose bridge, nose tip, nose bottom, upper lip, mouth, lower lip, chin, and the throat. For further explanation, the reader is referred to [11,13]. In addition, with regard to profile view, choosing either the left or right profile view has significant effect in the performance of the algorithms [6].



**Figure 2-1: Set of nine fudicial points.**

As presented in Chpater1, we can make a rough classification of the approaches to FR algorithms into part-based, holistic/appearance-based and a Synthesis model. Moreover, there are a number of factors that can directly or indirectly affect the development of FR technology. Methodologies for evaluating the performance of FR algorithms and the availability of large databases of face images are among the main factors that have considerable effects on FR technology. This Chapter briefly discusses the FR algorithms, evaluation methodologies, and databases reported in the literature that are closely related to the work in this thesis.

## **2.1 FR Algorithms**

### **2.1.1 Part-based Approach to FR**

Bobis et al. [20] suggested the use of geometric information to face called part-based approach. They described that part-based face recognition extracts and measures the overall geometrical configuration of face features by a vector of numeric data representing the size, shape and position of facial features such as eyes, nose, and mouth. There are several algorithms that fall in this category.

The Curvature-based face recognition is an example of part-based approach that tries to incorporate shape and curvature of face-surface information for recognition purpose [17, 20]. It considers features like eyes, nose, and mouth where interesting curvature events do occur. It

is mainly useful in resisting pose and illumination variation. However, it has high computational cost to compute the curvature measure of a feature and also needs a Rotation Laser Scanner which is much more expensive as compared to a still Camera. In addition, the curvature computation is very sensitive to noise (for example facial expression can affect mouth and chin curvature considerably).

The other part-based approach is Elastic Bunch Graph Matching (EBGM), which is a Neural Network<sup>2</sup> implementation of face recognition proposed by Wiskot et al. [20, 35]. The graph consists of facial landmarks such as the pupils, corners of the mouth, or tip of the nose and their connections. The feature vectors are stored at each graph node. The term “elastic” describes the dynamic adaptation of the graph in size and aspect ratio to better match features of the face. Many versions of the Neural Network approach to part-based besides EBGM, are found in the literature. Dynamic Link Architecture (DLA), which utilizes correlations in the fine-scale cellular signals to group neurons dynamically into high order entries [20] and Hyper Basis Function (HyperBF), which provides functionalities for gender classification as presented in [19], are among the most common ones. However, for dealing with age-progression, it is very difficult to just rely on a feature of a face, since we need to have the overall face characteristics to analyze the gradual, progressive degradation of face tissues [12, 13].

### **2.1.2 Holistic Approach to FR**

The Holistic approach to face recognition emphasizes with the global feature rather than a specific part of the face. Turk and Pentland [2, 4] were among the researchers who first introduced the concept of holistic approach. But in dealing with the global feature, researchers have realized that direct template matching suffers from the computational complexity because of extreme dimensionality [2, 4, 5]. So, there should be some kind of statistical approach for computational feasibility. Statistical approach, which employs dimensionality reduction, is most widely used. There are a number of algorithms that utilize statistical approach. Independent Component Analysis (ICA), the Fisherface approach that utilizes both PCA and LDA (Linear Discriminant Analysis), and Eigenface that uses PCA are cases in point [20, 29, 33]. Among these, the most widely used is the Eigenface. Many of the FR algorithms mentioned above are actually versions of the Eigenface algorithm. Detailed

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<sup>2</sup> The Neural network approach imitates the human neural system for recognition purpose.

description of this algorithm (which is used for this research) will be presented in Chapter 4. Since holistic method focuses on the face images as a whole and tries to extract features from the whole face region, it is suitable to make analysis on how a face is affected by age-progression.

### 2.1.3 Synthesis Approach to FR

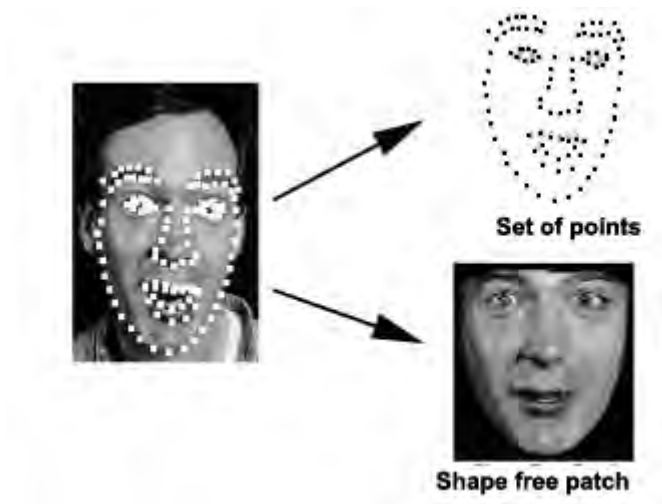
Synthesis models for face recognition mostly address the problem of rotation invariance such as pose rotation, neck articulation, out-of-plane rotation, and in-plane rotation. The models are generated by combining a model of shape variation with a model of the texture-variations in a shape-normalized frame. A number of Synthesis model approaches exist in the literature.

The morphable model is one of the widely used synthesis approaches to face recognition. The morphable model to face recognition can be constructed by extrapolating the information from 3D face images [36]. Blanz and Vetter [28] derived a morphable face model by transforming the shape and texture of the vector space representation. Their motivation was to solve pose and illumination invariants for face recognition. The 3D face models, mostly based on a combination of frontal and profile images of each person (see Fig. 2.2) are used in the system. The core step of building a morphable face model is to establish dense point-to-point correspondence between each face and a reference face. The morphable model represents shapes and textures of the face as vectors in a high-dimensional space. The shape vector, which represents the geometry of a face that contains  $x$ ,  $y$ ,  $z$  coordinates. The texture vector, which represents the intensity or photometric information of the face, contains the  $R$ ,  $G$ , and  $B$  values [28]. A PCA is performed on the set of shape and texture vectors  $S_i$  and  $T_i$  of the face image. Ignoring the correlation between shape and texture data, the shape and texture are examined separately. For both shape and texture, complete PCA steps are performed to obtain shape and texture eigenvectors  $s_i$  and  $t_i$ , respectively. For detailed description, the reader is referred to [28, 36].



**Figure 2-2: Sample Frontal (left) and Profile (right) images of an individual.**

The other synthesis model is Active Appearance Model (AAM). The AAM is a generalization of Active Shape Model (ASM) [35, 39, 40]. It was first introduced by Edwards *et al.* [26, 27]. It was then expanded and refined by Cootes *et al.* [27]. Cootes and his colleagues utilize both the shape and texture variability to express an object. They describe the shape of an object as a vector  $\mathbf{x}$  and the texture (intensity) as a vector  $\mathbf{g}$  [21]. AAM employs PCA separately on the texture and shape and combines them. However, the morphable model ignores the correlation between shape and texture data. Cootes and his colleagues used a training set of 400 images of faces. Each face is labeled with 122 points around the main feature (see Fig. 2.3). As can be seen from the figure, the training set consists of labeled images, where key landmark points are marked on the face. From this they generated a shape model with 23 parameters, a texture model with 114 parameters and a combined appearance model with 80 parameters. The Model used about 10,000 pixel values to make up the face patch (area). The AAM in general, seeks to minimize the difference between the synthesized model with the target image.



**Figure 2-3: Sample feature points for the AAM model.**

## **2.2 Evaluation Methodologies of FR Algorithms**

Evaluations of face recognition systems are divided into three categories: *Technology*, *Scenario* and *operational evaluations*. Each category uses different approaches to evaluate different characteristics of the system. *Technology evaluation* studies the face recognition algorithms only while the *Scenario evaluation* studies the entire system, including the camera and the camera-algorithm interface, in a given application [1, 3]. *Operational evaluation* is very similar to scenario evaluation, except that it is performed at the actual site and uses actual subjects. Several face recognition system evaluations have been performed in different times for different objectives. The most prominent are FERET and FRVT.

FERET was a general evaluation methodology designed to assess the state-of-the-art and feasibility of FR algorithms. Several versions of FERET evaluation methodologies are developed at different times for different purposes. The first FERET evaluation was administered in August 1994 [8]. This is a part of technology evaluation that was designed to examine and measure the performance of algorithms that could automatically locate, normalize and identify faces [3]. The second FERET evaluation was administered in March 1995 [6]. In this evaluation, the image database increased from 314 to 817 individuals. One emphasis of the evaluation was on probe sets that contain duplicate probes. A duplicate probe is an image of a person whose corresponding gallery image was taken on a different day; the duplicate images in this case were taken at about a year apart. Both of the above evaluations concentrated on identification analysis.

The third FERET evaluation was administered between September 1996 and March 1997 [1]. The design for this evaluation was more complex than the first two evaluations, and allowed more detailed performance characterization of face recognition systems. It dealt with both identification and verification analyses. The database consisted of 1,199 individuals and 365 duplicates of images. There are two duplicate groups. The Duplicate I probe images were obtained anywhere between one minute and 1031 days after their respective gallery matches. The Duplicate I probe set holds 722 images. The mean time between the gallery and the probe is 251 days and the median is 72 days. The Duplicate II probe images are those taken at least 18 months after their respective gallery images. The Duplicate II probe set contains 234 images from subjects whose gallery match was taken between 540 and 1031 days earlier. Detailed description is given in Chapter 3.

FRVT 2000 [9] aimed to quantify the effect of non-frontal images on recognition performance. The FRVT 2000 was administered in May and June 2000 by leading commercial face recognition vendors. FRVT 2000 consisted of a technology evaluation and a limited scenario evaluation [3]. Face Recognition at a chokepoint (metal detector) is an extension of FRVT 2000 evaluation. It was aimed at assessing the overall capabilities of entire systems for two chokepoint scenarios: *verification* and *watch list* [3].

As described in the introduction section, *verification* determines if the live image matches with the stored identity of a specified person within a certain threshold. Accuracy evaluation used for the *verification* scenario falls into four categories; namely, *valid user accepted*, *valid user rejected*, *imposter accepted* and *imposter rejected* [3]. The *watch list* evaluations classify recognition attempts at a chokepoint into several categories; Persons on Watch list (POWL) correctly identified, POWL incorrectly identified, POWL not alarmed, Non-POWL alarmed, and Non-POWL not alarmed. For a detailed description of both categories, the reader is referred to [3].

Face recognition at a chokepoint attempted to evaluate the temporal effect of the probe image with respect to the gallery image. It was pointed out that the performance of recognition attempt went up significantly for recently taken face images than older ones. However, the lightning and temporal parameters were not controlled separately. For the *watch list* scenario, it was concluded that, the performance of recognition attempt decreased significantly when using older images with less controlled lightning [3].

FRVT 2002 has followed four previous face recognition technology evaluations – three FERET evaluations (1994, 1995, 1996) and FRVT 2000. It was a large-scale technology evaluation of face recognition systems. The primary objectives of FRVT 2002 were to measure technical progress since 2000, to evaluate performance on real-life, large-scale databases, and to introduce new experiments to better understand face recognition performance. FRVT 2002 consisted of two sub-tests – the High Computational Intensity (HCInt) test and the Medium Computational Intensity (MCInt) test. HCInt consisted of 121,589 operational images of 37,437 people and MCInt comprised 9,612 operational images of 1,890 people [1].

FRVT 2002 is the most thorough and comprehensive evaluation of automatic face recognition technology to date. It addressed several important face recognition topics. It has examined the effect of three covariates on performance [1]. The covariates were: elapsed time between acquisitions of gallery and probe images of a person, sex, and age. The result of FRVT 2002 evaluation test indicated that Face recognition performance decreases approximately linearly with elapsed time of gallery and probe images; that males are easier to recognize than females, and younger people are harder to recognize than older people.

FERET and FRVT evaluation methodologies for FR in general have been used as de facto standards for evaluating the performance of FR algorithms and systems. They have established a well-defined protocol for comparing algorithms. The FERET and FRVT evaluation consists of three design principles.

- All faces are treated as unique faces. This principle enforces every image to have a unique identifier.
- The second principle is that the training phase should be completed prior to the start of an evaluation. This forces each algorithm to have general representations of faces. In other words, it avoids deliberate representation, which is tuned to a specific gallery.
- Similarity is measured between all combination of images from both probe and gallery images. This guarantees that performance statistics can be computed for all algorithms

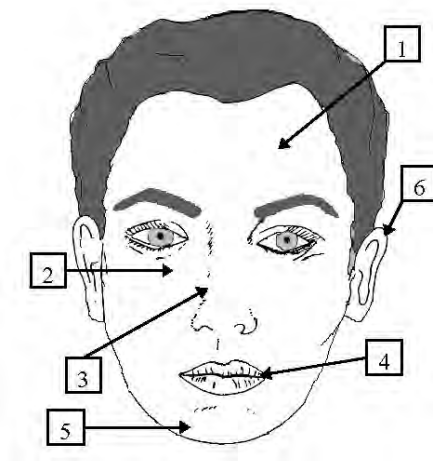
There have been several efforts intended to improve the performance of face recognition systems based on FRVT 2002 results. Face Recognition Grand Challenge (FRGC) is a case in point. FRGC studies have been conducted between may 2004 and July 2005 with the primary

goal to promote and advance face recognition techniques that are designed to support existing face recognition efforts [57]. The other goal is to develop still and 3D algorithms to improve performance by an order of magnitude over FRVT 2002. It has two versions. Version1 (Ver1) is designed to introduce participant to the FRGC and provide sample data. The second version (Ver2) is designed to challenge researchers to meet the FRGC performance goal. Its result will be used as input for FRVT 2005, which will be conducted in August/September 2005 time frame. For detail description, the reader is referred to [57].

### **2.3 Face databases**

Because of the fact that faces are highly deformable and complex structures that often differ in slight ways, appearance is affected by a large number of factors including pose, expression, lighting, and ageing. The development of algorithms that are robust to these variations requires sufficient and reasonable datasets of face images that consider the controlled variations of these factors. Along with the development of FR algorithms, various databases have been collected for evaluating the performance and capability of the algorithms under investigation. Besides FERET and FRVT, there are many face databases available for researchers in the face recognition community; Yale [43], PIE [44], AR [45], and HLR [46] are some examples of face databases that are publicly available for researchers. However, very few of them address image currency or age-progression.

As stated earlier, ageing causes major changes in the human facial appearance. As indicated in [14], the characteristic regions of a face that are affected by ageing are described in Fig. 2.4. The frontal region (1) is limited by the eyelids and the forehead control lines. It was reported that the distance between these limits enlarges with advanced ageing. The orbital region (2) is characterized by the appearance of a number of wrinkles as age increases. With forward ageing, the nasal region (3) is characterized by the enlargement of its contour. The lips (4) getting thinner and the lower limit (5) of the face descended with advanced ageing. In general, Brut and Perrett [12] indicated that ageing affects both the shape and texture of faces. With ageing, the growth of facial hair, change in skin elasticity, texture of skin (size of pores, occurrence of wrinkles and presence of capillary varicosities), distribution of adipose tissue (fat padding), length of nose and ears, thickness and texture of eyebrows, apparent size of the eyes, and the size and shape of the lips undergo significant changes.



**Figure 2-4: Face regions according to ageing parameters.**

In particular, Fig. 2.5 depicts the possible facial change in the reported year from 41 to 31 (Fig. 2.5 A: Backward ageing) and from 41 to 51 (Fig. 2.5 B: Forward ageing), and 41 to 61 (Fig. 2.5 C: Forward ageing), respectively as reported in [14].



Figure 2-5: The half-right image at age 41 and the half-left images (at 31,51 and 61 years old) .

As mentioned above, the performance of FR algorithms is affected by different factors and it is very difficult to even build a face database that can entertain all of the face parameters (as evidenced by many researches [5, 17, 23, 33]). The Performance evaluations made by FERET

and FRVT have shown that the performance of FR algorithms and systems decreases with age-progression. According to FRVT 2002, the performance of FR decreases by almost 5% for each year between recording the gallery and probe images [1]. It is concluded that the performance of FR algorithms decreases linearly as the time delay between gallery and probe images increases. But this conclusion is made based on the available dataset collected for the evaluation test, which was limited to 5 years.

So, to perform a robust evaluation of the temporal effect, there is a requirement of long-term face data that allow us to test the performance of an algorithm. The FG-NET (Face and Gesture Recognition Research Network), which has a number of databases for research purposes, is a European funded program. Among the databases that are directly related to the temporal effect, FG-NET ageing database and the MORPH are the prominent ones.

The FG-NET [47] database contains face images of individuals at different ages. The database has been developed in an attempt to assist researchers who investigate the effect of ageing on facial appearance. The database is divided into two parts, Part A and Part B. Part A is available for use by researchers in the FR community, but part B is not published yet at the writing of this report. Part A of FG-NET ageing database contains 1002 images of 82 individuals. The number of images per subject ranges from 6-18. The maximum age difference is 69. The images are stored in JPEG (Joint Photographic Expert Group) format. A sample of FG-NET Ageing database is shown in Fig. 2.6. This is the best sample one can get from FG-NET ageing database collected by individuals. However, the FG-NET database will not be used for this research as a result of small number of images that are not affected by pose variation.



**Figure 2-6: The longitudinal age-progression of a subject for FG-NET.**

As described in Chapter 1, the MOPRH database is the one to be used to assess the impact of face image currency on the recognition rates of the Eigenface algorithm. A detailed description about the MOPRH database is presented in Chapter 3.

## **2.4 Summary and Conclusion**

The Chapter briefly summarized the most important and relevant works to the subject of this thesis. Face recognition approaches have been categorized as part-based, holistic-based and synthesis approaches. Curvature-based technique, which deals with absolute measure of shape and size of the face feature; the Neural Network technique, which imitates the human neural system for recognition purpose; the Statistical technique, which assumes the underlying model as a set of probability and the Morphable and AAM models, which deal with both geometrical and photometrical characteristics of a face are among the most widely used approaches to face recognition.

In FR technology evaluation, there are three general design principles. The first one enforces every image to have a unique identifier. The second design principle imposes the training phase to be completed before the start of the evaluation in order to perform a controlled evaluation test. The third one deals with similarity measure in which the similarity or distance should be measured between all combinations of the images from the gallery and the probe sets

FERET has been used, as a standard evaluation methodology for face recognition research and applications for many years and is still a de facto standard for measuring the performance of FR algorithms. Regarding the impact of image currency on the recognition rates of FR algorithms, FERET and FRVT 2000 indicated that, as the elapsed time between the gallery and the probe images increases, recognition rate decreases. However, the rate at which performance declines had not been thoroughly examined. FRVT 2002 has provided a better characterization as compared to the previous evaluations.

In this research, technology evaluation is employed to assess the performance of FR algorithms, particularly on the currency of the probe and the training images. Both FERET and FRVT methodologies will be used. Evaluating the face recognition approaches using both FERET and FRVT datasets, it is concluded that image currency affects the recognition rate of algorithms. But the conclusions were not more than mere speculations based on the limited database at hand. The maximum time-span between the gallery and the probe images for

FERET and FRVT 2000 datasets are less than 2 years and for FRVT 2002, it doesn't exceed 5 years. Because of this insufficient time-span between the probe and the gallery images, FRVT 2002 addressed the research directions to specifically find out the effect of algorithms on covariate performance like image currency, demographic and gender factors on performance [1].

So, this thesis will add more credibility to the impact of age-progression on face recognition techniques utilizing Eigenface, which is one of the most widely used FR algorithms. As described above, we make use of both FERET and FRVT evaluation methodologies. The datasets of both FERET and FRVT are not going to be used for this research. The most important reason is that, the time span between the gallery and the probe images is not sufficient to make a thorough investigation of the effect of ageing on algorithm performance. Rather we need to have a better dataset in order to perform analysis on impact of age-progression on recognition attempt. Another reason is that FRVT 2002, which utilizes a better dataset for the problem domain, is not available for public use. Hence due to its suitability for assessing the temporal effect, the MORH database will be used as data source.

### 3. Methodology

As has been discussed in Chapter 1, the increase in the elapsed time between the acquisition of the gallery and probe images causes degradation in the performance of FR algorithms. This is known as age-progression and its effect is demonstrated in various performance evaluation tests by researchers in face recognition. The FERET evaluation studies, which created a large face database (1,196 images), have been used as a baseline for comparative evaluation of the performance of FR algorithms for many years. In this evaluation test, two probe sets (see Table 3.1) were considered to determine the impact of time delay between acquisition of the gallery and probe images; namely, Duplicate I (T1) and Duplicate II (T2). As mentioned earlier, T1 probe set contains 722 images whose corresponding matches were taken between 0 and 1031 days after their respective gallery counterpart. The T2 probe set contains 234 images whose gallery counterpart was taken between 540 and 1031 days. The median and mean for T1 were 72 and 569 days and for T2, 251 and 627 days, respectively. In the FERET evaluation test in general, the evaluated algorithms performed better on the T1 probe set than the respective probe set of T2. However, for both cases, the performance of FR algorithms degraded as the elapsed time between the gallery and probe images increased.

**Table 3-1:FERET Dataset for Temporal experiment.**

Experiment Name	Gallery (images) size	Probe (images) Set	Minimum time span	Maximum time span	Mean (days)	Median (days)
Duplicate I or T1	1196	722	0	1031	251	72
Duplicate II or T2	1196	234	504	1031	627	569

FRVT 2000, like FERET evaluation test, has taken into consideration, the impact of image currency on recognition rates of FR algorithms. It uses two databases for its evaluation: the FERET and the HumanId databases. The HumanId database was collected by the National Institute of Standards and Technology (NIST) in USA. Specifically, for the temporal effect experiments, it took T1 and T2 duplicates of the FERET probe data sets. From the HumanId database, three probe sets were constructed for temporal effect analysis namely T3, T4, and T5. The HumanId gallery contains a collection of about 227 images that were obtained between 11 and 13 months after their respective probe images. The three probe sets, which contained a total of 467 images, differ only in the lighting used for gallery images. The gallery set in T3 contains images taken with normal mugshot light, the T4 contains FERET-style images and the T5 comprises gallery images that were taken with overhead lighting. The evaluation experiment indicated that the FRVT 2000 performance for the duplicates named T1 and T2 probe sets have almost the same score as obtained for FERET. The T3, T4, and T5 experiments used the same probe set and different gallery images. The experiment showed that the top identification scores were 0.55 both for T3 and T4 and 0.35 for T5 from 1, which is the ideal case. It was concluded in both FERET and FRVT 2000 that to have solid understanding about the temporal effect, further research is required for images taken more than a year apart.

FRVT 2002 has taken into consideration the temporal effect in a better way. Although it was reported in FERET and FRVT 2000 that performance declines with age-progression between the acquisition of the gallery and the probe image sets, the conclusion made was performed at a coarse level with a limited dataset at hand. As stated earlier, FRVT 2002 tried to tackle this problem by introducing two different datasets of images, HCInt and MCInt.

In HCInt, the probe set was partitioned into 19 bins with a time interval of 60 days between each bin. The evaluation performed on this dataset on the impact of temporal variation between the gallery and the probe image sets was better as compared to the previous datasets.

For MCInt, the temporal effect was broken into two categories of probe image sets, namely the indoor-different day probe image set and the out-door different day probe set. The indoor-different day probe set contained 320 images of 320 individuals. The median and the maximum elapsed time between the gallery and the probe image sets were 147 and 730 days, respectively. The outdoor-different day probe set consisted of 145 images from 103

individuals. The median and maximum elapsed time between the gallery and probe images was 152, and 505 days, respectively. Like the previous evaluation tests, FRVT 2002 evaluation test indicated that as the elapsed time between the gallery and the probe increases, the recognition rate decreases. Particularly, the HCInt test indicated that the identification performance dropped off approximately linearly as the elapsed time between the acquisition of the gallery and the probe images.

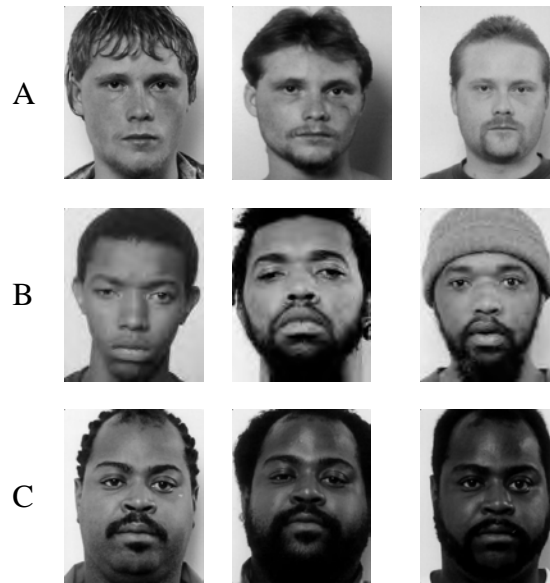
However, still the elapsed time between the gallery and the probe image sets in all of the above evaluation tests didn't exceed 5 years. And it is not reasonable to conclude with this small time interval. The reason is that, although the effects of ageing have not been studied directly by empirical methods, it was reported in [12,14] that, different changes can happen at different stages of life. Some age parameters start to grow and some cease to change at certain stages of life. For instance, facial bone growth ceases in the mid 20s [12]. So it is reasonable to argue that the ageing process may not follow a simple pattern. And it was reported in [23] that the ageing process is unlikely to be linear.

It is this overall temporal problem of facial recognition that this research is addressing. For the research, we will use the MORPH database for performing a detailed investigation of the effect of age-progression between the gallery and probe images on the recognition rate of FR algorithms.

### **3.1 The MORPH Database**

As described in the introduction section, the MORPH database consists of images that have been collected from public records in a mid-sized metropolitan area in the southern United States. The photographs were taken between October 26, 1962 and April 17, 1998. The average age of individuals at the time of acquisition is 27.3 years, with a standard deviation of 8.6 years, and the maximum age being 68 years. There are 516 individuals with a total of 1724 images stored in PGM (portable gray map) format. Each image has been cropped to 400 x 500 pixels. The images represent a diverse population with respect to age, gender, and ethnicity.

Fig. 3.1 shows some of the sample images in the MORPH database. Person A is a Caucasian decent male at age 19, 20, and 27. Person B is an African- American male at ages 20, 30, and 37. Person C is also African –American male with varying age, facial hair and imageing properties.



**Figure 3-1: Sample images from the MORPH database.**

The MORPH database has been constructed with the aim of focusing on changes of both texture and structure of the natural ageing process. As reported in [55], the specialty of the MORPH database is its capability to be used as a means for evaluating FR algorithms against gallery and probe image sets currency. In the MORPH database, the image gap between images goes up to 29 years. Ricanek *et al.* [55] noted that MORPH is very suitable for researchers who are interested in gaining a greater understanding of the range of normal human face variation as a result of age-progression. Hence, the MPROH database will be the data source for this research.

### **3.2 Preprocessing the images**

The preprocessing stage includes spatial-normalization to perform geometric adjustment like image size conversion to scale the face images to a fixed size, masking (background removal) to avoid the border pixels from inclusion onto a face image, photometric-normalization to adjust the lighting condition (e.g., histogram equalization to improve the contrast), and other operations that constrain the images to a representation required by the FR algorithms being used. In general, it is expected that the preprocessing stage should segment the face images, normalize the lighting, and extract important features.

There are various methods and steps for preprocessing. Phillips *et al.* [10] recommended the following four steps for preprocessing:

- **Spatial-normalization:** In this step, images are translated, rotated and scaled so that image sizes entering the system are exactly the same and the center of the eyes are placed at specific location. One advantage of spatial-normalization is that performing cropping, scaling, and rotating images basically reduces the amount of information to be processed by the FR system. Translation and rotation of images is important step for holistic/appearance based FR systems, which tend to be sensitive to these projections.
- **Masking:** Masking, if applied on face images, avoids border pixels to be included in the face image so that only the face from forehead to chin and from cheek to cheek is visible. Masking helps to achieve dimensionality reduction since it avoids wrongly introducing any unwanted background structure into face representation.
- **Histogram equalization:** Histogram equalization on the masked face images will improve FR performance by enhancing the image quality. This is because, histogram equalization modifies the contrast of the face images and as a result some of the important facial features become more apparent and contribute for efficient recognition. This step helps to minimize the effects of lighting, which is another sensitivity that impacts holistic/appearance based FR algorithms.
- **Pixel-normalization:** Pixel-normalization scales pixel values to have a mean of zero and a standard deviation of one in an attempt to minimize shadowing and other lighting effects.

Preprocessing can be done manually or automatically. For this research preprocessing will be conducted using the Colorado State University Face Identification and Evaluation System (CSU FIES) preprocessing tools. CSU FIES is used for consistency as other researchers in the realm of FR have used it. As can be seen from Fig. 3.2, application of the preprocessing system on the images in row A resulted in images in row B. For instance, the preprocessing stage reduces the dimension of images from 400 x 500 to 150 x 130. This effectively reduces the computation time.



**Figure 3-2: Sample images before preprocessing (A) and after preprocessing (B).**

### 3.3 Realization of the algorithm using Matlab

We used Matlab for realization of the performance evaluation. Matlab is a very powerful, high level programming tool. It comes with a wealth of libraries and toolboxes that one can directly use, so that one doesn't need to program low-level functions. The Matlab development environment offers the following:

- Matrix Computation
- Algorithm development
- Modeling, Simulation and Prototyping
- Data analysis and visualization
- Scientific and engineering graphics

This development environment is chosen for a number of reasons, including the following:

- It provides robust digital image processing and image visualization capabilities by the Image processing Toolbox, which is designed to free technical professionals from the time consuming tasks of analysis and operations from scratch. This helps for significant time saving and cost reduction enabling researchers to spend less time on coding the algorithm and more time exploring and discovering solutions.
- It has intensive support for linear algebra.
- It is a highly interactive system.

### **3.4 Summary**

The FERET evaluation methodology utilized two sets of images to analyze the impact of age-progression, T1 (duplicate I) and T2 (duplicate II). FRVT 2000 analyzed the effect of age-progression by using five sets images namely T1, T2, T3, T4, T5. T1 and T2 were taken from the FERET test and the rest were taken from HumanId database. The time difference for all images sets do not exceed 2 years. In general, FRVT 2002 analyzed the impact of age-progression on the system performance in a better way. However, the age span for the database doesn't exceed 5 years. (The age-progression database used in FRVT 2002 is not publicly available; therefore it could not be incorporated into this work.)

As described in the preceding Chapters, having a reasonable face database is a must to perform analysis on the effect of image currency (age-progression) on the recognition rate of the Eigenface FR algorithm. The MORPH database was created for the purpose of exploring the impacts of age-progression on algorithm performance. This research will utilize the MORPH database in order to determine the long age-range effects on recognition rates. This requirement has hampered researchers in this area until recently. The original MORPH face images have not undergone a preprocessing stage. The CSU FIES will be used to preprocess the images used in this work.

# CHAPTER 4

## FR USING THE EIGENFACE ALGORITHM

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### 4. FR Using the Eigenface Algorithm

This work will focus on evaluating the performance of the Eigenface FR algorithm against image currency (age-progression). As described in the previous Chapters, appearance-based methods use an information theory approach of coding and decoding face images, which does give insight into the information content of face images. The Eigenface algorithm is known to be the baseline for most of the FR algorithms developed recently.

An image in appearance-based methods can be considered as a vector or a point in a high dimensional space. It considers a face image as a matrix of  $N_x \times N_y$  pixels that is vectorized, dimensionally reduced, and projected into a space defined by the set of known images as “face space.” By projecting the face vector to the face space, the coefficients are used as feature representation of each face image. In general, the Eigenface can be considered as a linear transformation from the original image vector to a projection vector as:

$$Y_K = W^T X_K \quad (4.1)$$

where  $X_K$  is the original image vector,  $Y_K$  is the feature vector and  $W$  is the transformation matrix.

The realization of this algorithm is performed in Matlab development environment.

#### 4.1 The Eigenface Algorithm

To explain its principle, consider a grayscale (8 bits) face image of size  $N_x \times N_y$ . This image matrix can be considered as a vector or a point in an  $N_x \times N_y$  dimensional space. For example, a 256x256 pixel image will have  $256^2$  dimensional space. This is a considerably high dimension to make computation. However, since all faces have similar structure such as two eyes, a nose in between the eyes, a mouth and the like, they will be grouped or concentrated at a certain location in that high dimensional space. The Eigenface method tries to extract those

dimensions required for efficient representation of the face by ignoring those dimensions that have less contribution to face representation. To perform this, it utilizes a well-known statistical method for reducing dimension called Principal Component Analysis (PCA) also known as Karhunen-Loeve method.

In statistical terminology [34], PCA is a transform that chooses a new coordinate system for the data set, such that the greatest variance by any projection of the data set comes to lie on the first axis (the first principal component), the second axis corresponds to the maximal remaining variation in the dimension orthogonal to the first axis, and so on. The fundamental idea behind PCA is that if there are a series of multidimensional data vectors representing objects, which have similarities, it is possible to use a transformation matrix to create a dimensionally reduced space that accurately describes the original multidimensional vectors.

Kirby and Sirovich [11] proposed the use of PCA for analysis and representation of images and Turk and Pentland [2] then utilized the method for FR systems. The main purpose of utilizing PCA is to reduce the large dimensionality of the data space (image space for our case) into smaller dimensionality of feature space (i.e., face space), which is needed to describe the data economically. In other words, PCA can be used for reducing dimensionality in a data set while retaining those characteristics of the data set that contribute most of its variance by eliminating the later principal components by a more or less heuristic decision. Turk and Pentland [2] have considered the following presupposition to deal with PCA for FR.

- An image of a particular object occupies a relatively small but distinct region of the image space.
- Different objects occupy different regions of image space.
- The whole classes of objects occupy a still relatively small but distinct region from the image space.

PCA encodes face images and captures the characteristic features of the training images in the face database. Once the characteristics features of images are obtained, the comparison of the characteristics features of the training image with the characteristics features of the probe image will follow, based on the similarity measure of their characteristic features. The face can be classified as known (a subject in the gallery of images) or unknown person (a subject not within the gallery of images).

In general, PCA-based face recognition approach performs recognition on the characteristic representations of the face images called eigenvectors, where the eigenvectors of the covariance matrix (the product of the data matrix with its transpose) of a small set of characteristic images are sought. These eigenvectors are called Eigenfaces. Once the Eigenfaces are computed, they are used to represent the test image (the one to be recognized) and the training faces to be identified. Finally, recognition is done by assigning weight vectors to face images, based on their contributions to the face spanned by the Eigenfaces. The test face is then matched to the training face whose eigenvector representation is the most similar with respect to the similarity measure.

#### **4.1.1 Mathematical Formulation of the Eigenface Algorithm**

The original Eigenface recognition scheme involves two main phases: Construction of the face space (Training phase) and recognition using the face space (Recognition phase) as described in [4].

The training phase is an off-line initialization process that can only be recomputed if the gallery (training set) changes. The output is a set of eigenfaces and the corresponding eigenvalues. Finally, the gallery images are projected into face space to determine the weight of each eigenface representation of the images in the face space.

In the recognition phase, the probe images go through similar steps as the gallery images in the training phase and the weight of the probe image is compared with the weight of each of the gallery images to perform the recognition process.

##### **4.1.1.1 The Training phase**

The following are the followed steps in the training phase to perform the Eigenface analysis.

1. Acquire an initial set of face images (see Fig. 4.1) and represent each as a matrix of

$N_x \times N_y$  pixels to get an image matrix  $X$  as

$$X: N_x \times N_y \tag{4.2}$$



Figure 4-1: Sample preprocessed images of the MORPH dataset.

- Convert the image matrix  $X$  of size  $(N_x \times N_y)$  pixels into a vector  $\Gamma$  of size  $(P \times 1)$  where  $P$  is of size  $N_x \times N_y$ . Concatenate the vectors of the training images column wise to obtain the training set  $T$ .

$$T = [\Gamma_1 \Gamma_2 \Gamma_3 \dots \Gamma_M] \quad (4.3)$$

where matrix  $T$  is the training set of image vectors of size  $(P \times M)$  and  $M$  represents the number of training images.

- Compute the average face vector

$$\Psi = \frac{1}{M} \sum_{i=1}^M \Gamma_i \quad (4.4)$$



**Figure 4-2: The mean image of the MORPH dataset.**

where  $\Psi$  is the arithmetic mean of the training image vectors of each pixel point and its size is  $(P \times 1)$ . Fig. 4.2 shows the mean image of the MORPH gallery data set.

4. Center the data by subtracting the mean face.

$$\Phi_i = \Gamma_i - \Psi \quad (4.5)$$

where,  $\Phi_i$  is the difference of the training image and the mean image with size  $P \times 1$ .

5. Create the data matrix

Once the training images are centered, they are combined to create a data matrix  $A$ .

$$A = [\Phi_1 \Phi_2 \Phi_3 \dots \Phi_M] \quad (4.6)$$

where,  $A$  is the data matrix with size  $P \times M$ .

6. Compute the covariance matrix.

The data matrix  $A$  multiplied by its transpose to obtain the covariance matrix:

$$C = AA^T \quad (4.7)$$

where,  $C$  is the covariance matrix of the training image vector with size  $P \times P$ .

The original definition of  $C$  is given by  $C = \frac{1}{M} \sum_{i=1}^M \Phi_i \Phi_i^T$ , for detail description the reader is referred to [1].

7. Compute the eigenvectors<sup>3</sup> and eigenvalues of the covariance matrix. For a face image of size  $(N_x \times N_y)$  pixels, the covariance matrix is of size  $P \times P$ ,  $P$  being  $(N_x \times N_y)$ . This is a huge matrix and therefore, full computation of the eigenvectors is impractical. Fortunately, there are only  $M - 1$  non-zero eigenvalues, and they can be represented more efficiently and economically by an  $M \times M$  matrix, where  $M$  is the number of face images.

The eigenvectors and the corresponding eigenvalues are computed for the covariance matrix  $C$  by

$$C e = \lambda e \quad (4.8)$$

Here  $e$  is the set of eigenvectors associated with eigenvalues  $\lambda$

These are related to the eigenvectors  $v$  and the eigenvalues  $\mu$  of the matrix  $D = A^T A$ , which is of size  $(M \times M)$  in the following way

$$D v = \mu v \quad (4.9)$$

$$A^T A v = \mu v \text{ (Substituting the value of D)}$$

$$A A^T A v = A \mu v \text{ (Pre multiplying by A)}$$

$$C A v = \mu A v \text{ (Rearranging by moving the scalar } \mu \text{)}$$

$$C e = \lambda e, \text{ where } e = A v \text{ and } \mu = \lambda$$

This indicates that eigenvectors of the large matrix  $C$  are equal to the eigenvectors of the much smaller matrix  $D$ , pre-multiplied by the matrix  $A$ . The non-zero eigenvalues of  $C$  are equal to the eigenvalues of  $D$ .

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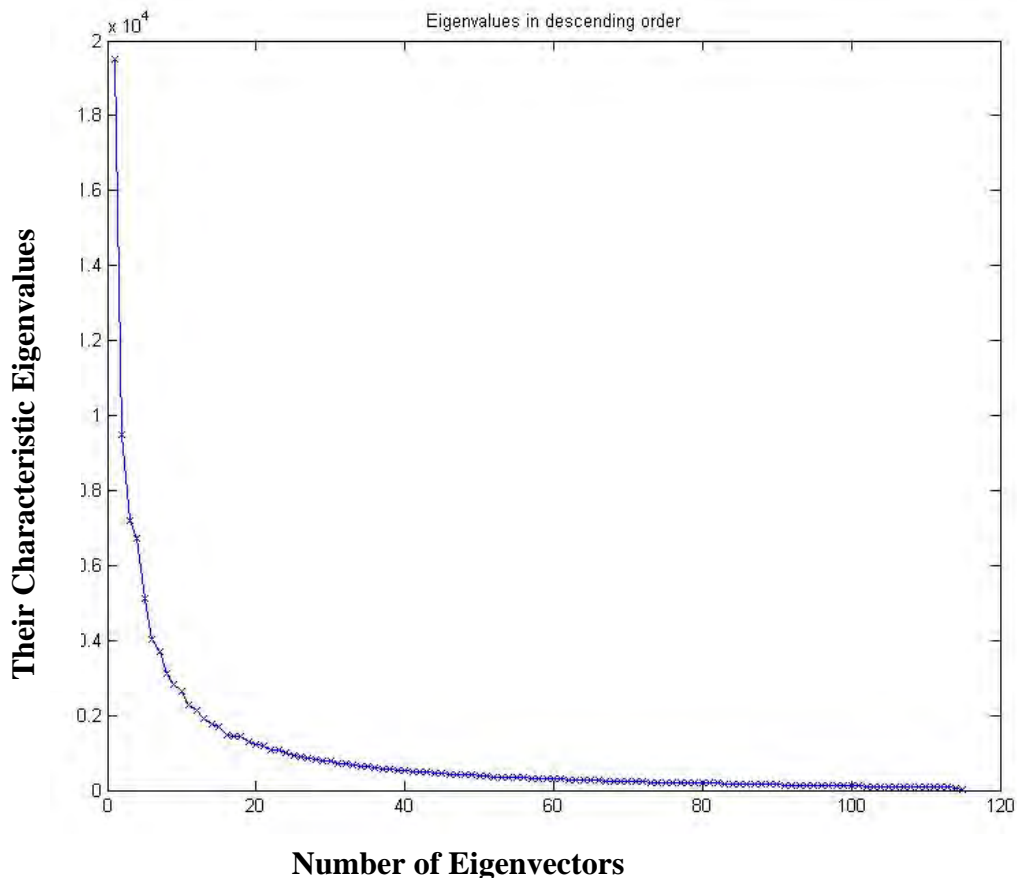
<sup>3</sup> An eigenvector of a matrix is a vector such that, if multiplied with the matrix, the result is always an integer multiple of that vector. This integer value is the corresponding eigenvalue of the eigenvector. This relationship can be described by the equation  $M \times u = \lambda \times u$ , where  $u$  is an eigenvector of the matrix  $M$  and  $\lambda$  is the corresponding eigenvalue.

Eigenvectors possess the following properties:

- There are  $n$  eigenvectors (and corresponding eigenvalues) in an  $n \times n$  matrix.
- All eigenvectors are perpendicular, i.e. at right angle, with each other.

## 8. Order eigenvectors

Keep only  $K$  eigenvectors (corresponding to the  $k$  largest eigenvalues). The motivation for selecting the eigenvectors with the largest eigenvalues is that the eigenvalues represent the amount of variance along a particular eigenvector. By selecting the eigenvectors with the largest eigenvalues one selects the dimensions along which the gallery images vary the most (see Fig. 4.3). Since the eigenvectors are ordered from high to low by the amount of variance found between each image along each eigenvector, it is possible to eliminate some of the eigenvectors (see Fig. 4.4 for sample Eigenvectors) with smaller eigenvalues, which actually contribute less variance to the data. The assumption is that noise is associated with the lower valued eigenvectors where smaller amount of variations are found among the images. The decision made for specifying the number of eigenvectors to choose is more or less heuristic.



**Figure 4-3: Sample sorted Eigenvectors based on Eigenvalues.**



**Figure 4-4: Sample Eigenfaces from MORPH dataset.**

9. Projection of the training images

The training images are projected into the face space and then the weight of each eigenvector is used as a representation of the images in the face space construction. In short, to project an image into the face space, calculate the dot product of the image with each of the ordered eigenvectors.

$$\omega_k = \Phi_t e_k^T \quad (4.10)$$

where,  $\omega_k$  is the projection of training image on each of the eigenvectors and

$$k = 1, 2, \dots, M$$

The important aspect of Eigenface transformation lies in this property. Each image is represented by an image of size  $(N_x \times N_y)$  in the image space whereas the same image is represented by a vector of size  $(M \times 1)$  in the face space.

10. Calculate the weight matrix

$$\Omega_i = [\omega_1 \omega_2 \omega_3 \omega_4 \dots \omega_m]^T \quad (4.11)$$

where,  $\Omega_i$  is the representation of the training image in the Eigenface space and its size is  $(M \times 1)$ . The training images now are just composed of weights in the face space.

#### 4.1.1.2 Recognition phase

After choosing a training set and constructing the weight vector of the training images, the system is ready to perform the recognition process. The user initiates the recognition process by choosing a face image. Ideally, two images of the same person should project to the same point in the face space. Any difference between the points is unwanted variation. On the other hand, two images of different persons should project to points that are as widely separated as possible. Following are the steps to follow to accomplish the recognition stage.

1. The input image is represented by  $X_p$  ( $N_x \times N_y$ ) matrix, where  $X_p$  is the probe image matrix
2. Transform this into vector  $\Gamma_p$ , of size  $(P \times 1)$ , where  $\Gamma_p$  is the vector of the probe image
3. Mean subtracted image

$$\Phi_p = \Gamma_p - \Psi, \quad (4.12)$$

it is the difference of the probe image from the mean image of size  $P \times 1$

4. Project the probe image:

After each probe image is first mean centered, it is then projected into the same face space as:

$$\omega_k = \Phi_p e_k^T \quad (4.13)$$

5. Calculate the weight matrix

$$\Omega_p = [\omega_1 \omega_2 \omega_3 \omega_4 \dots \omega_m]^T \quad (4.14)$$

where  $\Omega_p$  is the representation of probe image in the face space with size  $(M' \times 1)$

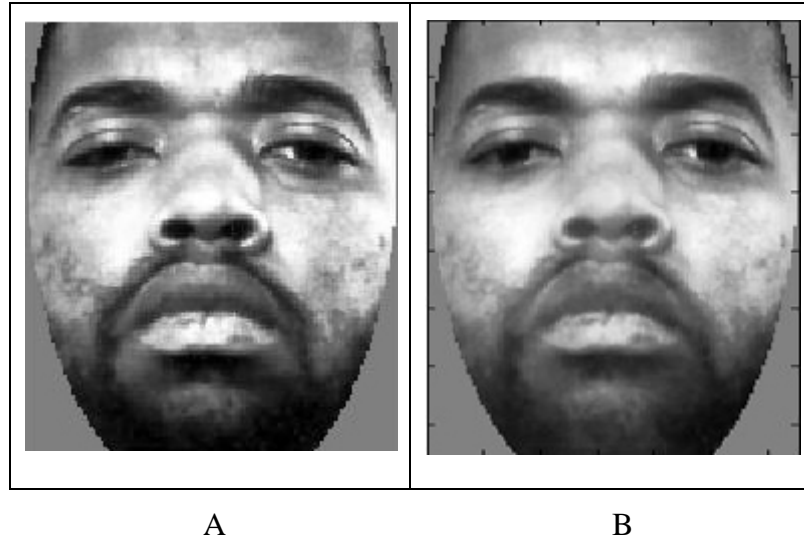
The projected probe image is then compared to every projected gallery image. In other words, the weight of each image including both the gallery and the probe image sets are compared for recognition purpose.

5. Reconstruct the images

Both training image vectors can be reconstructed by back transformation from the face space to the image space.

$$\Gamma_r = e.\Omega_i + \Psi \tag{4.15}$$

where  $\Gamma_r$  is the reconstructed image as shown in Fig. 4.5.



**Figure 4-5: A sample gallery image (A) and its projection onto the face space (B).**

Given a set of gallery images vector  $\Gamma_i$ , we can then determine the identity of the probe set  $\Gamma_p$  by finding which face is most closely positioned in the face space. One technique is to find the distance among the faces in the face space. There are several methods of measuring the distance for classification purpose [56]. A commonly used method for distance measure is the L2 Norm, also known as Euclidian distance used to classify the images. It is a simplistic way to find a minimum distance between the probe and the gallery images.

It is given by.

$$\varepsilon_n = \|\Omega_p - \Omega_i\| \tag{4.17}$$

where  $\Omega_i$  is the projection of  $\Gamma_i$  in the face space and  $\Omega_p$  is the projection  $\Gamma_p$  in the face space.



Figure 4-6: Sample Identification based on L2 norm.

In general the Eigenface method of FR can be visualized as shown in Fig. 4.7

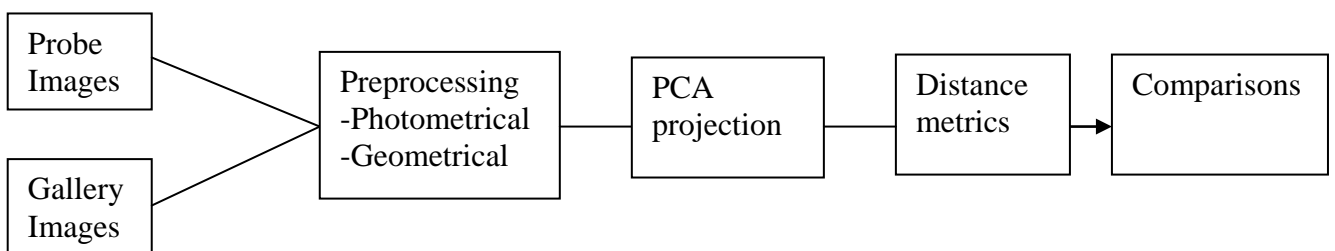


Figure 4-7: A generalization of the Eigenface technique.

To conclude, the Eigenface method creates the image subspace called face space, which best discriminates between faces (i.e., maximizes scatter between faces). In that face space, similar

faces occupy near points to one another. Recognition is performed by projecting the images into face space and measuring the distance such as using the Euclidean distance between them.

## 4.2 Summary

Appearance-based methods for automatic FR utilize the idea of using pixel values for encoding face information. In order to encode the pixel values, appearance-based methods start with the concept of a vector space known as image space. The image space representation is used to explain the relationships among the collection of images.

Among the widely used appearance-based techniques, the Eigenface is coined to be the baseline algorithm. It uses a statistical method called PCA for processing the face images. Statistical analysis is one of the most widely used appearance-based techniques to employ dimensionality reduction. The realization of the Eigenface algorithm is performed using the Matlab development environment due to its easiness in performing the matrix computation and image processing capabilities.

In general, there are two phases for the implementation of the Eigenface algorithm: The **Training** and the **Recognition** phases. The training phase is an off-line initialization process that can only be re-computed if the gallery image set is updated. In the recognition phase, the probe image set goes through similar steps as the gallery image set and the weighted value of both the gallery and the probe image sets are compared using a similarity distance measure.

### 5. Experimental Results

The MORPH database is partitioned into two groups: 1) gallery, which is the group of known persons and 2) the probe that is the group of images being submitted for identification. The gallery is composed of the first chronological image for each subject within the MORPH database. The probe group is made up of images of the subjects taken at a later date. There is a minimum of one image of each subject in the probe group, and up to five images of some subjects. Age differences from the initial image (contained in the gallery) to probe images are as small as a few days to as much as 29 years.

For the experiment outlined in this work, the gallery images are divided into four different groups, which correspond to the four different experiments. For experiment T (Total), the gallery size is 516; this gallery includes the chronological first image for each subject. The objective of this experiment is to assess the impact of age-progression on the Eigenface algorithm across all elements of the MORPH database. For subsequent experiments, the galleries are a subset of the T gallery. The M (Male) experiment has a gallery size of 420 individuals (i.e., 420 of the 516 subjects of the MORPH database are males). Similarly, experiment F (Female) is used to evaluate the performance of the algorithm on age-progression in relation to females. The size of the gallery for F experiment is 96. The experiments named AA (African-American) and W (White) are used to evaluate the impact of age-progression on specific racial origin. The size of the gallery for experiment AA is 377 where as it is 137 for experiment W.

For each experiment the corresponding probe images are divided into groups based on age difference from gallery image of subject. The age differences are clumped into five categories: 0-5, 6-10, 11-15, 16-20, and >20. Again, age difference is based on the difference in age of the subject from the gallery to the probe. As can be seen from Table 5.1, the size of the probe images for each age-range is specified for the T experiment. The same is true for the rest of the experiments (see Table 5.2-5.5). From Tables 5.1-5.5, one can see that there are

some combinations of gallery-probe that produce few to no probe candidates, which are highlighted. Therefore, analysis of the experiments cannot be performed for these combinations because there is not enough data to support the analysis.

**Table 5-1: Number of images for gallery T by age of individuals and age span**

Experiment Name	Gallery match age range of individuals	Number of probe images by age span*				
		0-5	6-10	11-15	16-20	21-
T1	<18	61	58	51	16	14
T2	18-29	219	191	97	50	13
T3	30-39	42	30	13	3	2
T4	40-49	10	6	2	0	0
T5	>=50	3	3	1	0	0

**Table 5-2: Number of images for gallery M by age of individuals and age span**

Experiment Name	Gallery match age range of individuals	Number of probe images by age span				
		0-5	6-10	11-15	16-20	21-
M1	<18	48	49	47	12	12
M2	18-29	164	143	84	41	12
M3	30-39	37	24	12	3	2
M4	40-49	10	6	2	0	0
M5	>=50	3	3	1	0	0

\* Note that age-span refers to the periods at which the images were taken, and not the age of individuals.

**Table 5-3: Number of images for gallery F by age of individuals and age span**

Experiment Name	Gallery match age range of individuals	Number of probe images by age span				
		0-5	6-10	11-15	16-20	21-
F1	<18	13	9	4	4	2
F2	18-29	55	38	13	9	1
F3	30-39	5	6	1	0	0
F4	40-49	0	0	0	0	0
F5	>=50	0	0	0	0	0

**Table 5-4: Number of images for gallery AA by age of individuals and age span**

Experiment Name	Gallery match age range of individuals	Number of probe images by age span				
		0-5	6-10	11-15	16-20	21-
AA1	<18	35	39	38	13	11
AA2	18-29	156	147	75	43	10
AA3	30-39	36	23	10	3	2
AA4	40-49	6	5	2	0	0
AA5	>=50	2	2	0	0	0

**Table 5-5: Number of images for gallery W by age of individuals and age span**

Experiment Name	Gallery match age range of individuals	Number of probe images by age span				
		0-5	6-10	11-15	16-20	20-
W1	<18	26	19	13	3	3
W2	18-29	63	44	22	7	3
W3	30-39	7	7	3	0	0
W4	40-49	4	1	0	0	0
W5	>=50	1	1	1	0	0

## 5.1 Identification test for experiment T (T1)

This section illustrates the procedure for computing the experimental results for identification test. In this section, for brevity, we will show the details only for a subset of the T experiment (i.e., for T1 only). Similar procedure is followed for the rest and details are given in Annex A. The identification test has been performed on the MORPH database. In the Identification test, the algorithm compares each probe image with every image in the gallery and reports the images with the best similarity scores with the range of ranked result. From the report, one can determine if the correct match of a specified probe is in the top 10, 25 or 50. For instance in our case, the correct match of probe Id =12032001 with gallery ID=12032 is ranked 6 (the algorithm reports that there are 5 other images that have better scores than gallery ID=12032). For a probe set we can find for how many probes the correct match is in the rank 10 or less. For instance, probe ID=12032001 is counted in the calculation of the cumulative match score of probes that are of 10th rank or less since its rank is 6. In general, during identification test, for a probe  $p \in P$ , the algorithm reports the gallery matches that have the highest similarity to the probe images. Over all probes, let  $R_k$  denotes the number of probes in the top k, then

$R_k / |P|$  (where  $|P|$  is the number of images in  $P$ ), is the fraction of probes in the top  $k$ . In other words,  $R_k / |P|$  indicates the percentage of probes that are rank  $k$  or less.

The size of the gallery for the T experiment is 516. The probe match of the gallery images are partitioned into 5 sets based on the age span between the gallery and the probe (see Table 5.1)

**Table 5-6: Sample Probe sets partitioned based on age span**

<b>5.1.1.1 Probes</b>	<b>Age-span</b>
Probe1	0-5
Probe2	6-10
Probe3	11-15
Probe4	16-20
Probe5	>20

The Identification rate (Probability of Identification) for Rank  $k$  is calculated by:

$$I_k = R_k / |P| \quad (5.1)$$

**Age < 18**

➤ Probe 1:

- Total Number of Probes: 61
- Identification rate at the 10<sup>th</sup> rank =  $R_{10} / |P| = 21 / 61 = 0.344$
- Identification rate at the 25<sup>th</sup> rank =  $R_{25} / |P| = 27 / 61 = 0.433$
- Identification rate at the 50<sup>th</sup> rank =  $R_{50} / |P| = 41 / 61 = 0.672$

➤ Probe 2:

- Total Number of Probes: 58
- Identification rate at the 10<sup>th</sup> rank =  $R_{10} / |P| = 9 / 58 = 0.155$
- Identification rate at the 25<sup>th</sup> rank =  $R_{25} / |P| = 16 / 58 = 0.276$
- Identification rate at the 50<sup>th</sup> rank =  $R_{50} / |P| = 25 / 58 = 0.431$

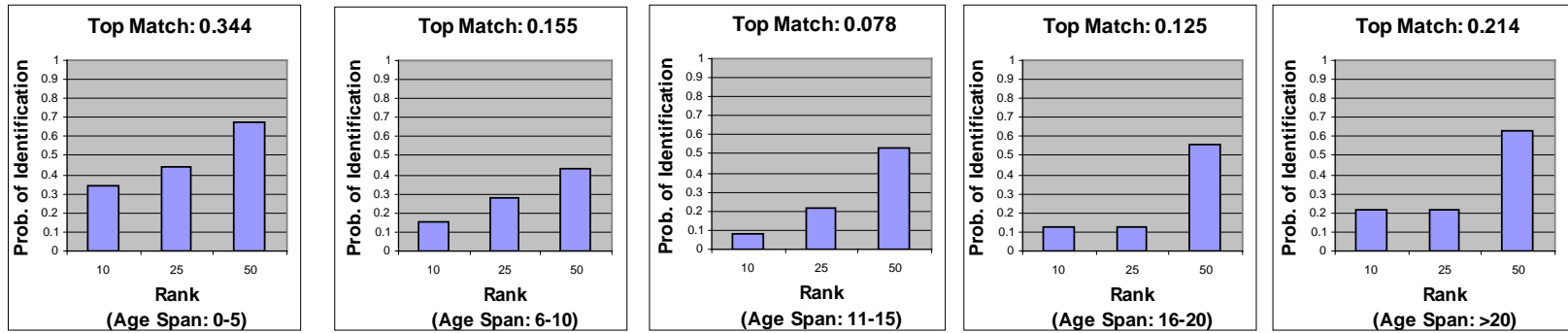
➤ Probe 3:

- Total Number of Probes: 51
- Identification rate at the 10<sup>th</sup> rank =  $R_{10} / |P| = 4 / 51 = 0.078$
- Identification rate at the 25<sup>th</sup> rank =  $R_{25} / |P| = 11 / 51 = 0.216$
- Identification rate at the 50<sup>th</sup> rank =  $R_{50} / |P| = 25 / 51 = 0.529$

- Probe 4:
  - Total Number of Probes: 16
  - Identification rate at the 10<sup>th</sup> rank=  $R_{10}/|P|= 2/16= 0.125$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|= 2/16= 0.125$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 9/16= 0.563$
- Probe 5:
  - Total Number of Probes: 14
  - Identification rate at the 10<sup>th</sup> rank=  $R_{10}/|P|= 3/14= 0.214$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|= 3/14= 0.214$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 9/14= 0.643$

As can be seen from Fig. 5.1, the Cumulative Match Characteristics (CMC) shows the pattern of the performance of the Eigenface algorithm as the increase in age span between the gallery and the probe images. CMC (also known as rank order statistics) is the measure of identification performance. It indicates the probability that the gallery image will be among the top matches to a probe. In other words, CMC is described as a plot of probability of correct match versus the number of best similarity scores. A similar procedure is applied to all groups of experiments. For the sake of brevity, the corresponding figures for all the experimental results are shown in Annex B.

**Age Range: <18**



**Figure 5-1:T1 CMC for age <18.**

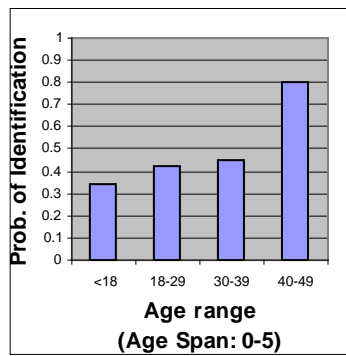
## 5.2 Results of the experiment on total images (Experiment T)

Impact of age-progression on the performance of the Eigenface algorithm could be analyzed in various age spans and age ranges. In the T experiment (see Table 5.6), for all age ranges, the best performance of the algorithm falls in the age span (0-5), which is of course, the smallest one. This signifies that the performance of the algorithm is maximum when there is a smaller time gap between the acquisition of the gallery and the probe images. In general, the performance declines approximately linearly with some exception.

With regard to age range, for a specified age span in this experiment, the performance of the algorithm increased from age range (< 18) to age range (40-49). This indicates that younger people are difficult to be recognized than older ones. For the specified age span (0-5), as can be seen from Table 5.7, the performance increased from 0.344 (age range <18), 0.420 (age span 18-29), 0.452 (age range 30-39), and 0.80 (age range 40-49), respectively (see Fig. 5.2). This clearly shows that the Eigenface algorithm performed better in identifying older people with the same age span than younger ones. This can be explained by either more changes occur naturally in the facial appearance of people in the younger age range than older ones or more environmental obstruction like make-up or hair (beard) style changes occur in the younger age which significantly affected the performance of the algorithm than the older age groups. To investigate these, it is reasonable to see the performance of the algorithm with differences in gender and race groups.

**Table 5-7: The Top Match results of experiment T.**

Experiment	Number of probe images by age span				
	0-5	6-10	11-15	16-20	>20
T1	0.344	0.155	0.078	0.125	0.214
T2	0.420	0.257	0.134	0.080	0.154
T3	0.452	0.300	0.231	*	*
T4	0.800	*	*	*	*
T5	*	*	*	*	*



**Figure 5-2: CMC of experiment T based on age range.**

\* indicates the number of probe images did not meet minimum criteria set forth for the experiment. The minimum number of probes to full fill the criteria is 10.

### **5.3 Results of the experiment on gender effect (experiment M and F)**

To investigate the impact of face image currency in the performance of the Eigenface algorithm on gender and age-progression, the gallery used for experiment T is partitioned in to two. The experiment M is performed to investigate the performance of the Eigenface algorithm on male gender group. As can be seen from Table 5.8, the results are more or less consistent with the result obtained in the experiment T. The top match scores (see Table 5.8) are best at the age span of 0-5 for all age groups. This clearly indicates that image currency affects algorithm performance. In addition, as the age span increases from 0-5 to 6-10 to 11-15, performance of the algorithm decreased. This indicates that further investigation is required to see whether this algorithm is affected by the natural slow change in the facial appearance.

To quantify the recognition rate of the Eigenface algorithm, performance evaluation is done on the female gender group. As can be seen from Tables 5.8 and 5.9, the top mach scores in the respective age spans and age ranges indicated that females are difficult to be recognized than males (see Fig 5.3). In other words, the result shows that the Eigenface algorithm performed better in recognizing males than females. Several explanations can be given for this experiment. One explanation could be females either get changed in their natural facial appearance faster than males in their younger age or due to a significant usage of make-up on their face as compared to males. Their facial appearance change is pronounced more frequently and made it difficult for the algorithm to perform well. To investigate the impact of age-age progression on race with equal gallery size, a subset of gallery images from both gender are used. The number of gallery for both gender groups is 100 (i.e., 100 for

each). The results obtained from the experiments are more or less similar to the results of the previous experiments (i.e., the entire gender group experiments). However, further investigation is required to come into a reasonable conclusion.

**Table 5-8: The Top Match results of experiment M.**

Experiment	Classification of probes based on age span				
	0-5	6-10	11-15	16-20	>20
M1	0.354	0.163	0.085	0.833	0.833
M2	0.431	0.294	0.199	0.073	0.167
M3	0.513	0.292	0.167	*	*
M4	0.800	*	*	*	*
M5	*	*	*	*	*

**Table 5-9: The Top Match results of experiment F.**

Experiment	Classification of probes based on age span				
	0-5	6-10	11-15	16-20	>20
F1	0.231	0.111	*	*	*
F2	0.382	0.184	0.308	*	*
F3	*	*	*	*	*
F4	*	*	*	*	*
F5	*	*	*	*	*

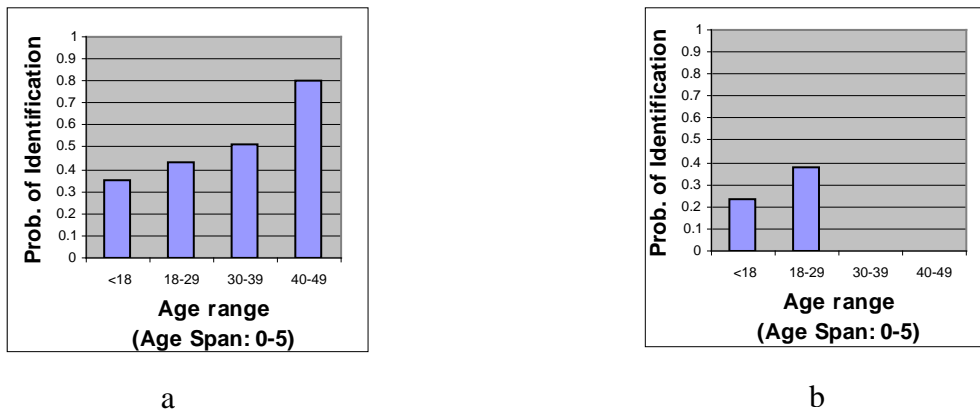


Figure 5-3: CMC of experiment M (a) and experiment F (b) based on age range

#### 5.4 Results of the experiments on the African-American and the White racial origin (Experiment AA and W).

Two groups of experiments are performed to see the impact of age-progression on ethnic variation. The experiments AA (African-American ethnic origin) and W (Whites) are performed to see whether the algorithm's performance is affected by people with different racial origin. Similar to experiments T, M, and F, in the experiment AA, the algorithm performed well for images that have smaller age span between the gallery and the probe images (see table 5.10) In addition, the older people are easier to be recognized than younger people up to a certain age range (i.e., up to 30-39) like the previous experiments. From age range (<18) to (30-39), the performance of the algorithm increased linearly.

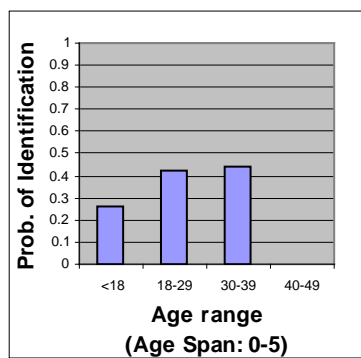
Results in the W experiment are more or less similar to the results of the previous experiment with the exception of one. As the age range increases the performance of the Eigenface algorithm increases constantly. As can be seen from Fig. 5.4, the performance of age range for the age span (0-5) indicates that there is an increase in the performance of the algorithm for both experiments (see Tables 5.9 and 5.10) as the ages get older. To investigate whether the change in performance occur due to gallery size. Equal number of galley is used for both African-American and the White racial origin and males. The result showed more or less similar result. However, further investigation is required with reasonable number of datasets for a plausible conclusion.

**Table 5-10: The Top Match results of experiment AA.**

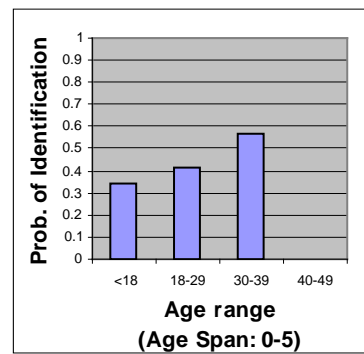
Experiment	Classification of probes based on age span				
	0-5	6-10	11-15	16-20	20-
AA1	0.257	0.051	0.105	0.077	0.273
AA2	0.423	0.252	0.107	0.093	0.2200
AA3	0.444	0.304	0.333	*	*
AA4	*	*	*	*	*
AA5	*	*	*	*	*

**Table 5-11: The Top Match results of experiment W.**

Experiment	Classification of probes based on age span				
	0-5	6-10	11-55	16-20	20-
W1	0.346	0.211	0.077	*	*
W2	0.413	0.250	0.227	*	*
W3	0.571	0.286	*	*	*
W4	*	*	*	*	*
W5	*	*	*	*	*



a



b

**Figure 5-4: CMC of experiment AA (a) and experiment W (b) based on age range.**

## 5.5 Summary

Summary analysis of the top match Identification score indicates the following:

- Identification performance dropped off approximately linearly in the increase age-span of each group. There is an upward trend in the last age difference category of >20 years. Additional analysis will be required to fully understand this problem, but one should note that the number of probes—images that are greater than 20 years in difference—is small. The Identification performance of the entire experiments (T, M, F, AA, W) drops with increase age-range (i.e. <18, 18-29, 30-39, 40-49). As the age difference increases, the identification performance decreases. For all experiments, there is an increase in the identification performance as the gallery age span increased. This suggests that the Eigenface algorithm performs better under age-progression for older subjects. This is further supported by the results of Phillips in FRVT 2002 [1]. Phillips reported on page 3 of Face Recognition Vendor Test 2002: Overview and Summary that “recognition rates for older people were higher than younger people...For every ten years increase in (gallery) age, on average performance increases approximately 5% through age 63.”
- With regard to racial origin, the algorithm doesn't perform in a predictable manner on the impact of age progression on racial origin. However, in general the impact of age progression on the algorithm performance obtained similar results when they are not partitioned. To investigate the impact of age-progression on race with equal gallery size is used for both races (100 for each), the result was more or less similar.
- As can be seen from Tables 5.7 and 5.8, the identification performance for the male-only gallery was higher than the female-only gallery. This result is in line with findings of Phillips *et al.* [52] where identification performance on men had a marked improvement over those of women. The algorithm performed better in resisting age-progression for males than for females. To investigate whether the change in performance occur due to gallery size, equal number of gallery images is used for both females and males. The result showed more or less similar result.

### 6. Conclusion and Future Work

#### 6.1 Conclusions

Face Recognition is a difficult intra-class problem; in particular the difficulties center around presentation – pose of the face differs from gallery, lighting, and disguises like glasses and facial hair – and, now ageing (temporal variation). The temporal variation (time difference between the recordings of the gallery and the probe images) is among the challenging factors that affect the recognition capabilities of FR algorithms.

The purpose of this research is to employ technology evaluation for assessing the impact of face image currency on the recognition rates of the Eigenface algorithm. The problem of recognizing images using the extended periods of time has a significant impact on the operations of FR systems. This problem has been raised in many researches in the FR community. FERET and FRVT are cases in point. Both FERET and FRVT have done a lot to improve the state-of-the-art of FR, but they didn't address this specific problem much. One reason for this is the unavailability of long-term data that can enable researchers to perform analysis on the impact of time delay between the acquisition of the gallery and the probe image sets. With the available data at hand, both FERET and FRVT evaluation studies reported that as the time gap between the gallery and the probe images increases, the recognition rate decreases. In this research, the MORPH database, which contains images that span from few days up to 29 years, is used to perform evaluation on the impact of age-progression on the performance of the Eigenface algorithm.

The performance evaluation on the impact of face image currency on the recognition rates of the Eigenface algorithm was first performed for first ranked results, which

are suitable for the Verification test. From the results obtained, it was found out that it is unrealistic to assume that the Eigenface algorithm could determine the exact identity of many individuals even if there is a large age gap between the acquisitions of the gallery and the probe image sets. So, the identification test, which actually considers the increase in chances of returning the correct results as the increase in the number of rank. For this research, the best 10, 25, and 50 ranks are considered to evaluate the performance of the Eigenface algorithm on age-progression.

This research highlights the effect of time delay between the acquirement of the first (gallery) and the subsequent captured (probe) image sets on the Eigenface algorithm. In general, the following results are obtained from the evaluation of the algorithm:

- The experiments made on T, M, F, AA, and W show that the challenging problem in FR- ageing significantly affects the performance of the Eigenface algorithm. The results obtained are reproducible with the research finding obtained by FRVT 2002 evaluation studies that the recognition rate of the Eigenface algorithm decreases approximately linearly with the increase in the time gap between the acquisitions of the gallery and probe image sets. This result is obtained because of the availability of long-term data, which was impossible for the previous evaluation studies. Again, the results obtained are reproducible with experiments made on short-term data. This shows that age-progression is a slow, relatively constant, change that occurs naturally throughout the lifetime of individuals.
- The experiments made on M and F results in-line with the previous research findings that males are easier to be identified by the algorithm than females.
- With regard to race, previous experiments have not been done on the impact of age-progression and race on the performance of the Eigenface algorithm. The results obtained on experiments AA and W indicate that the algorithm performed more or less similar for both racial origins. However, this finding needs further investigation with large number of data sets.

The final outcome of this research is to highlight the challenging problem of image currency on the recognition rate of FR algorithms-temporal effect. The research assessed the performance of the Eigenface algorithm on the impact of face image currency between the gallery and the probe image sets. Even if it was reported in [12] that the ageing process is unlikely to be linear, the research result with a long-term data showed that the performance of the Eigenface algorithm dropped-off linearly (in

general) as the time delay between the acquisition of the gallery and the probe images increases. This result is reproducible with the result obtained in the FRVT 2002. So, the overall performance evaluation test on the Eigenface algorithm indicates that the performance of the Eigenface approach is very sensitive to age-progression.

## **6.2 Future Works**

In our future work, we would like:

- to analyze which parts of the human face are affected significantly by the process of ageing and to modify the Eigenface algorithm so that it can resist changes of the ageing parameters.
- to extend our experiment to evaluate other algorithms such as the Fisherface, synthesis-based algorithms and compare the results with the Eigenface algorithm.

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## Annex A

**Following is a detailed Procedure for computing the identification test on the Eigenface algorithm.**

### **Experimental Result for T2 (Age < 18-29)**

- Probe 1:
  - Total Number of Probes: 219
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 92/219=0.420$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|= 131/219 = 0.598$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 158/219=0.721$
- Probe 2:
  - Total Number of Probes: 191
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 49/191=0.257$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=68/191 = 0.356$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 102/191=0.534$
- Probe 3:
  - Total Number of Probes: 97
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 13/97=0.134$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=31/97= 0.319$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 56/97=0.577$
- Probe 4:
  - Total Number of Probes: 50
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 4/50=0.080$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=6/50= 0.120$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 25/50=0.500$
- Probe 5:
  - Total Number of Probes: 13
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/13=0.154$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=3/13= 0.231$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 6/13=0.462$

### **Experimental result for T3 (Age 30-39)**

- Probe 1:
  - Total Number of Probes: 42
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 19/42=0.344$

- Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=30/42 = 0.714$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 37/42=0.880$
- Probe 2:
- Total Number of Probes: 30
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 9/30=0.300$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=14/30 = 0.467$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 22/30=0.733$
- Probe 3:
- Total Number of Probes: 13
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 3/13=0.231$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=4/13= 0.308$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 8/13=0.615$
- Probe 4:
- Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/3=0.333$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=1/3=0.333$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 1/3=0.333$
- Probe 5:
- Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/3=0.000$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=0/2= 0.000$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 0/2=0.000$

#### **Experimental result for T4 (Age 40-49)**

- Probe 1:
- Total Number of Probes: 10
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 8/10=0.800$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=9/10 = 0.900$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 10/10=1.000$
- Probe 2:
- Total Number of Probes: 6
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/6=0.3333$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=4/6 = 0.667$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 6/6=1.000$

- Probe 3:
  - Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/2=0.000$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=1/2= 0.500$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 2/2=1.000$
- Probe 4:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

### **Experimental result for T5 (Age >=50)**

- Probe 1:
  - Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/3=0.607$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=2/3 = 0.667$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 3/3=1.000$
- Probe 2:
  - Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/3=0.667$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=2/3 = 0.667$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 3/3=1.000$
- Probe 3:
  - Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/1=0.000$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=0/1= 0.000$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 1/1=1.000$
- Probe 4:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$

- Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 5:
- Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

### **Experimental Results for M (M1, M2, M3, M4, M5)**

#### **Experimental result for M1 (Age < 18)**

- Probe 1:
- Total Number of Probes: 48
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 17/48=0.354$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=23/48 = 0.479$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 33/48=0.6875$
- Probe 2:
- Total Number of Probes: 49
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 8/49=0.163$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=14/49 = 0.285$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 21/49=0.673$
- Probe 3:
- Total Number of Probes: 47
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 4/47=0.085$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=11/47= 0.234$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 24/47=0.511$
- Probe 4:
- Total Number of Probes: 12
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/12=0.0833$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/12=0.0833$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 4/12=0.333$
- Probe 5:
- Total Number of Probes: 12
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/12=0.0833$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/12=0.0833$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 6/12=0.500$

### Experimental result for M2 (Age 18-29)

- Probe 1:
  - Total Number of Probes: 164
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P| = 71/164 = 0.433$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P| = 104/164 = 0.634$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P| = 122/164 = 0.744$
- Probe 2:
  - Total Number of Probes: 143
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P| = 42/143 = 0.294$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P| = 52/143 = 0.364$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P| = 76/143 = 0.531$
- Probe 3:
  - Total Number of Probes: 84
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P| = 10/84 = 0.119$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P| = 23/84 = 0.273$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P| = 46/84 = 0.548$
- Probe 4:
  - Total Number of Probes: 41
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P| = 3/41 = 0.073$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P| = 7/41 = 0.171$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P| = 20/41 = 0.488$
- Probe 5:
  - Total Number of Probes: 12
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P| = 2/12 = 0.167$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P| = 3/12 = 0.25$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P| = 5/12 = 0.417$

### Experimental result for M3 (Age 30-39)

- Probe 1:
  - Total Number of Probes: 37
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P| = 19/37 = 0.513$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P| = 27/37 = 0.729$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P| = 32/37 = 0.865$

- Probe 2:
  - Total Number of Probes: 24
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 7/24=0.292$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=12/24 = 0.500$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 19/24=0.791$
- Probe 3:
  - Total Number of Probes: 12
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/12=0.167$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=4/12= 0.333$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 7/12=0.583$
- Probe 4:
  - Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/3=0.333$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/3=0.333$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 2/3=0.667$
- Probe 5:
  - Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/2=0.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0/2=0.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 1/2=0.500$

#### **Experimental result for M4 (Age 40-49)**

- Probe 1:
  - Total Number of Probes: 10
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 8/10=0.800$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=9/10 = 0.900$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 10/10=1.000$
- Probe 2:
  - Total Number of Probes: 6
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 3/6=0.500$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=5/6 = 0.833$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 6/6=1.000$
- Probe 3:
  - Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/2=0.000$

- Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/2=0.500$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=2/2=1.000$
- Probe 4:
- Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=0$
- Probe 5:
- Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=0$

### **Experimental result for M5 (Age >50)**

- Probe 1:
- Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=2/3=0.667$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=2/3=0.667$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=3/3=1.000$
- Probe 2:
- Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=2/3=0.667$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=2/3=0.667$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=3/3=1.000$
- Probe 3:
- Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=0/1=0.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0/1=0.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=1/1=1.000$
- Probe 4:
- Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=0/1=0.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0/1=0.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=1/1=1.000$

- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

### **Experimental Results for F (F1, F2, F3,F4, F5)**

#### **Experimental result for F1 (Age < 18)**

- Probe 1:
  - Total Number of Probes: 13
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 3/13=0.231$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=4/13 = 0.301$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 9/13=0.692$
- Probe 2:
  - Total Number of Probes: 9
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/9=0.111$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=2/9 = 0.222$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 4/4=0.444$
- Probe 3:
  - Total Number of Probes: 4
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/4=0.000$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=1/4= 0.250$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 3/4=0.750$
- Probe 4:
  - Total Number of Probes: 4
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/4=0.250$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/4=0.250$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 3/4=0.750$
- Probe 5:
  - Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/2=1.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=2/2=1.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 2/2=1.000$

### Experimental result for F2 (Age 18-29)

- Probe 1:
  - Total Number of Probes: 55
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 21/55=0.382$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=32/55 = 0.585$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 37/55=0.673$
- Probe 2:
  - Total Number of Probes: 38
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 7/38=0.184$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=11/38 = 0.289$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 20/38=0.526$
- Probe 3:
  - Total Number of Probes: 13
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 4/13=0.308$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=6/13= 0.462$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 8/13=0.615$
- Probe 4:
  - Total Number of Probes: 9
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/9=0.111$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=2/9=0.222$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 5/9=0.556$
- Probe 5:
  - Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/1=0.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0/1=0.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0/1=0.000$

### Experimental result for F3 (Age 30-39)

- Probe 1:
  - Total Number of Probes: 5
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/5=0.400$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=4/5 = 0.800$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 5/5=1.000$

- Probe 2:
  - Total Number of Probes: 6
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/6=0.333$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=2/6 = 0.333$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 4/6=0.667$
- Probe 3:
  - Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/1=0.000$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=0/1= 0.000$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 0/1=0.000$
- Probe 4:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

#### **Experimental result for F4 (Age 40-49)**

- Probe 1:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 2:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 3:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$

- Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
- Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 4:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

### **Experimental result for F5 (Age 40-49)**

- Probe 1:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 2:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 3:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 4:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

### **Experimental Results for AA (AA1,AA2, AA3, AA4, AA5)**

#### **Experimental result for AA1 (Age < 18)**

- Probe 1:
  - Total Number of Probes: 35
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 9/35=0.257$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=17/35 = 0.486$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 25/35=0.714$
- Probe 2:
  - Total Number of Probes: 39
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/39=0.051$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=8/39 = 0.205$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 17/39=0.436$
- Probe 3:
  - Total Number of Probes: 38
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 4/38=0.105$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=9/38= 0.237$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 20/38=0.526$
- Probe 4:
  - Total Number of Probes: 13
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/13=0.077$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/13=0.077$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 5/13=0.385$
- Probe 5:
  - Total Number of Probes: 11
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 3/11=0.273$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=3/11=0.273$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 7/11=0.636$

### Experimental result for AA2 (Age 18-29)

- Probe 1:
  - Total Number of Probes: 156
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 66/156=0.423$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=86/156 = 0.551$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 117/156=0.750$
- Probe 2:
  - Total Number of Probes: 147
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 37/147=0.252$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=53/147 = 0.361$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 78/147=0.531$
- Probe 3:
  - Total Number of Probes: 75
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 8/75=0.107$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=21/75= 0.280$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 44/75=0.586$
- Probe 4:
  - Total Number of Probes: 43
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 4/43=0.091$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=5/43=0.116$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 24/43=0.465$
- Probe 5:
  - Total Number of Probes: 10
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/10=0.200$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=3/10=0.300$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 5/10=0.500$

### Experimental result for AA3 (Age 30-39)

- Probe 1:
  - Total Number of Probes: 36
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 16/36=0.444$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=25/36 = 0.694$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 32/36=0.889$

- Probe 2:
  - Total Number of Probes: 23
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 7/23=0.304$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=11/23 = 0.478$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 17/23=0.739$
- Probe 3:
  - Total Number of Probes: 10
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 3/10=0.300$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=4/10= 0.400$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 7/10=0.700$
- Probe 4:
  - Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/3=0.333$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/3=0.333$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 2/3=0.667$
- Probe 5:
  - Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/2=0.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0/2=0.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 1/2=0.500$

#### **Experimental result for AA4 (Age 40-49)**

- Probe 1:
  - Total Number of Probes: 6
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 6/6=1.000$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=6/6=1.000$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 6/6=1.000$
- Probe 2:
  - Total Number of Probes: 5
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/5=0.200$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|= 3/5 = 0.600$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 5/5=1.000$
- Probe 3:
  - Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/10=0.000$

- Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/2=0.500$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=2/2=1.000$
- Probe 4:
- Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=0$
- Probe 5:
- Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=0$

### **Experimental result for AA5 (Age > 50)**

- Probe 1:
- Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=1/2=0.500$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/2=0.500$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=2/2=1.000$
- Probe 2:
- Total Number of Probes: 2
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=1/2=0.500$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/2=0.500$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=1/2=0.500$
- Probe 3:
- Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=0$
- Probe 4:
- Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|=0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|=0$

- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

### **Experimental Results for W (W1,W2, W3, W4, W5)**

#### **Experimental result for W1 (Age < 18)**

- Probe 1:
  - Total Number of Probes: 26
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 9/26=0.346$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=11/26 = 0.423$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 18/26=0.692$
- Probe 2:
  - Total Number of Probes: 19
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 4/19=0.211$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=8/19 = 0.421$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 13/19=0.684$
- Probe 3:
  - Total Number of Probes: 13
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/13=0.077$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=4/13= 0.308$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 9/13=0.692$
- Probe 4:
  - Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/3=0.333$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/3=0.333$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 2/3=0.667$
- Probe 5:
  - Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/3=0.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0/3=0.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 1/3=0.333$

### Experimental result for W2 (Age 18 –29)

- Probe 1:
  - Total Number of Probes: 63
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P| = 26/63=0.413$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=37/63 = 0.587$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 43/63=0.692$
- Probe 2:
  - Total Number of Probes: 44
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 11/44=0.250$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=14/44 = 0.318$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 23/44=0.523$
- Probe 3:
  - Total Number of Probes: 22
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 5/22=0.227$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=9/22= 0.409$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 17/22=0.723$
- Probe 4:
  - Total Number of Probes: 7
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/7=0.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=3/7=0.429$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 4/7=0.571$
- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

### Experimental result for W3 (Age 30-39)

- Probe 1:
  - Total Number of Probes: 7
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 4/7=0.571$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=5/7 = 0.714$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 6/7=0.857$

- Probe 2:
  - Total Number of Probes: 7
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 2/7=0.286$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=3/7 = 0.429$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 4/7=0.571$
- Probe 3:
  - Total Number of Probes: 3
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/3=0.000$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=0/3= 0.000$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 1/3=0.333$
- Probe 4:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

#### **Experimental result for W4 (Age 40-49)**

- Probe 1:
  - Total Number of Probes: 4
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 3/4=0.750$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=3/4=0.750$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 4/4=1.000$
- Probe 2:
  - Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/1=1.000$
  - Identification rate at the 25<sup>th</sup> rank=  $R_{25}/|P|=1/1 = 1.000$
  - Identification rate at the 50<sup>th</sup> rank=  $R_{50}/|P|= 1/1=1.000$
- Probe 3:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$

- Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
- Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 4:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$
- Probe 5:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

### **Experimental result for W5 (Age >50)**

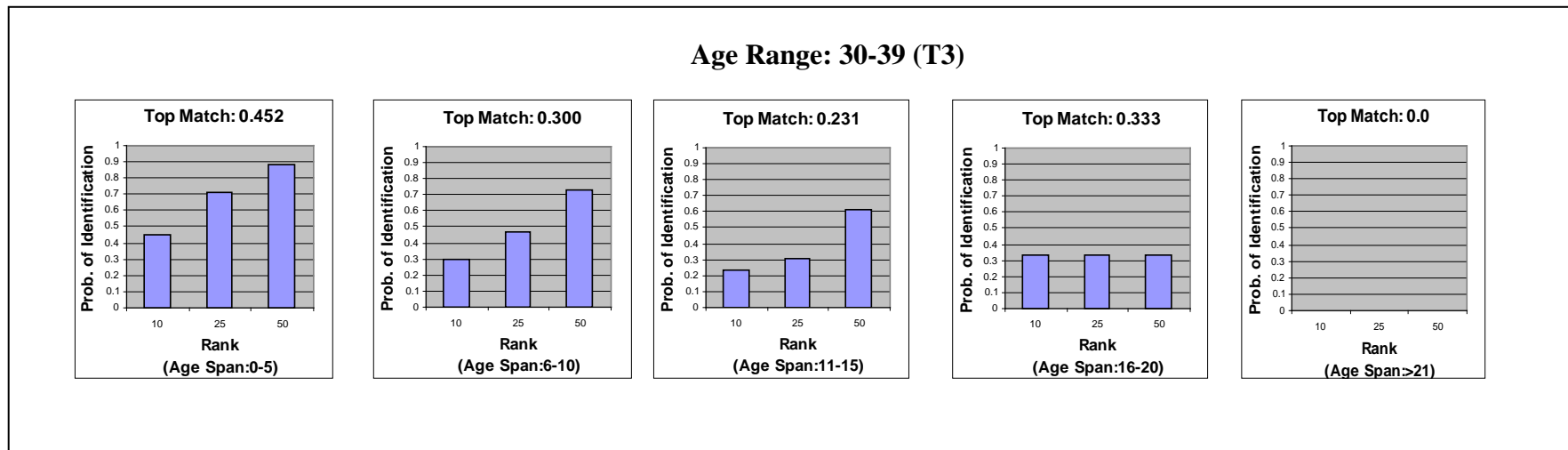
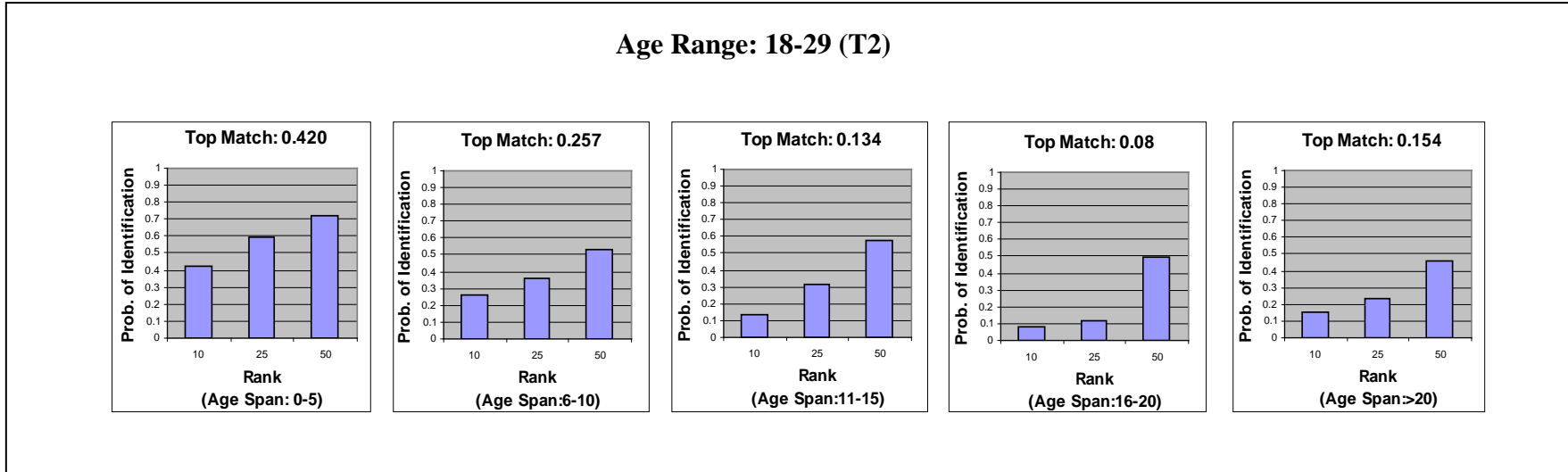
- Probe 1:
  - Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/1=1.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/1 = 1.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 1/1= 1.000$
- Probe 2:
  - Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 1/1=1.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=1/1 = 1.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 1/1=1.000$
- Probe 3:
  - Total Number of Probes: 1
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0/1=1.000$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|=0/1 = 1.000$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 1/1=1.000$
- Probe 4:
  - Total Number of Probes: 0
  - Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
  - Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
  - Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

➤ Probe 5:

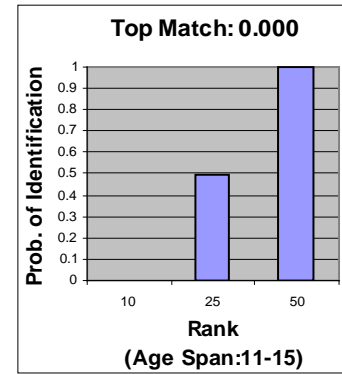
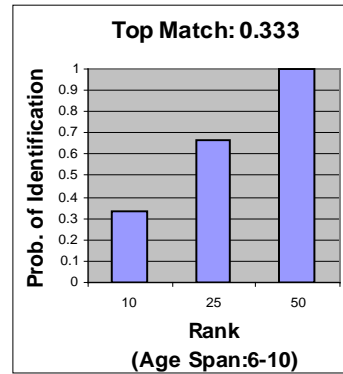
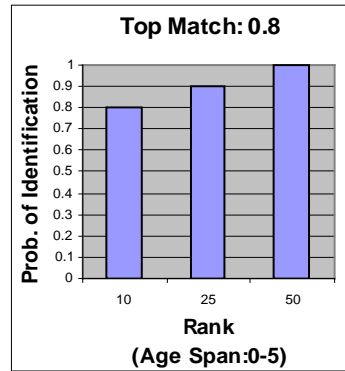
- Total Number of Probes: 0
- Identification rate at the 10<sup>th</sup> rank =  $R_{10}/|P|= 0$
- Identification rate at the 25<sup>th</sup> rank =  $R_{25}/|P|= 0$
- Identification rate at the 50<sup>th</sup> rank =  $R_{50}/|P|= 0$

## ANNEX B

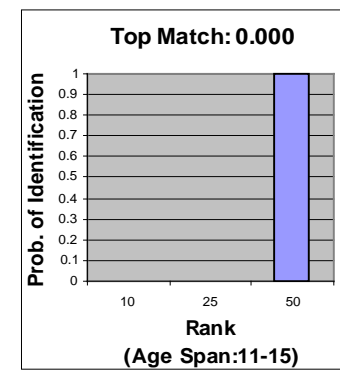
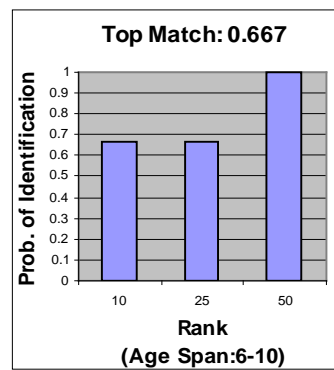
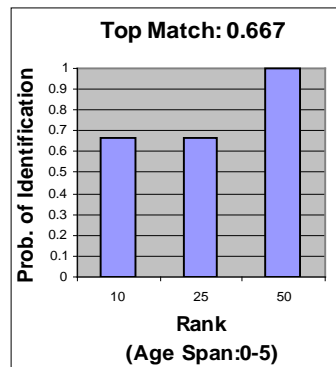
The Cumulative Match Characteristic computation for Identification test for Experiments performed in this research is given below.



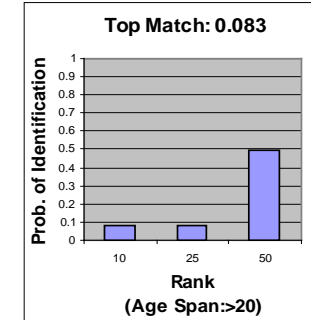
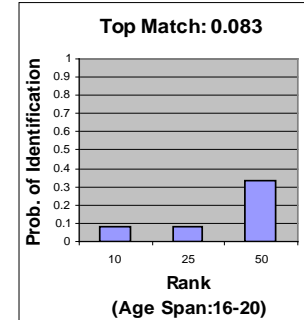
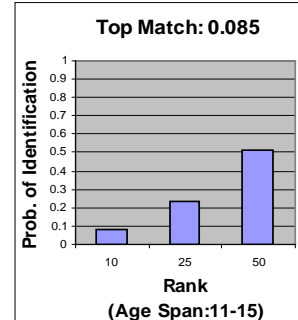
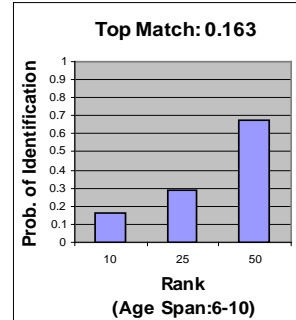
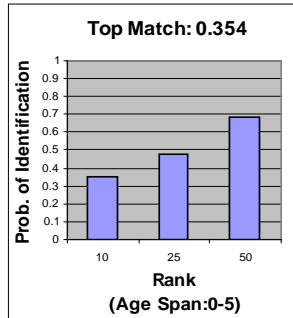
**Age Range: 40-49 (T4)**



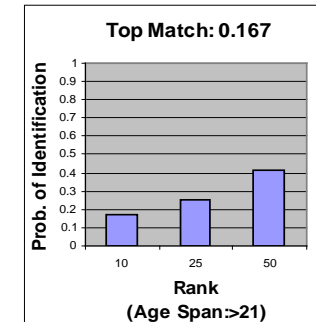
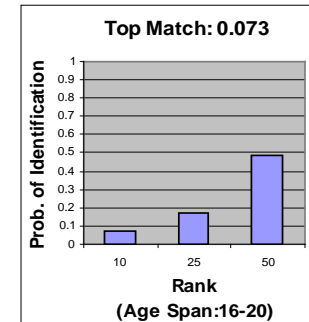
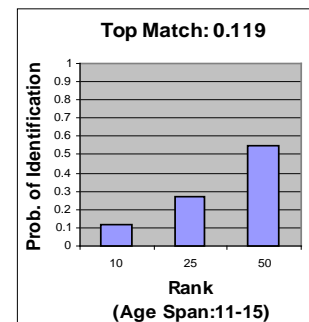
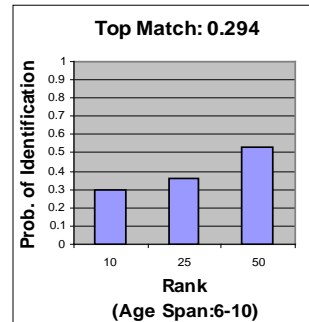
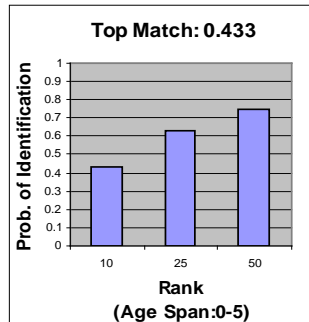
**Age Range: >=50 (T5)**



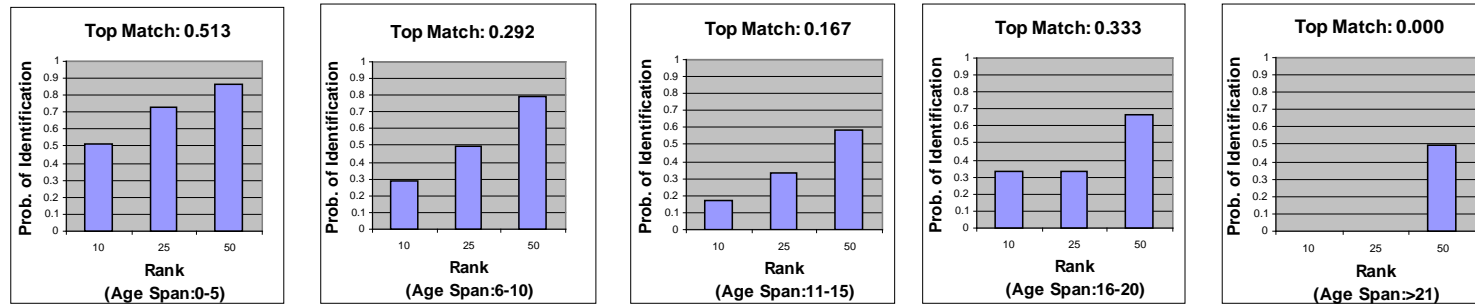
### Age Range: <18 (M1)



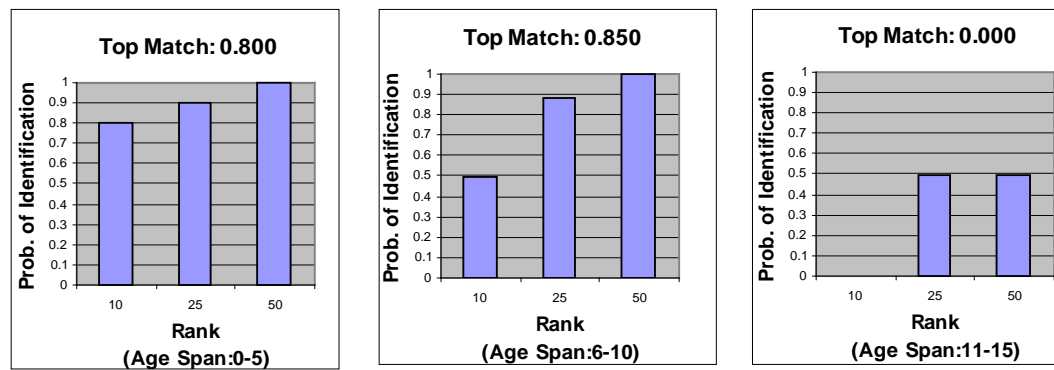
### Age Range: 18-29 (M2)



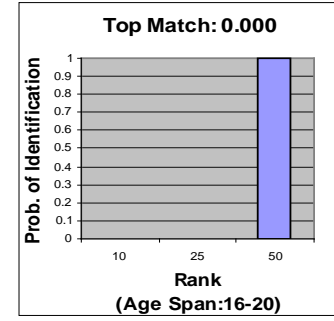
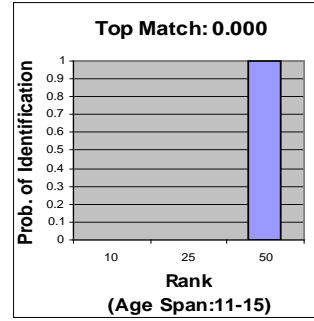
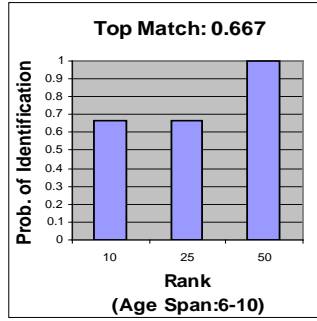
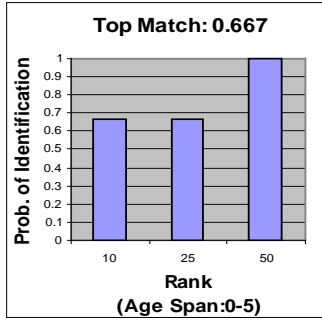
### Age Range: 30-39 (M3)



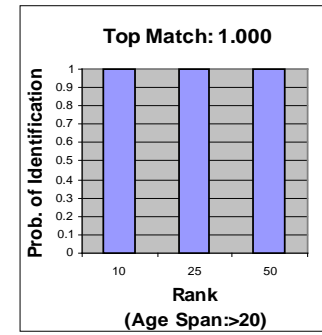
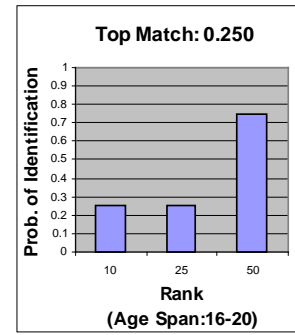
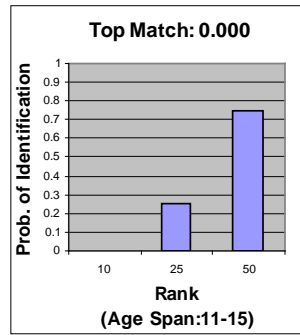
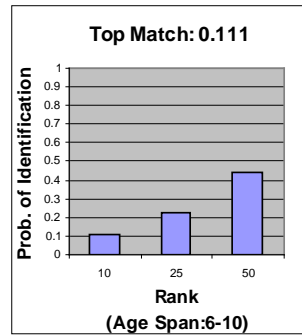
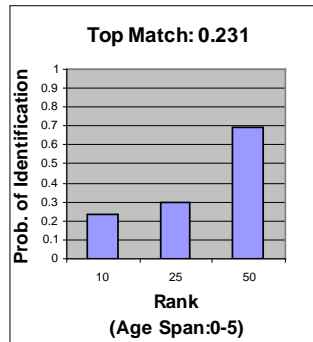
### Age Range: 40-49 (M4)



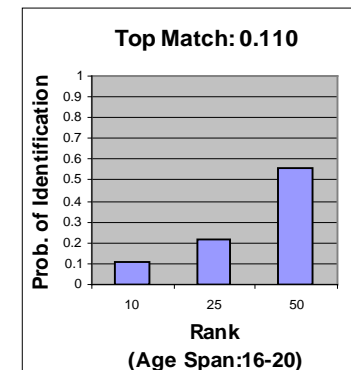
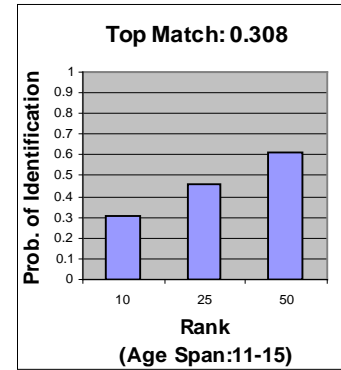
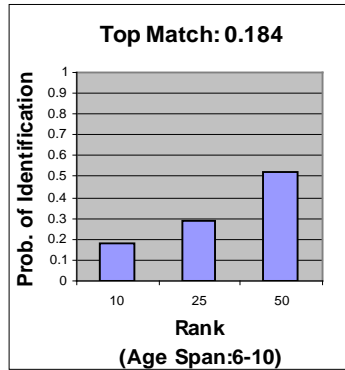
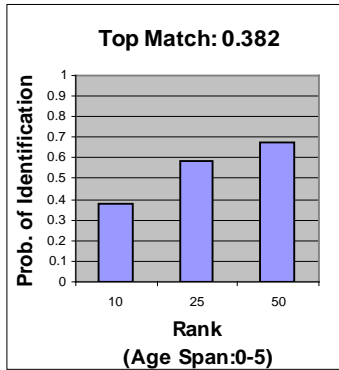
**Age Range:  $\geq 50$  (M5)**



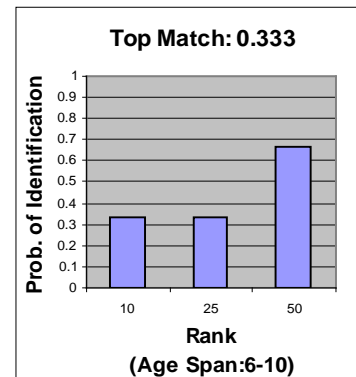
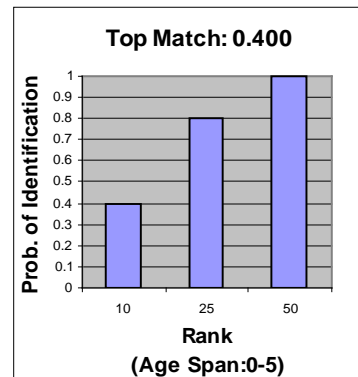
**Age Range:  $< 18$  (F1)**



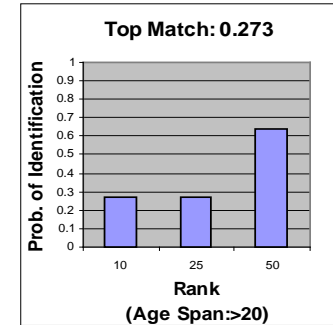
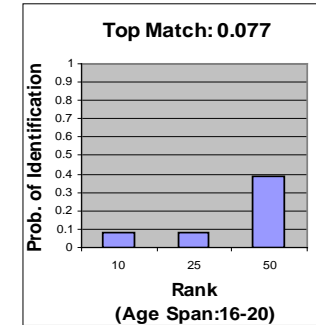
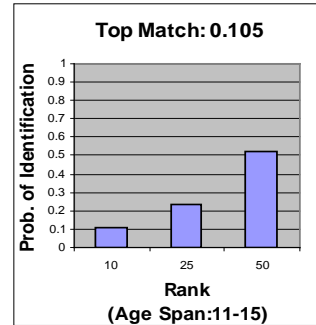
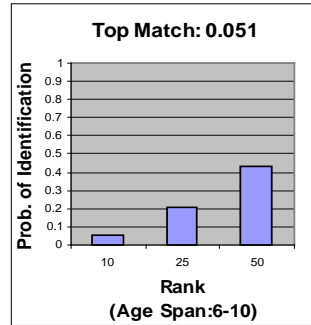
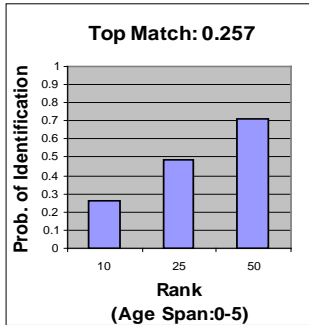
**Age Range: 18-29 (F2)**



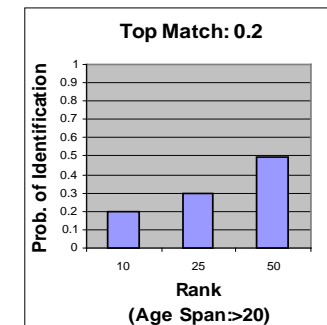
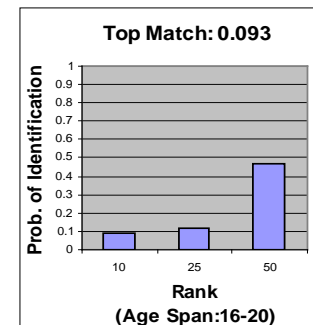
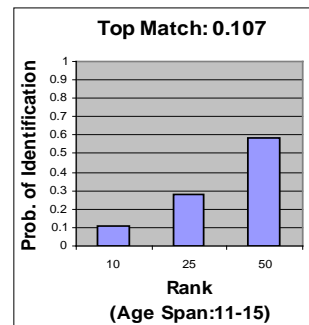
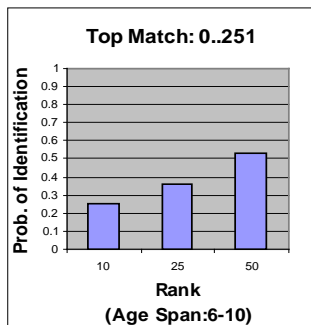
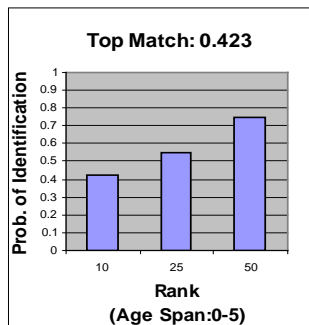
**Age Range: 30-39 (F3)**



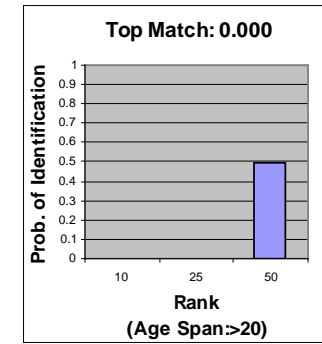
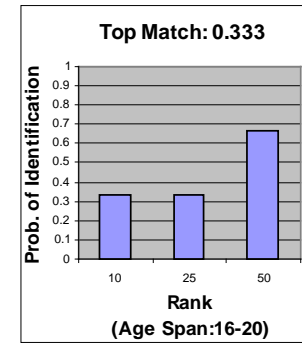
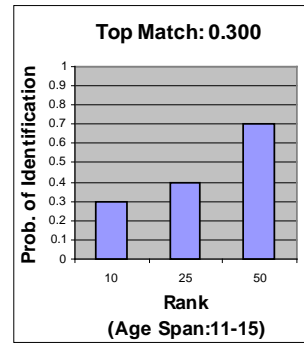
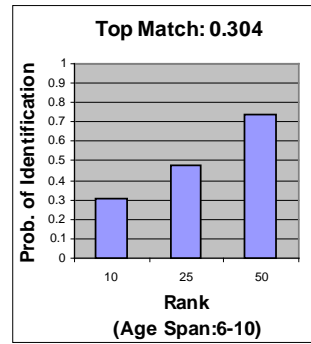
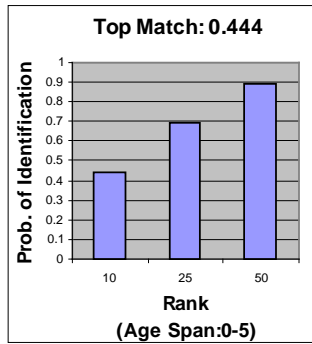
### Age Range: <18 (AA1)



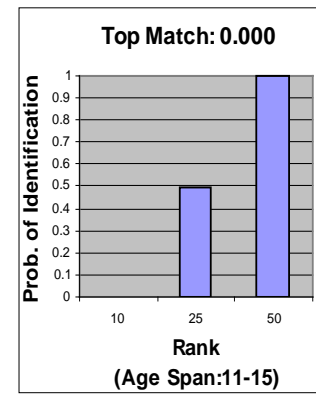
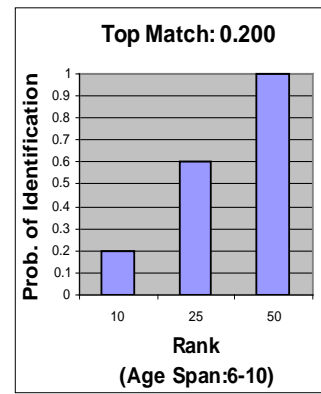
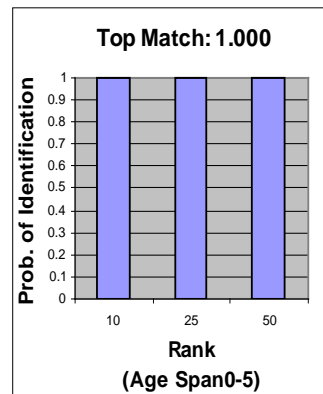
### Age Range: 18-29 (AA2)



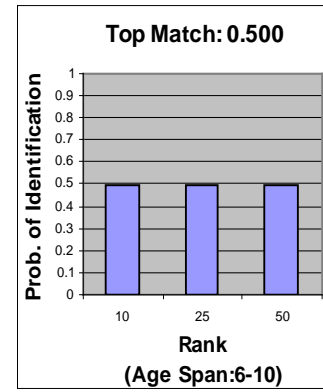
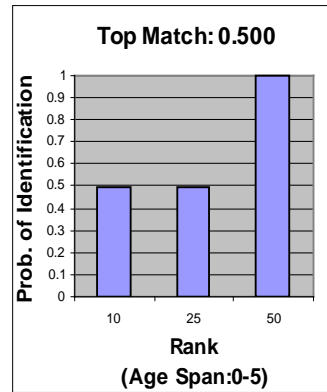
### Age Range: 30-39 (AA3)



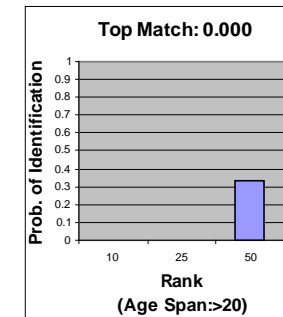
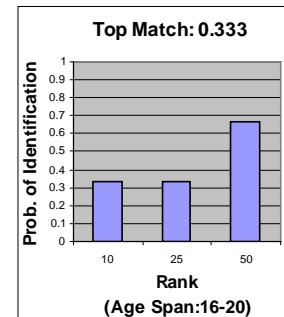
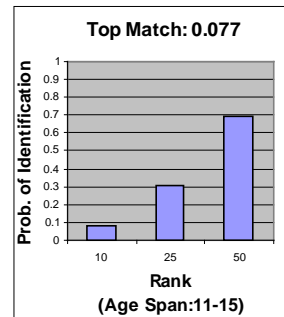
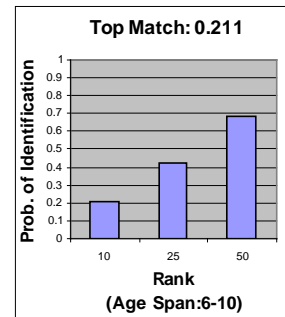
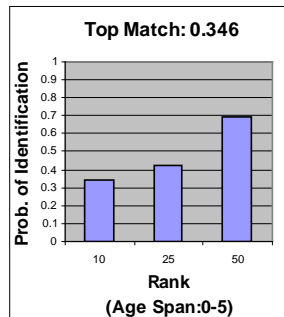
### Age Range: 40-49 (AA4)



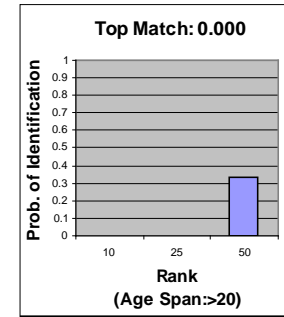
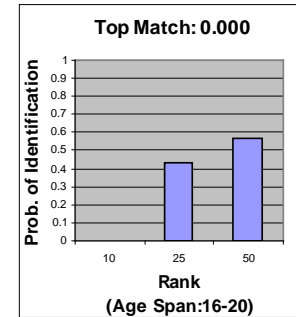
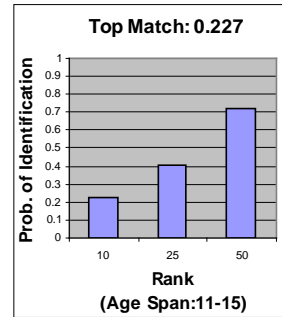
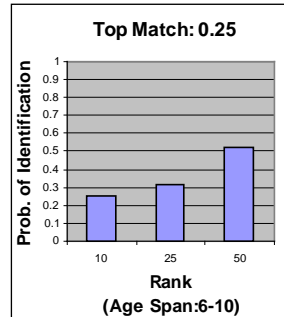
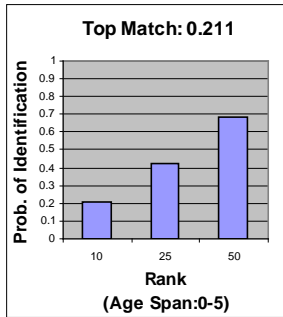
**Age Range:  $\geq 50$  (AA5)**



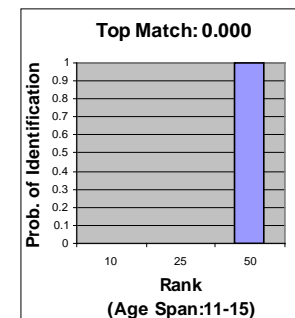
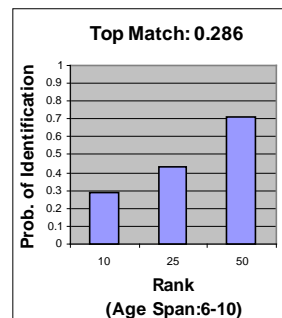
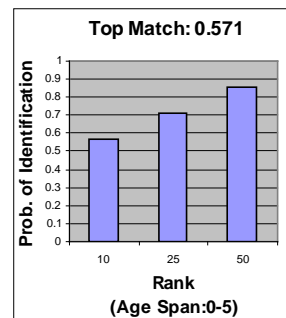
**Age Range:  $< 18$  (W1)**



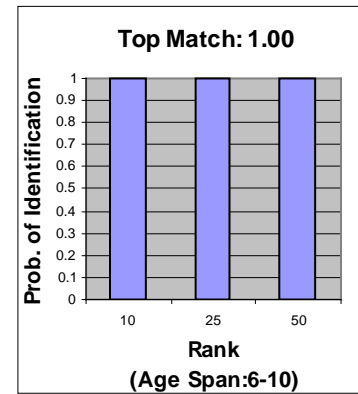
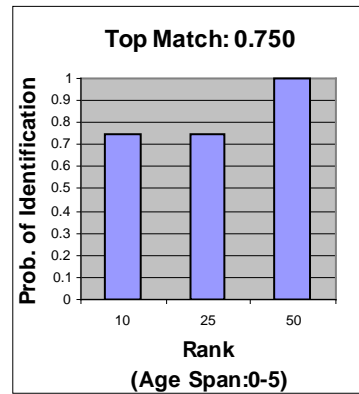
### Age Range: 18-29 (W2)



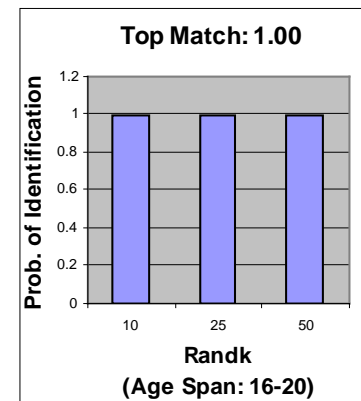
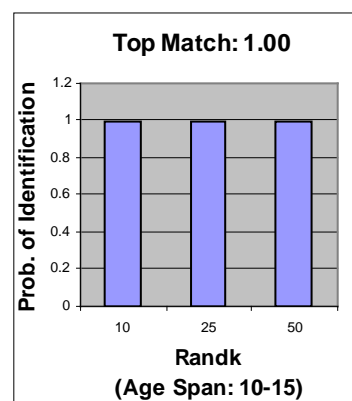
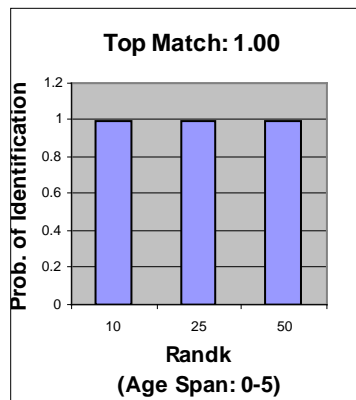
### Age Range: 30-39 (W3)



**Age Range: 30-39 (W4)**



**Age Range: >=50 (W5)**



## **DECLARATION**

The thesis is my original work and has not been presented for a degree in any other university, and that all sources of material used for the thesis have been duly acknowledged.

Tamirat Tesfaye

Dr. Karl Ricanek, Jr (External advisor)

Dr. Mulugeta Libsie (Local advisor)