2012

Genetic And Evolutionary Biometrics:Multiobjective, Multimodal, Feature Selection/Weighting For Tightly Coupled Periocular And Face Recognition

Aniesha Alford
North Carolina Agricultural and Technical State University

GENETIC AND EVOLUTIONARY BIOMETRICS: MULTIOBJECTIVE, MULTIMODAL, FEATURE SELECTION/WEIGHTING FOR TIGHTLY COUPLED PERIOCULAR AND FACE RECOGNITION

by

Aniesha Alford

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of
DOCTOR OF PHILOSOPHY

Department: Electrical & Computer Engineering
Major: Electrical Engineering
Major Professor: Dr. John C. Kelly

North Carolina A&T State University
Greensboro, North Carolina
2012

ABSTRACT

Alford, Aniesha. GENETIC AND EVOLUTIONARY BIOMETRICS: MULTIOBJECTIVE, MULTIMODAL, FEATURE SELECTION/WEIGHTING FOR TIGHTLY COUPLED PERIOCULAR AND FACE RECOGNITION **(Major Professor: Dr. John C. Kelly)**, North Carolina Agricultural and Technical State University.

The Genetic & Evolutionary Computation (GEC) research community has seen the emergence of a new subarea, referred to as Genetic & Evolutionary Biometrics (GEB), as GECs have been applied to solve a variety of biometric problems. In this dissertation, we present three new GEB techniques for multibiometric recognition: Genetic & Evolutionary Feature Selection (GEFeS), Weighting (GEFeW), and Weighting/Selection (GEFeWS). Instead of selecting the most salient individual features, these techniques evolve subsets of the most salient combinations of features and/or weight features based on their discriminative ability in an effort to increase accuracy while decreasing the overall number of features needed for recognition. We also incorporate cross validation into our best performing technique in an attempt to evolve feature masks (FMs) that also generalize well to unseen subjects and we search the value preference space in an attempt to analyze its impact in respect to optimization and generalization.

Our results show that by fusing the periocular biometric with the face, we can achieve higher recognition accuracies than using the two biometric modalities independently. Our results also show that our GEB techniques are able to achieve higher recognition rates than the baseline methods, while using significantly fewer features. In

addition, by incorporating machine learning, we were able to create FMs that also generalize well to unseen subjects and use less than 50% of the extracted features. Finally, by searching the value preference space, we were able to determine which weights were most effective in terms of optimization and generalization.

School of Graduate Studies
North Carolina Agricultural and Technical State University

This is to certify that the Doctoral Dissertation of

Aniesha Alford

has met the dissertation requirements of
North Carolina Agricultural and Technical State University

Greensboro, North Carolina
2012

Approved by:

John C. Kelly
Major Professor

Gerry V. Dozier
Co-Advisor

Kelvin S. Bryant
Committee Member

Robert Y. Li
Committee Member

Abdollah Homaifar
Committee Member

John C. Kelly
Department Chairperson

Sanjiv Sarin
Associate Vice Chancellor for Research and Graduate Dean

DEDICATION

This dissertation is dedicated to my parents, Joseph and Fannie Johnson. Thank you for always believing in me and supporting me each and every day. I am everything that I am today because of you. I love you!

BIOGRAPHICAL SKETCH

Aniesha Alford was born on July 28, 1986 in Lumberton, NC. She attended South Robeson High School and graduated in 2004 as salutatorian. She then attended Fayetteville State University, where she was a member of their inaugural Honors Program. She received a Bachelor of Science degree in Computer Science and a minor in Mathematics in 2008 and she was also co-valedictorian of her graduating class.

ACKNOWLEDGEMENTS

First and foremost, I thank God for blessing me and giving me the strength and ability to complete this difficult process. I also thank God for surrounding me with an amazing group of supportive people.

I thank my immediate family, my friends, and my church family for their continuous support, prayers, and encouragement. I offer special thanks to my "uncle", Dr. Joseph Monroe. He was the first person to believe that I could obtain my Ph.D. in Electrical Engineering and was also instrumental in providing me with the opportunity to pursue this degree. I thank Dr. Gay Davis for always being there when I needed someone to talk to or a shoulder to cry on, for making me laugh, and for keeping me motivated. I would not have made it through without having you all in my corner. I will forever be grateful and I love you all!

I thank the members of my dissertation committee for their time, their guidance, and their ideas that helped make this dissertation possible. I thank Dr. John Kelly for allowing me to enter the direct Ph.D. program and for being there during the tough times. I thank my co-advisor, Dr. Gerry Dozier, for allowing me to work with CASIS, for all of his brilliant ideas and rigorous criticisms, and for his diligent work in the completion of this dissertation. I thank Dr. Kelvin Bryant for his guidance, his numerous pep-talks, and his support at all times. I thank Drs. Homaifar, Li, and Ricanek, for their support and advice.

Finally, I thank my fellow CASIS members. You “brought me up to speed” on your research, you encouraged me, and you were all my friends. It was a pleasure working with all of you and I know that all of you will accomplish great things!

This research was funded by the Office of the Director of National Intelligence, the Center for Advanced Studies in Identity Sciences, and the National Science Foundation Science & Technology Center: Bio/computational Evolution in Action Consortium. In addition, my graduate study was funded by the Title III HBGI Program. I am deeply grateful for all of this funding.

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LIST OF ABBREVIATIONS

CMC	Cumulative Match Characteristic
CS	Candidate Solution
EDA	Estimation of Distribution Algorithm
FAR	False Accept Rate
FE	Feature Extractor
FM	Feature Mask
FRR	False Reject Rate
FS	Feature Subset
FRGC	Face Recognition Grand Challenge
GA	Genetic Algorithms
GEB	Genetic & Evolutionary Biometrics
GEC	Genetic & Evolutionary Computation
GEFeS	Genetic & Evolutionary Feature Selection
GEFeW	Genetic & Evolutionary Feature Weighting
GEFeWS	Genetic & Evolutionary Feature Weighting/Selection
$GEFeWS_{ML}$	Genetic & Evolutionary Feature Weighting/Selection-Machine Learning
LBP	Local Binary Patterns
ML	Machine Learning
MOP	Multiobjective Problem

NMD	Normalized Manhattan Distance
PCA	Principal Component Analysis
PDF	Probability Density/Distribution Function
SSGA	Steady-State Genetic Algorithm
X-TOOLSS	eXploration Toolset for the Optimization of Launch and Space Systems

LIST OF SELECTED PUBLICATIONS

This dissertation is mainly based on the following publications:

I. **Alford, A.**, Adams, J., Shelton, J., Dozier, G., Bryant, K., Kelly, J.C. "Genetic & Evolutionary Biometrics: Exploring Value Preference Space for Hybrid Feature Weighting and Selection", Submitted to the International Journal of Intelligent Computing and Cybernetics (IJICC).

II. **Alford, A.**, Steed, C., Jeffrey, M., Sweet, D., Shelton, J., Small, L., Leflore, D., Dozier, G., Bryant, K., Abegaz, T., Kelly, J.C., Ricanek, K. (2012). "Genetic & Evolutionary Biometrics: Hybrid Feature Selection and Weighting for a Multi-Modal Biometric System", *Proceedings of IEEE SoutheastCon 2012*, March 15-18, Orlando, FL.

III. **Alford, A.**, Bryant, K., Abegaz, T., Dozier, G., Kelly, J., Shelton, J., Small, L., Williams, J., and Woodard, D.L., (2011). "Genetic & Evolutionary Methods for Biometric Feature Reduction", *Special Issue on: "Computational Intelligence in Biometrics: Theory, Methods and Applications"*, Guest Editor: Qinghan Xiao, *International Journal of Biometrics.*

IV. **Alford, A.**, Popplewell, K., Dozier, G., Bryant, K., Kelly, J., Adams, J., Abegaz, T., Shelton, J., Woodard, D., and Ricanek, K. (2011). "Hybrid GEMs for Multi-Biometric Recognition via X-TOOLSS", *Proceedings of the 2011 International*

Conference Genetic and Evolutionary Methods (GEM-2011) , July 19-21, Las Vegas, NV.

V. **Alford, A.**, Hansen, C., Dozier, G., Bryant, K., Kelly, J., Woodard, D., and Ricanek, K. (2011). "GEC-Based Multi-Biometric Fusion," *Proceedings of the 2011 IEEE Congress on Evolutionary Computation (CEC-2011)*, June 5-8, New Orleans, LA.

VI. **Alford, A.**, Popplewell, K., Dozier, G., Bryant, K., Kelly, J., Adams, J., Woodard, D., and Ricanek, K. (2011). "A Comparison of GEC-Based Feature Selection and Weighting for Multimodal Biometric Recognition", *Proceedings of the 2011 IEEE Congress on Evolutionary Computation (CEC-2011)*, June 5-8, New Orleans, LA.

VII. **Alford, A.**, Popplewell, K., Dozier, G., Bryant, K., Kelly, J., Adams, J., Abegaz, J., and Shelton, J. (2011). "GEFeWS: A Hybrid Genetic-Based Feature Weighting and Selection Algorithm for Multi-Biometric Recognition," *Proceedings of the 2011 Midwest Artificial Intelligence and Cognitive Science Conference (MAICS-2011)*, April 16-17, Cincinnati, OH.

VIII. Popplewell, K., Dozier, G., Bryant, K., **Alford, A.**, Adams, A., Abegaz, T., Purrington, K., and Shelton, J. (2011). "A Comparison of Genetic Feature Selection and Weighting Techniques for Multi-Biometric Recognition," *Proceedings of the 2011 ACM Southeast Conference*, March 24-26, Kennesaw, GA.

CHAPTER 1

Introduction

Biometrics is the field of study devoted to the automatic identification and verification of individuals based on their physiological, chemical, and/or behavioral characteristics (also referred to as traits, modalities, indicators, or identifiers) [1, 108, 112]. Unlike traditional methods of identification that rely on "something you know" (e.g. passwords, PINs) or "something you possess" (e.g. smart cards, ID cards), biometrics rely on "what you are" or "what you do" [1, 2, 50, 76, 110, 111, 112, 113] for identification. As a result, biometrics are said to be more reliable because the traits are harder to steal and they cannot be forgotten, lost, or shared [1, 108, 109, 112].

Examples of biometric traits that are currently in use for automatic recognition include the face [3, 5, 13, 30, 43, 58, 60, 62, 79, 80, 85, 92], iris [29, 46, 47, 48, 49, 62, 74, 105], periocular [7, 10, 11, 12, 90], voice [55, 60], signature [4, 98], and gait [56]. However, any characteristic can be used as a biometric trait as long as the following requirements are met [1, 76, 108, 110, 111, 113]: universality, distinctiveness, permanence, collectability (or measurability [1]), performance, acceptability, and circumvention. Universality means that every individual possesses that given characteristic. Distinctiveness means that the given characteristic is different for any two individuals. To satisfy the permanence requirement, the given characteristic should not change significantly over an extended period of time. The collectability/measurability requirement refers to the ability to acquire the given characteristic and to measure it quantitatively. The performance requirement ensures that the given characteristic results in acceptable recognition rates and that the required resources (i.e. computational speed and space) are suitable for the given application. The acceptability requirement makes sure that individuals are willing to use the given characteristic. The final requirement, circumvention, must be met so that it is not easy to spoof the system.

The remainder of this chapter is as follows. Section 1.1 provides an overview of biometric recognition systems, Section 1.2 provides an overview of multibiometric systems, and Section 1.3 introduces the field of Genetic & Evolutionary Biometrics (GEB). In Section 1.4, we provide a brief overview of machine learning, and in Section 1.5, we provide an overview of multiobjective optimization. Section 1.6 provides the scope of this work and Section 1.7 provides the outline for the rest of this dissertation.

1.1 Overview of Biometric Systems

Jain et al. [1] defined biometric systems as pattern recognition systems that acquire a biometric sample from an individual, extracts a set of features from the acquired sample, compares the resulting feature sets to those stored in a database, and then makes a decision based on the comparison. Therefore, a biometric system can be viewed as a collection of modules or components. In the literature, the modules in a typical biometric system seem to vary. In [51, 61, 108, 109], they defined four major modules: a sensor module, a feature extraction module, a matching module, and a decision module. However, in [78, 110, 111], they defined the following four modules: a sensor module, a feature extraction module, a matcher module, and a database module. Therefore, essentially, a biometric system consists of five major modules: a sensor, a feature extractor, a database, a matcher, and a decision-making module. An overview of these modules follows.

The sensor module is used to acquire a biometric sample from an individual. This newly acquired biometric sample, which is referred to as a probe, is then passed to the feature extraction module, which extracts a set of salient features known as a feature set, feature vector, or feature template. It is important that the resulting feature templates exhibit the following properties [1,86, 112]: small intra-class variation, which means that there is little difference between feature templates belonging to the same individual, and large inter-class variation, which means that there is a bigger difference between templates belonging to different individuals in comparison to templates belonging to the same individual. The matching module then compares the resulting feature template to those stored within the database module (or gallery) during the enrollment process. The resulting match score, which is a measure of the similarity between a probe and gallery template, is then passed to the decision-making module. The resulting decision depends on the recognition task being performed.

A biometric system can perform two tasks [1, 86, 112]: verification or identification. A verification system performs a one-to-one comparison, comparing an individual's newly acquired feature template to his/her own feature templates stored in the database. In such a system, the decision-making module returns either true (i.e. the person is who he/she claims to be) or false (i.e. the person is not who he/she claims to be). In contrast, an identification system performs a one-to-many comparison, comparing an individual’s newly acquired template to those stored within the database in an attempt to establish identity. The individual is either accepted or denied access by the system.

Unfortunately, like traditional methods used for recognition, biometric systems are not perfect, due to factors such as imperfect sensing conditions, variation in an individual’s biometric trait, and illumination variations [1, 92, 113]. As a result, two types of errors can occur: false accepts and false rejects. False accepts occur when unauthorized individuals are incorrectly matched to gallery templates, while false rejects occur when individuals that should be recognized are denied access.

1.2 Overview of Multibiometrics

Biometric systems that use only a single biometric modality are referred to as unimodal biometric systems [1, 50, 51]. Although unimodal biometric systems can achieve high recognition accuracies, numerous issues can affect the system’s performance during implementation including noisy sensor data, intra-class variation, inter-class similarities, failure to capture a quality biometric sample, and susceptibility to spoof attacks [1, 2, 50, 51, 112]. These issues can be addressed by multibiometric systems. In addition, multibiometric systems can achieve higher recognition rates in comparison to the unimodal systems. Multibiometric systems fuse the information returned by multiple sources including multiple sensors (i.e. multi-sensor systems), samples (i.e. multi-sample system), modalities (i.e. multimodal systems), instances (i.e. multi-instance systems), algorithms (i.e. multi-algorithm systems), and combinations of these sources (i.e. hybrid systems) [2, 50, 51].

Multibiometric fusion techniques can be classified into two categories [51, 60]: pre-mapping and post-mapping (or pre-classification and post-classification [112]) fusion. Pre-mapping fusion techniques (i.e. sensor-level and feature-level fusion) perform fusion before matching, while post-mapping fusion techniques (i.e. rank-level, decision-level, and score-level fusion) perform fusion after matching. Figure 1.1 depicts the various fusion levels and an overview of these fusion levels follows.

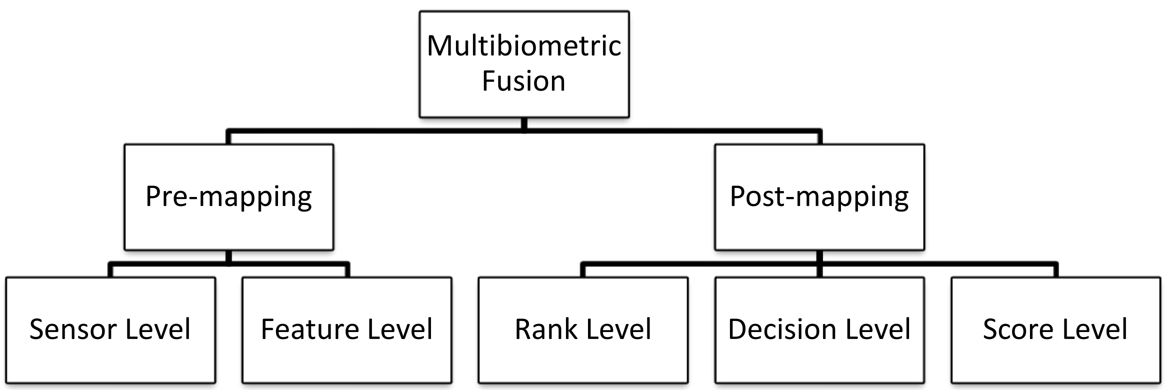

Figure 1.1. Various Fusion Levels.

Sensor-level fusion combines the raw data acquired from multiple sensors or from multiple samples obtained via a single sensor. Feature-level fusion combines the feature templates obtained for multiple biometric modalities or from multiple feature extraction algorithms into a single feature template. These pre-mapping fusion techniques are believed to achieve higher recognition rates in comparison to the post-mapping fusion techniques because they are said to combine the richest source information [50, 51, 61, 112]. However, performing fusion at these levels is difficult due to problems such as incompatible sensors and large dimensionality feature templates [51]. Therefore, post-mapping fusion techniques are usually preferred.

For rank-level fusion, first a subset of possible matches is returned for each biometric modality. The individuals within the subsets are then sorted or ranked in decreasing order of confidence [112]. The ranks are then combined and the final decision is made based on the combined ranking. For decision-level fusion, the decisions returned for each biometric modality (e.g. accept/reject) are combined using for example majority rules [51, 61]. Finally, for score-level fusion, the individual match scores obtained by the different biometric modalities are normalized and combined into a single match score, which is then used to make the final decision.

Of the various fusion levels, score-level fusion (also known as measurement or confidence level fusion [51]) is the most commonly used because the match score is easy to access, easy to combine, and contains rich information about the feature templates [51]. Figure 1.2 depicts the match score-level fusion process. Consider a multibiometric system that uses l biometric modalities, b_1, b_2, ..., b_l, to authenticate an individual and that s_i is the normalized match score returned for b_i. The normalized scores, s_1, s_2, ..., s_l, are then fused together using a fusion rule. The resulting fused score, S, is then used to make the final decision for the multibiometric system.

Several fusion rules have been proposed in the literature [51, 55, 61, 62]. Ross et al. [61] proposed using the sum rule to fuse the match scores obtained for a multibiometric system that used face, fingerprint, and hand geometry modalities. Assigning each biometric modality equal weights, the fused match score using the sum

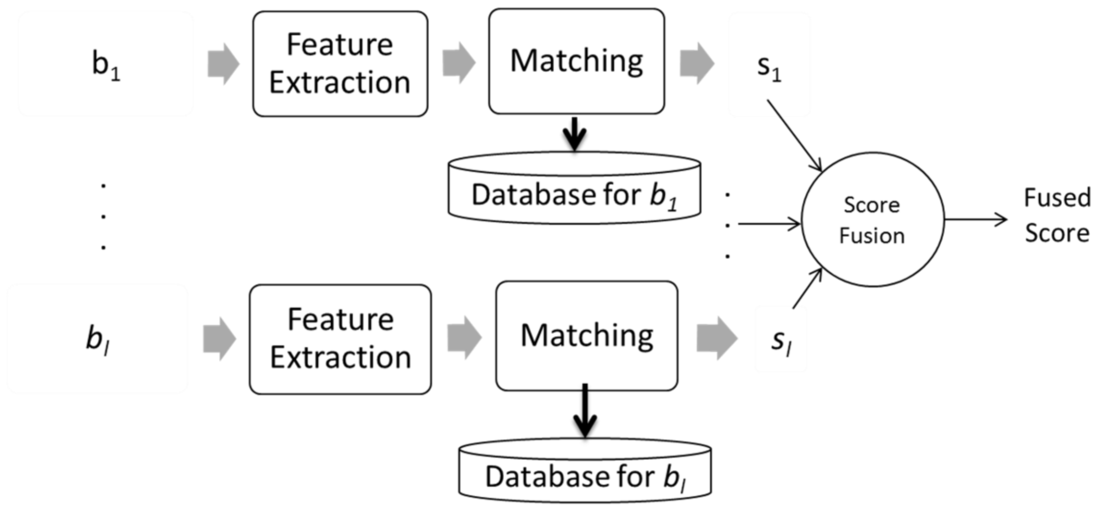

Figure 1.2. Score Level Fusion Process.

rule is the average of the scores obtained by the multiple modalities. Wang et al. [62] proposed using the weighted sum rule to fuse match scores returned for a multibiometric system that used iris and face modalities, and compared its performance to that of the sum rule. For the weighted sum rule, different weights are assigned to each biometric modality based on its false accept rate (FAR) and false reject rate (FRR). Essentially, higher weights are assigned to biometric modalities that result in lower error rates. Their results showed that the weighted sum rule performed better than the sum rule at increasing the accuracy of multibiometric recognition.

1.3 Overview of Genetic & Evolutionary Biometrics (GEB)

Genetic & Evolutionary Computation (GEC) [6, 16, 17, 23, 24, 37, 38] is the field of study devoted to the design, development, and analysis of problem solvers based on natural selection [31]. GECs have been successfully used to solve a wide variety of complex, real world, search, optimization, and machine learning problems for which traditional problem solvers yield unsatisfactory results [6, 32, 33]. GECs have been successfully applied to problems in the areas of robotics (commonly referred to as Evolutionary Robotics) [25], design (commonly referred to as Evolutionary Design) [24], scheduling (commonly referred to as Evolutionary Scheduling) [22], parameter optimization [27], data-mining [44], bioinformatics [35] and cyber security [26], just to name a few.

GECs typically discover optimal or near optimal solutions to problems as follows. First, a population of candidate solutions (CSs) is randomly generated and each candidate solution is assigned a fitness based on a user-defined evaluation function. The fitness is a measure of how well the CS solves the given problem. Parents are then selected from the population, typically based on their fitness, and are allowed to create offspring. Next, the offspring are assigned a fitness and usually replace the worst performing CS within the population. This evolutionary process is continued until one of the following user-specified stopping conditions is satisfied: a (near) optimal solution has been found, the population converges on a solution, a user-defined number of function evaluations have been performed, or a user-specified threshold has been reached. Figure 1.3 shows a flowchart of the GEC process.

Recently, the GEC research community has seen an increased interest in the application of GECs to problems within the area of biometrics [3, 4, 5, 7, 8, 18, 43, 45, 63, 64, 65, 66, 67, 68, 69, 106]. This growing sub-area of GEC, which we will refer to as Genetic & Evolutionary Biometrics (GEB), is devoted to the discovery, design, and analysis of evolution-based methods for solving some of the traditional problems within the biometrics community. To date, GEB techniques have been focused on three areas: feature extraction, feature selection, and feature weighting. An overview of GEB techniques in these areas follows.

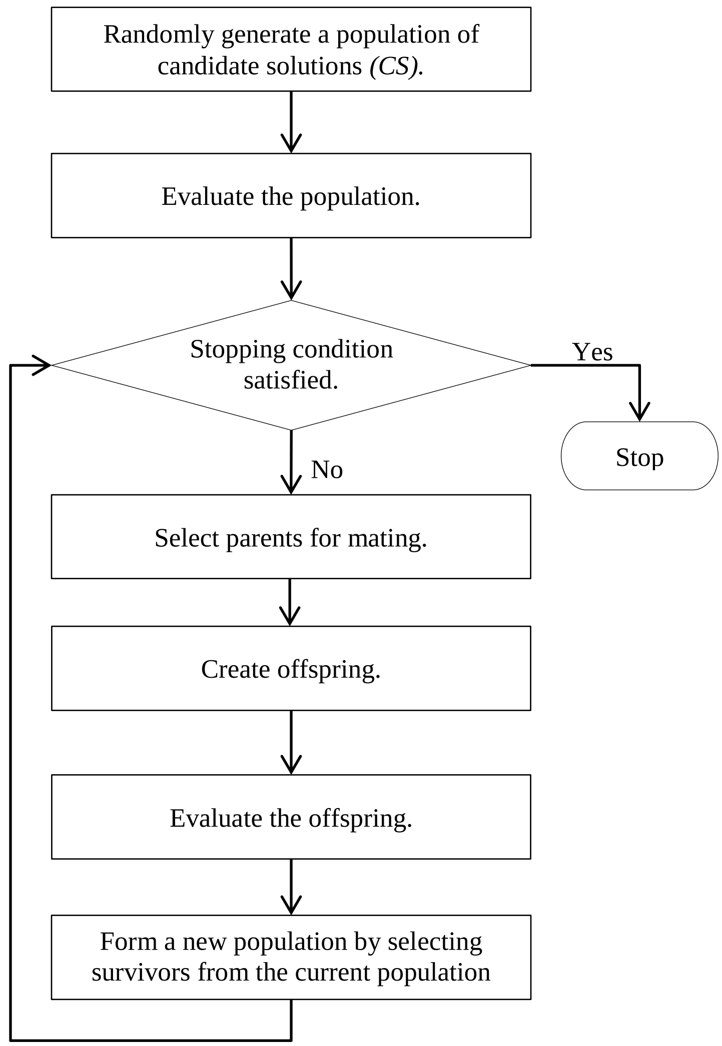

Figure 1.3. Flowchart of a Typical GEC.

1.3.1 GEB Techniques for Feature Extraction

Concerning GEB techniques for feature extraction, Shelton et al. [18] proposed Genetic & Evolutionary Feature Extraction (GEFE). GEFE evolved two types of Local Binary Pattern (LBP) based feature extractors (FEs): (a) those that consisted of patches that were of non-uniform size and (b) those that consisted of patches that were of uniform size. Their results showed that GEFE can evolve FEs that use a smaller number of patches (approximately 8) and that cover a smaller area of the image (approximately 25%) when compared to the traditional method, which used 24 patches and covered the entire image.

1.3.2 GEB Techniques for Feature Selection

Concerning GEB techniques for feature selection, Galbally et al. [4] developed binary-coded and integer-coded Genetic Algorithms (GAs) for feature selection applied to the signature verification problem. The signatures of 330 subjects from the MCYT Signature database [19] were used. Two training sets were formed: one consisting of five signatures of each subject and the other consisting of 20 signatures of each subject. The remaining signatures were used as the test set. Their results showed that both schemes, when compared to the baseline method, which used all of the features, were able to reduce the number of features used and improve the recognition accuracy of the system.

Ramadan and Abdel-Kader [3] compared the performances of Particle Swarm Optimization (PSO) [33] and a GA for feature selection for a facial recognition problem. They used the Cambridge ORL database [20], which consists of 10 images of 40 subjects, to evaluate the performances of the PSO and the GA. Four images of each subject were used to form the training set, and six images of each subject were used to form the test set. The Discrete Cosine Transform and Discrete Wavelet Transform methods were used to extract the original set of features. Their results showed that both GECs performed well in terms of recognition accuracies; however, the PSO used fewer features than the GA.

Kumar et al. [5] compared the performances of a Memetic Algorithm (MA) and a GA for feature selection for a face recognition system. The MA and GA were tested on two facial databases: the ORL database [20], and a subset of the YaleB [21] database (20 subjects). The original feature sets were obtained using the following feature extraction methods: Principal Component Analysis (PCA), Linear Discriminant Analysis, and Kernel PCA. After the original feature sets were created, the MA and GA were applied in an effort to reduce the feature set size as well as to increase recognition accuracy.

For their experiments, Kumar et al. used two approaches for designing their training and test sets for each dataset. In the first approach, three random images of each subject were used to form the training set, and the remaining images were used to form the test set. In the second approach, five random images of each subject were used to form the training set, and the remaining images were used to form the test set. Their results showed that in terms of accuracy and feature reduction, both GECs outperformed the baseline methods, which used all of the extracted features. However, the MA proved to be superior to the GA.

1.3.3 GEB Techniques for Feature Weighting

Abegaz et al. [43] compared the performances of two GECs, Genetic & Evolutionary Feature Selection (GEFeS) and Weighting (GEFeW), on four facial datasets: Face Recognition Grand Challenge (FRGC) [9], Face Recognition Technology (FERET) [57], Essex [59], and Yale [58]. Their results showed that GEFeS obtained higher recognition accuracies than the baseline methods while using 50% fewer features. In addition, their results showed that GEFeW performed better in terms of recognition accuracy.

1.4 Overview of Machine Learning

The goal of any machine learning technique is to develop an artifact (in the form of a neural network, classifier, decision tree, neuro-fuzzy inference system, etc.) that generalizes well to unseen instances [39, 40, 41, 42]. Most machine learning techniques, including GECs [34, 44], will tend to overfit the set of training instances – those instances that are 'seen' by the machine learning technique as it attempts to develop a high performance artifact for classification or regression. This means that the best performing artifact, with respect to the training set, will perform well on these 'seen' instances but will perform relatively poorly on the 'unseen' instances of a test set.

The concept of cross validation [34, 39, 40, 41, 42] was developed in an effort to prevent overfitting. In cross validation, the total set of available instances is broken up into three sets: a training set, a validation set, and a test set. The training set contains instances that are 'seen' by the machine learning technique, while the validation and test sets contain instances that are 'unseen' by the learning technique.

As a machine learning technique attempts to develop artifacts that reduce the classification/regression error on the training set, periodically, artifacts are checked with the validation set. An artifact's performance on the validation set is kept 'hidden' from the machine learning technique. After a user-specified number of artifacts have been developed without reducing the overall best error on the validation set, the learning technique is halted and the artifact with the best performance on the validation set is extracted and applied to the test set and future unseen instances.

As long as a machine learning technique interacts with a training set, the corresponding error rates of successive artifacts will typically move towards zero. The validation set is used to approximate the actual error associated with an artifact if it were to be applied to a test set of unseen instances [34].

1.5 Overview of Multiobjective Optimization

The goal of an optimization problem is to find the best solution to a given minimization or maximization problem. For a single-objective optimization problem, usually a single solution, the optimal solution, is found. However, there are several problems for which multiple objectives are to be optimized, many of which are conflicting. These problems are defined as multiobjective optimization problems (MOPs) [52, 53, 54, 77]. The MOP problem can be stated as follows [54]: Given a set of objective functions, $\vec{F} = \{f_1, f_2, \ldots, f_e\}$, find a candidate solution x_i, where $\vec{X} = \{x_0, x_1, \ldots, x_c\}$ represents the solution space, such that the objective functions of $\vec{F}$ are simultaneously optimized.

For a MOP, there is usually not a single optimal solution. Instead, there is often a set of trade-off solutions called the Pareto-optimal set [52, 53, 54, 77]. The solutions within this set are said to be non-dominated, or in other words, for a given solution x_i, there is no solution, x_j, that performs better than (or dominates) x_i for every objective. When these non-dominated solutions are plotted in the objective space, they form what is referred to as a Pareto front [52, 53, 77]. However, in practice, only one solution is needed for a given MOP. In order to discriminate between the solutions, a preference structure must be imposed [53, 54]. A preference structure defines the relevance of each objective function in $\vec{F}$. Yu [53] proposed three preference structures for a MOP: Pareto preference, lexicographical preference, and value preference. An overview of these preference structures follows.

The most commonly used preference structure is Pareto preference [54]. In Pareto preference, a solution x_i is preferred over (or dominates) solution x_j (denoted by $x_i \prec x_j$) if and only if the following condition is satisfied [54]:

$$\forall_l f_l(x_i) \preccurlyeq f_l(x_j) \wedge \exists_l f_l(x_i) \prec f_l(x_j) \tag{1}$$

In other words, for every objective function, x_i is better than or equal to x_j and there exists an objective function for which x_i is strictly better. The problem with Pareto preference is that a decision maker must be in the loop to select a solution from the resulting Pareto front.

For lexicographical preference, first, a decision-maker must arrange the objective functions in order of importance, such that f_l is more important than f_{l+1} for $l = 1, \ldots, e-1$. A solution x_i is preferred over x_j if [54]:

$$f_d(x_i) \prec f_d(x_j) \wedge f_l(x_i) = f_l(x_j) \text{ for } l = 1, \dots, d-1 \quad (2)$$

The problem with this preference structure is that a decision maker must assign a priority to each objective function.

For value preference structure, the MOP is represented as a single objective function. A function y is defined on $\vec{F}$ such that x_i is preferred over x_j if and only if $y(x_i) \prec y(x_j)$, where:

$$y(x) = \eta_1 f_1(x) + \eta_2 f_2(x) + \ldots + \eta_e f_e(x) \quad (3)$$

and where η_i is the weight assigned to f_i, and the sum of the η values is 1.

1.6 Scope of the Work

In this dissertation, we will present new GEB techniques for multibiometric recognition: Genetic & Evolutionary Feature Selection (GEFeS), Weighting (GEFeW), and Weighting/Selection (GEFeWS). These techniques will be used to decrease the number of features necessary for recognition as well as increase the recognition accuracy. In addition, we will show how incorporating machine learning into GEFeWS results in an increase in the generalization performance of the evolved feature masks. Finally, we will analyze the value preference space and its impact with respect to optimization and machine learning.

The significance of this work stems from the fact that the use of GEC within the field of biometrics has been extremely limited. To our knowledge, GEC has not been used for feature selection and/or weighting of multibiometric systems that use facial and periocular features. In addition, we provide an analysis of the results of our GEB techniques to determine which areas of the face were considered important for recognition.

1.7 Organization of Dissertation

The remainder of this dissertation is as follows. Chapter 2 provides some background information on the feature extraction techniques used within this work, as well as an overview of feature selection and weighting in general and within the biometrics community. We will also provide an overview of the optimization software program and the GECs utilized within this work. Chapter 3 presents Genetic & Evolutionary Feature Selection (GEFeS), Chapter 4 presents Genetic & Evolutionary Feature Weighting (GEFeW), and Chapter 5 presents Genetic & Evolutionary Feature Weighting/Selection (GEFeWS). Chapter 6 presents GEFeWS-Machine Learning ($GEFeWS_{ML}$) and in Chapter 7, we investigate the value preference space for $GEFeWS_{ML}$. In Chapter 8, we provide an analysis of the feature masks evolved by our best performing GEB techniques, and we evaluate the advantages and disadvantages of our proposed technique over a conventional biometric recognition system. Finally, in Chapter 9, we present our conclusions and in Chapter 10, we present our recommendations for future work.

CHAPTER 2

Background

This chapter provides background information on feature extraction, feature selection, and feature weighting. In addition, we provide an overview of the software program used to perform our experiments, and some additional background information on the GECs used within this research.

2.1 Feature Extraction

Feature extraction is one of the most essential tasks performed for biometric recognition and can be categorized into holistic and local approaches [87]. Holistic approaches extract features from the entire biometric sample, while local approaches extract features from selected regions of an acquired sample.

In this section, we discuss the two feature extraction techniques used within our research: the Eigenface method [79, 80, 82, 83, 85], which is a holistic approach, and the Local Binary Patterns (LBP) method [13, 14, 15, 88, 89], which is a local approach.

2.1.1 The Eigenface Method

The Eigenface method is a technique proposed by Turk and Pentland [79, 85] for facial recognition and is based on Principle Component Analysis (PCA) [81, 83]. This method is a statistical dimensionality reduction technique that is used to extract only those dimensions of a facial image that are necessary to efficiently represent a face. This reduced dimensionality feature space is referred to as 'face space' [79, 85].

The idea of using PCA to represent facial images was first proposed by Kirby and Sirovich [82]. They used PCA to calculate the best coordinate system for facial image representation, which is defined by the most significant eigenvectors (referred to as eigenpictures). Kirby and Sirovich then claimed that any collection of facial images could be (approximately) reconstructed by storing a small collection of weights for each facial image. These weights were determined by projecting a facial image onto each eigenpicture.

Turk and Pentland extended the research of Kirby and Sirovich, showing that not only could the eigenpictures be used to reconstruct facial images, but that they could also be used to learn and recognize them. Because the eigenpictures appeared to be ghostly images of the original faces, they referred to them as eigenfaces and referred to the process of creating them as the Eigenface method.

Assume that there is a set of H training facial images, $I = \{I_1, I_2, \ldots, I_H\}$, where each image I_i is a grayscale image of size $M \times M$ pixels. The set of training images are first converted into a set of M^2-dimensional vectors, $\Gamma = \{\Gamma_1, \Gamma_2, \ldots, \Gamma_H\}$, by concatenating the successive pixel rows (or columns). Next, the average face vector of the set of images is calculated using Equation 4.

$$\Psi = \frac{1}{H}\sum_{i=1}^{H}\Gamma_i \qquad (4)$$

The average face vector, Ψ, is then subtracted from each image vector, Γ_i, as shown in Equation 5. This provides the amount for which each image differs from the average.

$$\Phi_i = \Gamma_i - \Psi \qquad (5)$$

Typically, PCA would then be used to determine the eigenvectors and eigenvalues of the following covariance matrix:

$$C = \frac{1}{H}\sum_{i=1}^{H} \Phi_i \Phi_i^T = AA^T \tag{6}$$

where A is a matrix consisting of the concatenation of the Φ_is, or expressed mathematically, $A = [\,\Phi_1\Phi_2 \ldots \Phi_H]$. However, the resulting covariance matrix would have dimensions $M^2 \times M^2$, making this operation computationally expensive.

Instead of performing PCA on this large covariance matrix, matrix L is constructed using Equation 7. This matrix is of size $H \times H$ and is much more manageable in comparison to matrix C.

$$L = A^T A \tag{7}$$

PCA is then performed on L to determine a set of H eigenvectors (referred to as eigenfaces), μ_l, and their associated eigenvalues, λ_l.

The resulting v eigenvectors are then sorted based on their associated eigenvalue. Because the eigenvectors with the highest associated eigenvalues account for most of the variance within a set of facial images, only the G, where $G < H$, best eigenvectors (those with the highest eigenvalues), are retained and are used to define the subspace of face images which is referred to as 'face space'.

Next, the training images are projected into 'face space' (or transformed into their eigenface components [79]) using the following formula:

$$\omega_i = \mu_i^T(\Gamma - \Psi) \tag{8}$$

where $i = \{1, 2, \ldots, G\}$ and where ω_i represents the weight of each eigenvector. The vector $\Omega^T = [\omega_1\ \omega_2 \ldots\ \omega_G]$ is then used to represent a training image in 'face space'.

Once 'face space' has been defined, to recognize a test image, I_{test}, the image is first converted to a M^2-dimensional vector, Γ_{test}, and the average face, Ψ, is subtracted from the vector, resulting in Φ_{test}. The resulting vector is then projected into 'face space' using Equation 8 and the weight vector, Ω_{test}, is formed. A similarity measure (e.g. Manhattan distance) is then used to compare Ω_{test} to the set of training weight vectors. The training weight vector that matches closest to Ω_{test} is considered as the matching template if the distance is below a certain threshold, θ. Otherwise, the test image is not considered to match any of the images within the training set.

2.1.2 The Local Binary Patterns (LBP) Method

The Local Binary Patterns (LBP) method is a texture classifying algorithm proposed by Ojala et al. [14]. Although originally designed for contrasting pixels within a grayscale image for the purposes of image analysis, the LBP method has become a popular feature extractor within the biometrics community [7, 8, 10, 11, 12, 13, 18, 30, 64, 65, 69, 90, 91], due to its discriminative power, computational simplicity, and its tolerance for monotomic grayscale changes which makes it less sensitive to illumination changes [13].

LBP descriptors of an image are formed by first segmenting the image into a user-defined number of regions, referred to as patches. The pixels within each patch are then compared to their P neighboring pixels. The original LBP method [14] works with a neighborhood size of eight. However, in [15], Ojala et al. extended the method to use different neighborhood sizes. This is denoted by the $LBP_{P,R}$ notation, where P represents the number of neighbors at radius R from a center pixel.

For a given center pixel at location (x_c, y_c), its intensity value, i_c, is compared to the intensity value of its P neighboring pixels, i_p, where $p = 0, \ldots, P\text{-}1$. As shown in

Equation 9, if the difference in the intensity values is negative, it is represented by a 0, otherwise the difference is represented by a 1.

$$s(i_p - i_c) = \begin{cases} 0, if\, i_p < i_c \\ 1, if\ i_p \geq i_c \end{cases} \tag{9}$$

A texture, τ, is then formed by concatenating the resulting values as shown in Equation 10.

$$\tau = \{s(i_0 - i_c), \ldots, s(i_{P-1} - i_c)\} \tag{10}$$

Next, a binomial weight is given to the elements in τ as follows:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(i_p - i_c)2^p \tag{11}$$

By doing so, the differences in the intensity values are transformed into a unique LBP code. Using a neighborhood size of P, there are 2^P possible texture patterns and therefore 2^P distinct LBP codes. However, Ojala et al. [15] showed that a subset of the 2^P patterns could be used to describe the texture of an image without losing too much information. The subset of patterns, known as uniform patterns, contain at most two one-to-zero or zero-to-one bit transitions when the texture, τ, is traversed circularly (i.e. 11110001). They also observed that these patterns contained the most texture information and accounted for a high percentage of the resulting texture patterns (approximately 90% for $LBP_{8,1}$).

For each patch, the occurrence of each LBP code is then encoded in a histogram. Instead of having a bin for each of the 2^P possible LBP codes, only uniform patterns are distinguished within the histogram. Therefore, each histogram consists of $P(P-1)+3$ bins, because there are $P(P-1)+2$ possible uniform patterns, where P is the number of uniform patterns with exactly two bit changes, *P-1* is the number of possible variations, and there are 2 uniforms patterns with zero bit changes (i.e. all zeros, and all ones). The remaining bin is used to store the frequency of the non-uniform patterns.

The resulting histograms for each patch are then concatenated to form a feature vector for each image consisting of the number of bins, *P(P-1)+3,* times the number of patches used.

2.2 Feature Selection and Weighting

As mentioned earlier, in order for a biometric system to achieve high recognition rates, it is important that the extracted features are consistent for the same subject (i.e. exhibit small intra-class variation) as well as distinct between different subjects (i.e. exhibit large inter-class variation) [1, 86, 112]. However, due to factors such as poor image quality, illumination variation, and varying poses and facial expressions, the extracted set of features do not always exhibit these properties [1, 92, 113].

To improve the recognition performance, feature selection and weighting techniques are often used. Feature selection techniques attempt to reduce the dimensionality of feature templates by selecting optimal or near optimal subsets of the features while maintaining or improving the recognition accuracy [95, 96]. Typically, features that do not contribute positively to recognition are eliminated (or assigned a weight of 0), while features that are relevant are retained (or assigned a weight of 1) [98]. Feature weighting is a more general case of feature selection. Instead of eliminating features, feature weighting techniques multiply each feature by a continuous weight proportional to its discriminative ability [95, 97, 98]. Typically, higher weights are given to those features that aid most in recognition.

For any feature selection technique, there are two major components [100]: (1) a search (or generation [99]) procedure, and (2) an evaluation procedure. The search procedure explores the feature space to create candidate feature subsets (FSs), while the evaluation procedure measures the goodness of the resulting FSs.

In the literature, three types of algorithms have been used for the search procedure [95, 96, 99, 100, 101, 102]: enumeration search algorithms, sequential search algorithms, and randomized search algorithms. Enumeration (also referred to as exponential [101] or complete [99]) search algorithms evaluate all of the possible subsets of the features and then choses the best performing subset. Although these algorithms guarantee that the optimal feature subset is found, the number of subsets grows exponentially with the dimensionality of the search space [100]. Sequential (or heuristic [99]) search algorithms are greedy algorithms that add or remove features from a candidate FS while evaluating its performance based on some criterion. When compared to enumeration search algorithms, sequential search algorithms have reduced computational complexity, however, they tend to gravitate toward local minima [102]. Randomized search algorithms, such as genetic algorithms (GAs), incorporate randomness into the search procedure. These algorithms are able to find good solutions within a large search space and are able to avoid the problem of falling into local minima [101, 102]. However, the appropriate parameter values must be determined in order to find the best FSs.

In addition, there are two types of evaluation procedures [97, 100, 104]: filter models and wrapper models. In the filter model, first, subsets of features are evaluated based on some statistical measurement (e.g. interclass distance, statistical independence [102]). Once the 'optimal' FS is determined, classification is then performed. In the wrapper model, the 'optimal' FS is determined based directly on its recognition accuracy. Although the filter model is more computationally efficient, the resulting FSs tend to consist of more features in comparison to the wrapper model. In addition, the wrapper model results in FSs that achieve higher classification accuracy [102].

2.2.1 Feature Selection in the Biometrics Community

In the biometrics community, feature selection techniques have typically focused on retaining the most variant individual dimensions, the most consistent individual features, or the most discriminative individual features. An overview of feature selection techniques currently used in the biometrics community follows.

In the face recognition community, there has been an emphasis on finding optimal feature sets. The Eigenface method, as discussed previously, uses only the best eigenvectors (those associated with the highest eigenvalues), and discards those that correspond to the lower eigenvalues [79, 82, 85]. The retained eigenvectors are said to capture the greatest variance within a set of facial images. However, Swets and Weng [107] stated that the retained eigenvectors do not necessarily correlate to the most discriminative features. Instead, they stated that the Eigenface method provides the Most Expressive Features (MEFs), which describe major variations in a class, such as those due to lighting direction.

Hollingsworth et al. [48], Gentile et al. [105], and Baker et al. [106] proposed feature selection techniques for iris recognition. Hollingsworth et al. investigated the existence of fragile (inconsistent) bits within iris codes. A fragile bit is any bit that flips more than 40% of the time. By removing these fragile bits, they were able to lower the false reject rate (FRR) of the system. Gentile et al. proposed using Kolmogorov-Smirnov (KS) analysis, a statistical technique, to determine which regions of the iris were most discriminative. The most discriminative regions were then further reduced by sub-sampling them uniformly to produce short-length iris codes (SLICs). Their results showed that the SLICs, although 12.8 times smaller than the full-length iris codes, were able to achieve comparable accuracy rates. Baker et al. used GEC to reduce the number of iris code bits while retaining the most discriminative regions (i.e. rings). They were able to further reduce the number of bits by sub-sampling these regions to produce genetic and evolutionary based short length iris codes (GESLICs) that were comparable to those developed by Gentile et al.

Instead of selecting the most salient individual features, in this dissertation we present feature selection and weighting techniques that either: (a) evolve subsets of the most salient combinations of features and/or (b) weight features based on their discriminatory ability in an effort to increase accuracy while decreasing the overall number of features needed for recognition. Our techniques utilize randomized search algorithms, specifically GECs, to create FSs (which we will refer to as feature masks). The candidate FSs are then evaluated using a wrapper model, in which an evaluation function that takes into account the number of recognition errors associated with the given subset is used to assign a fitness to the candidate FSs. Candidate FSs with lower recognition errors and that use fewer features are considered as the best.

2.3 X-TOOLSS

The experiments presented in this dissertation were performed using the eXploration Toolset for the Optimization of Launch and Space Systems (X-TOOLSS). X-TOOLSS is an open-source optimization software package that is currently being developed by the Center for Advanced Studies in Identity Sciences at NC A&T State University (CASIS@A&T) [70]. X-TOOLSS consists of a suite of twelve GECs, which interface with evaluation functions expressed as executables of any programming language [70, 71]. The GECs included in the X-TOOLSS suite are as follows: Generational GA (GGA) with Blend Crossover (BLX), Steady-State GA (SSGA), SSGA with BLX, Steady-Generational GA (SGGA) with BLX, Particle Swarm Optimization (PSO), Generational Differential Evolutionary Algorithm (DEA), Steady-State DEA, Elitist Estimation of Distribution Algorithm (EDA), Standard Evolutionary Programming (EP), Continuous Standard EP, Meta-EP, and Continuous Meta-EP.

In order for X-TOOLSS to run a simulation, a module file must be provided. An example module file is shown in Figure 2.1. The module file, which is a text file with a .xts extension, specifies the following: the input variables (variable name, range, and type), the input file name, the code file (name and type), the name of the output (fitness) variable that is outputted by the code file, and the output file name. The input variables specify the representation of the candidate solutions (CSs) that will be evolved by a GEC.

The resulting CSs are then written to the input file. The code file, which is an executable, evaluates each CS read in from the input file and returns its fitness to the output file.

After the required files have been created, the .xts file is loaded into the X-TOOLSS Application Builder, and the user selects the type of GEC to be used and modifies the parameters for that specific GEC. Upon completion of the simulation, the best performing CS and its associated fitness are returned.

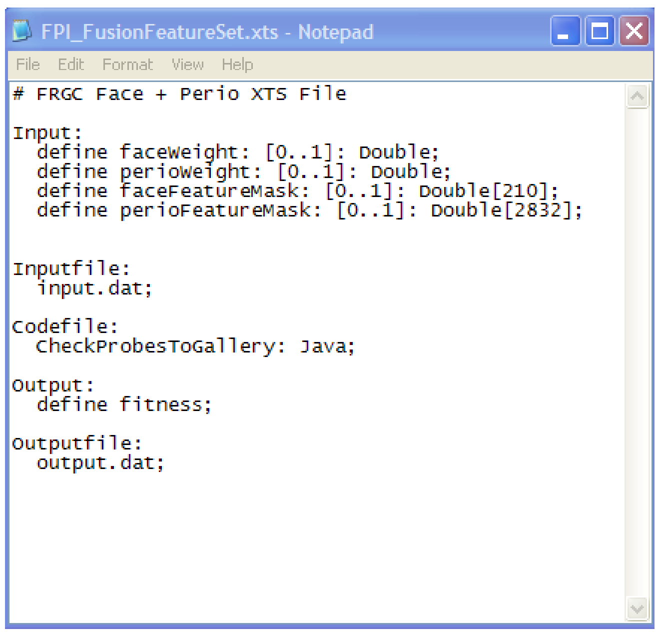

Figure 2.1. An Example .xts File.

In this dissertation, we utilize two types of GEC within the X-TOOLSS suite: the SSGA and the Elitist EDA. An overview of these two GECs follows.

2.3.1 Steady State Genetic Algorithm (SSGA)

Introduced in 1975 by John Holland, Genetic Algorithms (GAs) were the first GEC paradigms [38]. There are two basic types of GAs: generational GAs (GGAs) [6, 24] and steady-state GAs (SSGAs) [32]. These GAs differ in the replacement strategy used to create a new population [16, 23, 24, 38]. For GGAs, all parents are replaced by their offspring. For SSGAs, typically two parents are selected and allowed to create one or two offspring. The offspring then replace the worst performing individuals within the population, even if the offspring have better fitness values than the individuals they replace.

SSGAs work as follows. First, an initial population of CSs is randomly generated. Each CS within the population is then evaluated and assigned a fitness based on a user-specified evaluation function. Next, individuals from the population are selected to be parents. Several selection strategies can be used, including random selection, proportional selection, tournament selection, and rank-based selection. In this dissertation, we use binary tournament selection to select two parents from the population. In binary tournament selection, two individuals are randomly selected from the population and the best individual is chosen as a parent.

Once the parents have been chosen, crossover operators are applied in an effort to create offspring. Crossover operators recombine the genetic material of the selected parents [16, 24]. Several crossover operators have been used for GAs, including single-point crossover, two-point crossover, and uniform crossover. In this dissertation, we use uniform crossover, where genes have equal probability of being selected from each parent to create a new offspring.

Mutation operators are then applied to the offspring in an attempt to add diversity to the population. The probability that an offspring will undergo mutation is known as the mutation usage rate. The mutation rate, p_m, is the probability an offspring's gene will undergo mutation. In this dissertation, we use Gaussian mutation. The Gaussian Mutation Amount, σ, determines the range that the gene's value can mutate. Therefore, using Gaussian mutation, the value of an offspring's gene after mutation is:

$$o_{i,j} = o_{i,j} + \sigma\left(ub_j - lb_j\right)N(0,1) \tag{12}$$

where $o_{i,j}$ is the j^{th} gene of offspring o_i, ub_j and lb_j are the upper and lower bounds for the gene, and where $N(0,1)$ is a sample from the Gaussian random variable with a mean of 0 and a standard deviation of 1.

The offspring are then evaluated and assigned a fitness, and a new population is then formed by replacing the worst performing individual in the current population with the offspring. This process is then repeated until some stopping condition has been satisfied. Figure 2.2 shows a pseudocode version of a SSGA.

```
Procedure SSGA {
  t = 0;
  Initialize(Pop(t));
  Evaluate(Pop(t));
  While(Not Done){
     Parent1 = Select_Parent(Pop(t));
     Parent2 = Select_Parent(Pop(t));
     Offspring = Crossover(Parent1, Parent2);
     Mutate(Offspring);
     Evaluate(Offspring);
     Pop(t+1)=Replace(Worst(Pop(t)),Offspring);
     t = t+1;
  }
}
```

Figure 2.2. Pseudocode Version of a Steady-State Genetic Algorithm (SSGA).

2.3.2 Estimation of Distribution Algorithm (EDA)

Estimation of Distribution Algorithms (EDAs) were developed as an alternative to GAs. Unlike GAs, EDAs do not use crossover and mutation operators to create offspring [17]. Instead, EDAs create a new population by sampling the probability density/distribution function (PDF) of selected individuals from the current population.

Figure 2.3 shows a pseudocode version of an EDA. First, an initial population of ρ CSs is randomly generated. Next, a user-specified evaluation function is used to assign a fitness to each CS within the population. The top 0.5ρ CSs are then selected to be parents and are used to create a PDF. The PDF is then sampled to create $(1\text{-}\alpha)\rho$ offspring, where α is the percentage of the best performing CSs (known as the elites [24]) that are allowed to survive into the next generation. Each offspring's gene is determined using the following equation:

$$o_{i,j} = \mathrm{mean}_j + std_j N(0,1) \tag{13}$$

where $o_{i,j}$ is the j^{th} gene of offspring o_i, $mean_j$ is the mean of the parents' j^{th} gene, std_j is the standard deviation of the parents' j^{th} gene, and $N(0,1)$ is a sample from the Gaussian random variable with a mean of 0 and a standard deviation of 1. The offspring are then evaluated, and a new population is created using the elites and the offspring.

```
Procedure EDA {
  t = 0;
  Initialize(Pop(t));
  Evaluate(Pop(t));
  While(Not Done){
     Elites = Best(Pop(t));
     Parents = Select_Top(Pop(t), 50%);
     Offspring = Sample(PDF(Parents));
     Evaluate(Offspring);
     Pop(t+1)= Offspring + Elites;
     t = t+1;
  }
}
```

Figure 2.3. Pseudocode Version of an Estimation of Distribution Algorithm (EDA).

CHAPTER 3

Genetic & Evolutionary Feature Selection (GEFeS)

This chapter introduces Genetic & Evolutionary Feature Selection (GEFeS) [8, 9, 63, 64, 65, 66, 67, 68, 69]. The goal of GEFeS is to evolve subsets of the most salient features in an effort to increase the recognition accuracy of a biometric system, while decreasing the number of features needed for recognition.

GEFeS evolves a population of real-valued candidate feature masks (FMs). Each candidate FM, fm_i, can be viewed as a tuple $\langle \mathrm{M}_i, fit_i \rangle$ where $\mathrm{M}_i = \{\mu_{i,0}, \mu_{i,1}, \dots, \mu_{i,n-1}\}$ and where $\mu_{i,j}$ is the j^{th} mask value for fm_i. The value fit_i represents the fitness of fm_i. The mask values are initially within the range [0..1]. For GEFeS, mask values that are less than 0.5 are set equal to 0, meaning that the corresponding feature in the biometric template will not be used. Otherwise, the value is set equal to 1 and the associated biometric feature will be used.

In this dissertation, we used GEFeS to evolve FMs for facial, periocular, and multibiometric (facial and periocular) recognition. For the multibiometric system, the FMs consist of $n_1 + n_2$ mask values, where values $[\mu_{i,0} \dots \mu_{i,n_1-1}]$ represent the facial feature submask and features $[\mu_{i,n_1} \dots \mu_{i,n_1+n_2-1}]$ represent the periocular feature submask. The facial and periocular biometric modalities are fused at the score-level. Score-level fusion is performed in the following manner. For each candidate FM, there exist two weights, w_f and w_p. These weights are associated with the facial and periocular feature submasks respectively [45, 51, 56]. The weights range from [0..1] and are coevolved with the candidate FM. The evolved weights are first normalized as follows [45]:

$$w_f' = \frac{w_f}{w_f + w_p} \tag{14}$$

$$w_p{}' = \frac{w_p}{w_f + w_p} \tag{15}$$

where w_f' and $w_p{}'$ are the normalized weights for the facial and periocular feature submasks. The resulting normalized weights are then used to fuse the facial and periocular features using the following weighted sum rule [29, 45]:

$$S_i = w_f{}' s_{f,i} + w_p{}' s_{p,i} \tag{16}$$

where S_i is the fused score for Subject i, and $s_{f,i}$ and $s_{p,i}$ are the weighted Manhattan distances between the probe and gallery templates for the facial and periocular templates for Subject i.

For GEFeS, the weighted Manhattan distance between two feature templates, h_j and h_l, is defined as:

$$wMD_1(h_j, h_l, fm_i) = \sum_{k=0}^{n-1} |h_{j,k} - h_{l,k}| g(\mu_{i,k}) \tag{17}$$

$$g(\mu_{i,k}) = \begin{cases} 1, if\ \mu_{i,k} \geq 0.5 \\ 0, otherwise \end{cases} \tag{18}$$

where wMD_1 represents the weighted Manhattan distance (the subscript 1 denotes our first technique, GEFeS), n is the original number of features, $\mu_{i,k}$ is a FM value, k is the k^{th} feature, and the function g represents the process of feature selection as performed by GEFeS.

For the unimodal systems, the associated subject of the template within the gallery with the smallest weighted Manhattan distance when compared to the probe is considered the match. Similarly, for the multibiometric system, the associated subject of the template within the gallery set with the smallest fused score, S, when compared to the probe template is considered the match. If the subject of the gallery template matches the subject of the probe template, the probe subject is accurately recognized; otherwise, a recognition error has occurred.

Each candidate FM is assigned a fitness using the following evaluation function:

$$fit_i = 10\varepsilon + \frac{m}{n} \tag{19}$$

where ε is the number of recognition errors that occurred when the candidate FM was applied to the probe and gallery templates, where m is the number of features used by the candidate FM, and where n is the original number of features in the biometric templates. Note that by multiplying the number of errors by 10, we are placing more emphasis on the reduction of errors. The goal of GEFeS is to minimize the fitness function, therefore candidate FMs with lower fitnesses are preferred.

3.1 Experiments

To evaluate the effectiveness of GEFeS, the following experiment was performed. The objective of the experiment is to evolve short-length biometric templates that can be used in a 'Gentile-style' recognition system. In [74], Gentile et al. proposed a hierarchical two-stage iris recognition system that used a reduced feature set size in an effort to reduce the total number of feature checks required. For a conventional biometric recognition system, a probe is compared to every individual within a biometric database. The number of feature checks performed by a conventional biometric system, γ_c, is:

$$\gamma_c = Nn \tag{20}$$

where N is the number of individuals in the database and n is the number of features used to represent an individual. Gentile's two-stage hierarchical biometric system reduces the number of feature checks performed by first using the reduced length biometric template to select a subset of the r closest matches to a probe. The subset is then compared to the probe using all of the n features. The number of feature checks performed by a hierarchical system, γ_h, is the summation of the calculations of the two stages, represented by:

$$\gamma_h = Nm + rn \tag{21}$$

where, once again, N represents the number of individuals in the database, m is the number of features in the reduced feature set, r is the subset of the closest r-individuals to the probe, and n is the number of features used to represent an individual. The savings gained by using the hierarchical biometric system, γ_s, instead of the conventional biometric system is:

$$\gamma_s = \frac{\gamma_h}{\gamma_c} = \frac{Nm + rn}{Nn} = \frac{m}{n} + \frac{r}{N} \tag{22}$$

The dataset used for our experiment consisted of images of 105 subjects taken from the Face Recognition Grand Challenge (FRGC) database [9], and will be referred to as the FRGC-105 dataset. One image of each of the selected subjects was used to form the probe set and two additional images of each subject were used to form the gallery set. The images selected were frontal views of the subjects with neutral facial expressions. We will refer to this experiment as the FRGC-105 Optimization Experiment because we are attempting to optimize two objectives: (a) maximize the recognition rate and (b) minimize the number of features.

The facial images were pre-processed as follows. The images within FRGC-105 were first cropped to include only the face region (i.e. no background and little hair). The images were then resized to 100 × 127 pixels, converted to grayscale, and histogram equalization [72] was performed. The Eigenface method was then used to extract 210 facial features from each image. The LBP method was also used to extract 2124 (*36* patches × 5*9* bins) facial features from each image.

The periocular images were pre-processed as follows. First, the left and right periocular regions were cropped individually from each image within FRGC-105. The extracted periocular regions were then converted to grayscale and histogram equalization [72] was performed. In addition, the centers of the periocular regions were masked to eliminate the effect of texture and color in the iris and sclera area, as was done in [12]. The LBP method was then used to extract 1416 (*24* patches × *59* bins) periocular features from each region. The resulting feature templates for the left and right periocular regions were then concatenated together to form a feature template consisting of 2832 (*1416* features per periocular region) periocular features.

For the FRGC-105 Optimization Experiment, GEFeS was used to evolve FMs for the face-only, periocular-only, and face + periocular feature templates. The performance of GEFeS on these biometric templates was compared to the performance of the biometric feature templates without the use of GEFeS.

3.2 Results

For the FRGC-105 Optimization Experiment, the X-TOOLSS SSGA and EDA techniques were used to form $\text{GEFeS}_{\text{SSGA}}$ and $\text{GEFeS}_{\text{EDA}}$. $\text{GEFeS}_{\text{SSGA}}$ evolved a population of 20 FMs, had a crossover rate of 1.0, a mutation usage rate of 1.0, and a Gaussian Mutation Amount of 0.2. $GEFeS_{EDA}$ evolved a population of 20 FMs and always retained the 5 (α = 25% of the population) best FMs within the population, known as the elites. $GEFeS_{SSGA}$ and $GEFeS_{EDA}$ were run 30 times with a maximum of 1000 function evaluations allowed for each run.

The results of our experiment are shown in Table 3.1. The first column represents the biometric modalities used. The second column represents the methods that were compared. The third and fourth columns record the average recognition accuracy and the average percentage of features used.

In Table 3.1, the performances of a number of baseline feature extraction techniques are recorded as well. These baseline techniques are denoted by their subscripts, where *E* denotes the Eigenface method, and where *L* denotes the LBP method. For the multibiometric system, the first subscript denotes the facial feature extraction technique and the second subscript denotes the periocular feature extraction technique. In addition, for the multibiometric systems, the numbers within the parentheses are the weights assigned to the face and periocular biometric modalities for score-level fusion. The weights represent fusing the modalities evenly and optimizing the weights for each biometric modality [45]. Note that the baseline methods were deterministic (used 100% of the extracted features) and were only run once.

In addition, the feature templates that were used by the GEFeS instances are denoted in parentheses. $Face_E$ refers to the Eigenface features, $Face_L$ refers to the facial LBP features, and $Perio_L$ refers to the periocular LBP features.

Table 3.1. FRGC-105 Optimization Experiment Results of GEFeS

Modalities	Method	Average Recognition Accuracy	Average % of Features Used
Face-Only	Baseline$_E$	65.76%	100.00%
	GEFeS$_{SSGA}$(Face$_E$)	86.13%	50.30%
	GEFeS$_{EDA}$(Face$_E$)	85.59%	42.86%
	Baseline$_L$	98.00%	100.00%
	GEFeS$_{SSGA}$(Face$_L$)	100.00%	43.59%
	GEFeS$_{EDA}$(Face$_L$)	99.71%	39.66%
Periocular-Only	Baseline$_L$	94.29%	100.00%
	GEFeS$_{SSGA}$(Perio$_L$)	95.14%	48.03%
	GEFeS$_{EDA}$(Perio$_L$)	95.87%	41.03%
Face + Periocular	Baseline$_{EL}$(0.5, 0.5)	90.77%	100.00%
	Baseline$_{EL}$(0.11, 0.89)	95.24%	100.00%
	GEFeS$_{SSGA}$(Face$_E$, Perio$_L$)	97.40%	48.18%
	GEFeS$_{EDA}$(Face$_E$, Perio$_L$)	96.70%	45.24%
	Baseline$_{LL}$(0.5, 0.5)	99.52%	100.00%
	Baseline$_{LL}$(0.69,0.31)	100.00%	100.00%
	GEFeS$_{SSGA}$(Face$_E$, Perio$_L$)	100.00%	45.16%
	GEFeS$_{EDA}$(Face$_E$, Perio$_L$)	100.00%	41.94%

For each biometric modality, the average recognition rate and the average percentage of features used by the instances of GEFeS were divided into equivalence classes using a t-test [75]. For our analysis, the two instances of GEFeS were considered statistically different if $t_{stat} > t_{crit}$.

3.2.1 Face-Only

3.2.1.1 Face$_E$

With respect to the Face-Only Eigenface results, in terms of recognition accuracy and the percentage of features used, the performances of the instances of GEFeS outperformed the baseline method. When the performances of the instances of GEFeS were compared in terms of accuracy, both were in the same equivalence class. However, in terms of the percentage of features used, $GEFeS_{EDA}$ used significantly fewer features than $GEFeS_{SSGA}$.

3.2.1.2 $Face_L$

With respect to the Face-Only LBP results, in terms of recognition accuracy and the percentage of feature used, the instances of GEFeS outperformed the baseline method. Comparing the performances of the instances of GEFeS in terms of accuracy, $GEFeS_{SSGA}$ was in the first equivalence class, accurately recognizing all of the subjects for each of the 30 runs. $GEFeS_{EDA}$ was in the second equivalence class. However, in terms of feature reduction, $GEFeS_{EDA}$ was in the first equivalence class, using an average of 39.66% of the features. $GEFeS_{SSGA}$ was in the second equivalence class using an average of 43.59% of the features.

3.2.2 Periocular-Only

With respect to the Periocular-Only results, when compared to the baseline LBP method, the instances of GEFeS used significantly fewer features to achieve higher recognition accuracies. $GEFeS_{EDA}$ performed the best in terms of recognition accuracy and the percentage of features used, having a 95.87% average accuracy while using only 41% of the features.

3.2.3 Face + Periocular

3.2.3.1 $Face_E$ + $Perio_L$

With respect to the $Face_E$ + $Perio_L$ results, comparing the performances of the $Baseline_{EL}$ methods and the instances of GEFeS, GEFeS used less than 50% of the features to achieve higher recognition accuracies. When the performances of the instances of GEFeS were compared in terms of accuracy, there was not a statistically significant difference between their performances. However, in terms of the percentage of features used, $GEFeS_{EDA}$ was in the first equivalence class.

3.2.3.2 $Face_L$ + $Perio_L$

With respect to the $Face_L$ + $Perio_L$ results, when the performances of the *$Baseline_{LL}$* methods were compared to the performances of the instances of GEFeS, the GEFeS performed the best. $GEFeS_{SSGA}$ and $GEFeS_{EDA}$ achieved a 100% recognition accuracy while using significantly fewer features. In terms of feature reduction, $GEFeS_{EDA}$ used the lowest percentage of features and was in the first equivalence class.

3.3 Discussion of Results

The results of the FRGC-105 Optimization Experiment showed that GEFeS could be used to efficiently increase the recognition accuracy of a biometric system while reducing the number of features necessary for recognition. Thus, GEFeS would be ideal for developing short-length biometric templates for use in a 'Gentile-style' biometric system. In addition, our results show that the multibiometric system can achieve higher recognition accuracies than the unimodal biometric systems.

To illustrate the performance of GEFeS in comparison to the baseline methods, the Cumulative Match Characteristic (CMC) curves are shown in Figures 3.1 to 3.5. A CMC curve plots the percent of times a correct match was made for a given rank, where rank is defined as the number of attempts necessary to correctly match a given probe subject [1, 10]. Each figure shows the CMC curve of the baseline method and the best performing FM evolved by $\text{GEFeS}_{\text{SSGA}}$ and $\text{GEFeS}_{\text{EDA}}$ for the respective biometric modality up to Rank 10. In other words, if given a subset of the 10 closest matches to a given probe, how often would these methods match the subject of the probe correctly?

Figures 3.1 and 3.2 show the CMC curves for the Face-Only results. In Figure 3.1, $\text{GEFeS}_{\text{SSGA}}$ and $\text{GEFeS}_{\text{EDA}}$ both outperformed the baseline Eigenface method for Ranks 1-10. In Figure 3.2, the GEFeS instances outperformed the baseline LBP method for Ranks 1-7. By Rank 8, the three methods reach 100% recognition accuracies.

Figure 3.3 shows the CMC curve for the Periocular-Only results. For Ranks 1-4, the GEFeS instances outperformed the baseline method. At Rank 5, the baseline LBP method performed the best. At Ranks 6-8, the three methods have equal performances, however by Rank 9, $\text{GEFeS}_{\text{SSGA}}$ outperforms $\text{GEFeS}_{\text{EDA}}$ and the baseline method.

Figures 3.4 and 3.5 show the CMC curves for the Face + Periocular results. In Figure 3.4, for Ranks 1-10, the GEFeS instances have equal performances and both outperform the baseline method, which fuses the facial Eigenface features and the LBP periocular features. In Figure 3.5, the GEFeS instances achieved 100% Rank 1 accuracies, outperforming the baseline method, which fuses the LBP facial and periocular features.

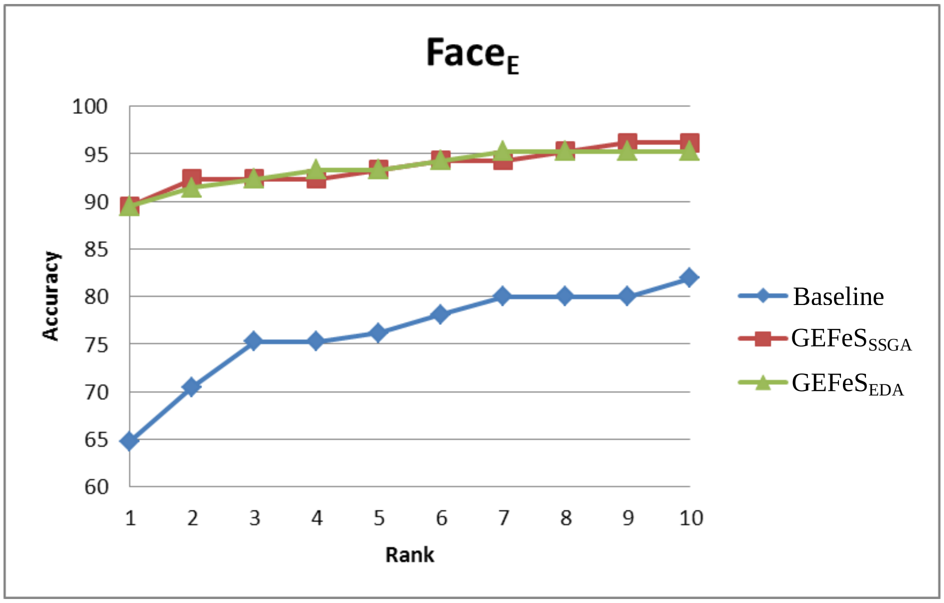

Figure 3.1. CMC Curves for GEFeS($Face_E$).

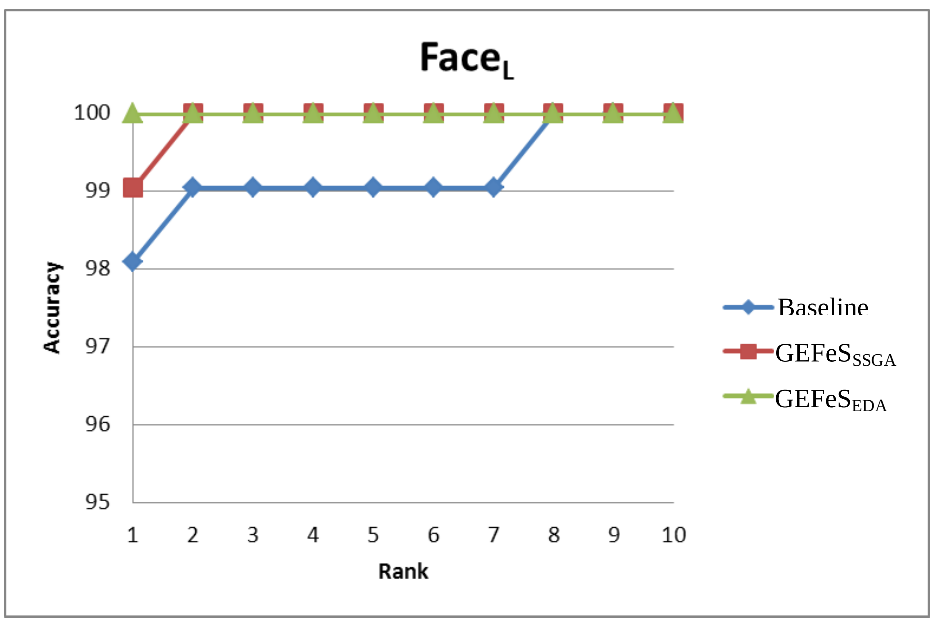

Figure 3.2. CMC Curves for GEFeS($Face_L$).

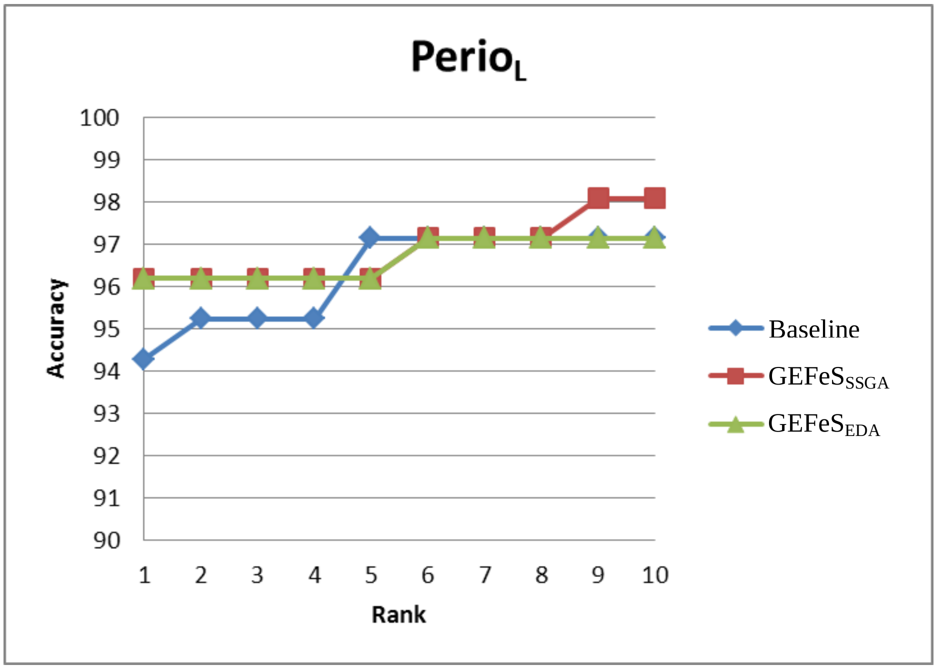

Figure 3.3. CMC Curves for GEFeS(Perio$_L$).

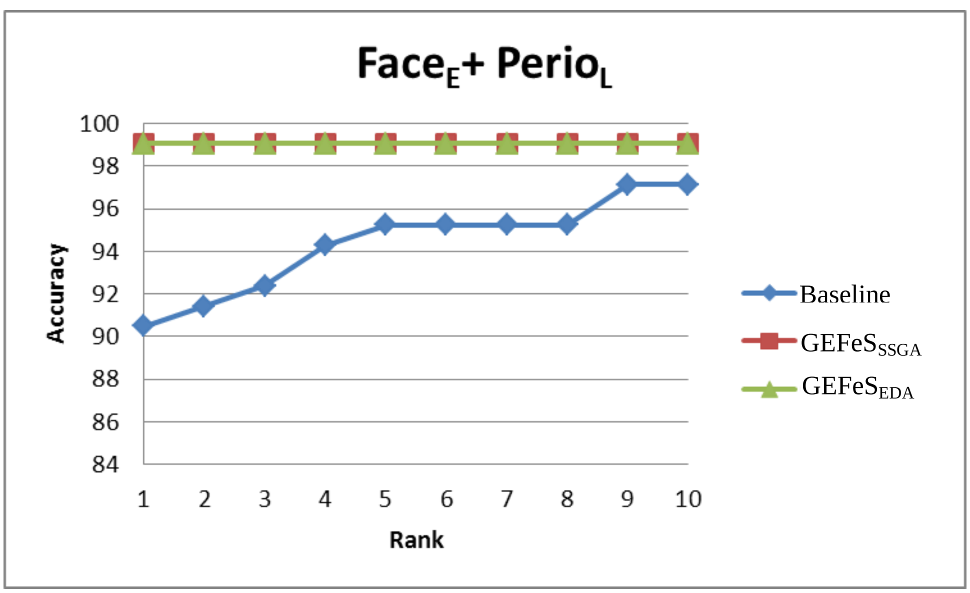

Figure 3.4. CMC Curves for GEFeS(Face$_E$, Perio$_L$).

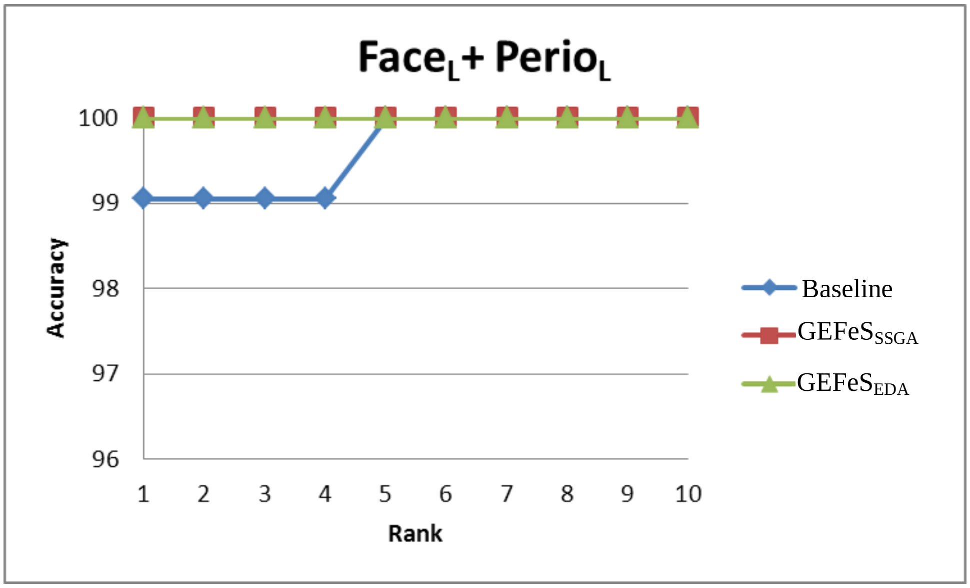

Figure 3.5. CMC Curves for GEFeS(Face$_L$, Perio$_L$).

CHAPTER 4

Genetic & Evolutionary Feature Weighting (GEFeW)

In the previous chapter, we presented Genetic & Evolutionary Feature Selection (GEFeS). Our results showed that GEFeS could effectively reduce the dimensionality of biometric feature templates and increase the recognition accuracy. In this chapter, we introduce a variant of GEFeS, referred to as Genetic & Evolutionary Feature Weighting (GEFeW) [8, 9, 63, 64, 65, 66, 67, 68, 69]. Unlike GEFeS, which evolves subsets of features, GEFeW evolves a weight for each feature. Ideally, higher weights are given to features that contribute more towards recognition accuracy.

In similar fashion to GEFeS, GEFeW evolves a population of real-valued candidate FMs. However, instead of converting these values to a binary FM (as does GEFeS), GEFeW uses these values as weights for each associated feature. In addition, the candidate FMs are evaluated using the same function used by GEFeS (Equation 19).

For GEFeW, the weighted Manhattan distance between two templates is calculated differently than for GEFeS. Given two templates, h_j and h_l, and a candidate FM, fm_i, the weighted Manhattan distance is calculated using Equation 23, where wMD_2 represents the weighted Manhattan distance (the subscript *2* denotes our second technique, GEFeW), where n is the original number of features, and where $\mu_{i,k}$ is the k^{th} weight in fm_i associated with the k^{th} feature.

$$wMD_2(h_j, h_l, fm_i) = \sum_{k=0}^{n-1} |h_{j,k} - h_{l,k}| \mu_{i,k} \qquad (23)$$

The subject associated with the template within the gallery set with the smallest weighted Manhattan distance (smallest fused score for the multibiometric system) when compared to the probe was considered the match.

4.1 Experiments

As in Chapter 3, we performed the FRGC-105 Optimization Experiment, allowing GEFeW to evolve weights for the face-only, periocular-only, and face + periocular templates formed from the FRGC-105 dataset. The performance of GEFeW on these templates was then compared to the performance of GEFeS and the baseline methods presented in Table 3.1.

4.2 Results

Like GEFeS, GEFeW was implemented using the SSGA and EDA techniques within the X-TOOLSS suite. The parameters for $\text{GEFeW}_{\text{SSGA}}$ and $\text{GEFeW}_{\text{EDA}}$ were the same as those used in Chapter 3 for $\text{GEFeS}_{\text{SSGA}}$ and $\text{GEFeS}_{\text{EDA}}$. The GEFeW instances were also run 30 times with a maximum of 1000 function evaluations allowed on each run.

Table 4.1 shows the comparative results of the performances of GEFeS and GEFeW. As in Table 3.1, the first column represents the biometric modalities used, the second column represents the methods that were compared, the third column records the average recognition accuracy, and the fourth column records the average percentage of features used.

Table 4.1. FRGC-105 Optimization Experiment Results of GEFeS and GEFeW

Modalities	Method	Average Recognition Accuracy	Average % of Features Used
Face-Only	$Baseline_{E}$	65.76%	100.00%
	$GEFeS_{SSGA}(Face_{E})$	86.13%	50.30%
	$GEFeS_{EDA}(Face_{E})$	85.59%	42.86%
	$GEFeW_{SSGA}(Face_{E})$	87.56%	87.16%
	$GEFeW_{EDA}(Face_{E})$	87.81%	96.53%
	$Baseline_{L}$	98.00%	100.00%
	$GEFeS_{SSGA}(Face_{L})$	100.00%	43.59%
	$GEFeS_{EDA}(Face_{L})$	99.71%	39.66%
	$GEFeW_{SSGA}(Face_{L})$	99.37%	85.69%
	$GEFeW_{EDA}(Face_{L})$	99.05%	94.99%
Periocular-Only	$Baseline_{L}$	94.29%	100.00%
	$GEFeS_{SSGA}(Perio_{L})$	95.14%	48.03%
	$GEFeS_{EDA}(Perio_{L})$	95.87%	41.03%
	$GEFeW_{SSGA}(Perio_{L})$	95.46%	86.22%
	$GEFeW_{EDA}(Perio_{L})$	94.67%	95.78%
Face + Periocular	$Baseline_{EL}(0.5, 0.5)$	90.77%	100.00%
	$Baseline_{EL}(0.11, 0.89)$	95.24%	100.00%
	$GEFeS_{SSGA}(Face_{E}, Perio_{L})$	97.40%	48.18%
	$GEFeS_{EDA}(Face_{E}, Perio_{L})$	96.70%	45.24%
	$GEFeW_{SSGA}(Face_{E}, Perio_{L})$	98.98%	87.59%
	$GEFeW_{EDA}(Face_{E}, Perio_{L})$	96.64%	97.40%
	$Baseline_{LL}(0.5, 0.5)$	99.52%	100.00%
	$Baseline_{LL}(0.69,0.31)$	100.00%	100.00%
	$GEFeS_{SSGA}(Face_{L}, Perio_{L})$	100.00%	45.16%
	$GEFeS_{EDA}(Face_{L}, Perio_{L})$	100.00%	41.94%
	$GEFeW_{SSGA}(Face_{L}, Perio_{L})$	100.00%	86.80%
	$GEFeW_{EDA}(Face_{L}, Perio_{L})$	100.00%	95.37%

The performances of the baseline methods, GEFeS, and GEFeW were compared with respect to average recognition accuracy and the average percentage of features used. An ANOVA test [73] was used to determine whether the differences of these performances were statistically significant and to divide them into equivalence classes. For an ANOVA test, if the *p-value* < 0.05, the performances of the methods were different. The method with the highest average was then excluded from analysis, and the performances of the remaining methods were analyzed with either an ANOVA test (if more than two methods remain) or a t-test (if only two methods are being compared). For the t-test, as in Chapter 3, two methods were considered statistically different if $t_{stat} > t_{crit}$. The results of the statistical tests were then used to classify the performance of the methods into equivalence classes. The equivalence classes were ordered based on superiority, therefore methods in lower equivalence classes outperformed those in higher equivalence classes. In addition, methods within the same equivalence class were the same statistically.

4.2.1 Face-Only

4.2.1.1 Face$_E$

With respect to the Face-Only Eigenface results, the instances of GEFeW performed better than the baseline method. The instances of GEFeW also outperformed the instances of GEFeS in terms of accuracy. In terms of equivalence classes, the performances of GEFeW$_{SSGA}$ and GEFeW$_{EDA}$ were in the first equivalence class, while the performances of GEFeS$_{SSGA}$ and GEFeS$_{EDA}$ were in the second equivalence class. However, in terms of feature reduction, the instances of GEFeS outperformed the instances of GEFeW.

4.2.1.2 Face$_L$

With respect to the Face-Only LBP results, when compared to the baseline method, the instances of GEFeW had higher recognition accuracies and used fewer features. Yet, the instances of GEFeS outperformed the instances of GEFeW in terms of accuracy and the percentage of features used.

In terms of accuracy, $GEFeS_{SSGA}$ was the best performing GEC, achieving 100% recognition accuracy. The performance of $GEFeS_{EDA}$ was in the second equivalence class, while the performance of $GEFeW_{SSGA}$ was in the third equivalence class, and the performance of $GEFeW_{EDA}$ was in the fourth equivalence class.

In terms of feature reduction, the performance of $GEFeS_{EDA}$ was in the first equivalence class, $GEFeS_{SSGA}$ was in the second equivalence class, $GEFeW_{SSGA}$ was in the third equivalence class, and $GEFeW_{EDA}$ was in the fourth equivalence classes.

4.2.2 Periocular-Only

With respect to the Periocular-Only results, GEFeW outperformed the baseline method. However, when compared to GEFeS in terms of accuracy, $GEFeS_{EDA}$ had the best performance. The performances of $GEFeS_{SSGA}$ and $GEFeW_{SSGA}$ were in the second equivalence class while the performance of $GEFeW_{EDA}$ was in the fourth equivalence class.

In terms of the percentage of features used, $GEFeS_{EDA}$ also had the best performance. The performances of $GEFeS_{SSGA}$, $GEFeW_{SSGA}$ and $GEFeW_{EDA}$ were in the second, third, and fourth equivalence classes respectively.

4.2.3 Face + Periocular

4.2.3.1 $Face_E$ + $Perio_L$

With respect to the $Face_E$ + $Perio_L$ results, in terms of accuracy, $GEFeW_{SSGA}$ had the highest average recognition accuracy. The performances of the instances of GEFeS were in the second equivalence class, and the performance of $GEFeW_{EDA}$ was in the third equivalence class.

In terms of the percentage of features used, $GEFeS_{EDA}$ performed the best. The performance of $GEFeS_{SSGA}$ was in the second equivalence class, $GEFeW_{SSGA}$ was in the third equivalence class, and $GEFeW_{EDA}$ was in the fourth equivalence class.

4.2.3.2 $Face_L$ + $Perio_L$

With respect to the $Face_L$ + $Perio_L$ results, the instances of GEFeW achieved 100% recognition accuracies. There was not a statistically significant difference in the performance of the instances of GEFeS and GEFeW in terms of accuracy. However, in terms of the percentage of features used, the instances of GEFeS performed better than the instances of GEFeW. $GEFeS_{EDA}$ performed the best in terms of feature reduction. The performance of $GEFeS_{SSGA}$ was in the second equivalence class, while the performance of $GEFeW_{SSGA}$ was in the third equivalence class. The performance of $GEFeW_{EDA}$ was in the fourth equivalence class.

4.3 Discussion of Results

Our results showed that GEFeW performed better than the baseline methods in terms of accuracy and the percentage of features used. However, it would not be the best technique to use if we were to implement Gentile's two-stage hierarchical system because it uses a higher percentage of features when compared to GEFeS.

To illustrate the performance of GEFeW, GEFeS, and the baseline methods, the CMC curves for the unimodal and multimodal results are shown in Figures 4.1 to 4.2. Figures 4.1 and 4.2 show the CMC curves for the Face-Only results. In Figure 4.1, the instances of GEFeS and GEFeW outperformed the baseline Eigenface method for Ranks 1-10. At Rank 1, $GEFeW_{EDA}$ has the highest accuracy. However, by Rank 3, GEFeW$_{SSGA}$ performs the best. In Figure 4.2, at Rank 1 the instances of GEFeS and GEFeW outperformed the baseline LBP method. GEFeS$_{EDA}$ and GEFeW$_{SSGA}$ achieved 100% Rank 1 accuracies. GEFeS$_{SSGA}$ reaches 100% recognition accuracy at Rank 2, and GEFeW$_{EDA}$ achieves 100% recognition accuracy at Rank 5.

Figure 4.3 shows the CMC curve for the Periocular-Only results. The instances of GEFeS and GEFeW achieved higher Rank 1 accuracies than the baseline LBP method. In addition, GEFeS$_{SSGA}$, GEFeS$_{EDA}$, and GEFeW$_{SSGA}$ performed best for Ranks 1-4.

Figures 4.4 and 4.5 show the CMC curves for the Face + Periocular results. In these CMC curves, the instances of GEFeS and GEFeW achieved 100% recognition accuracy at Rank 1, outperforming the baseline method while using significantly fewer features.

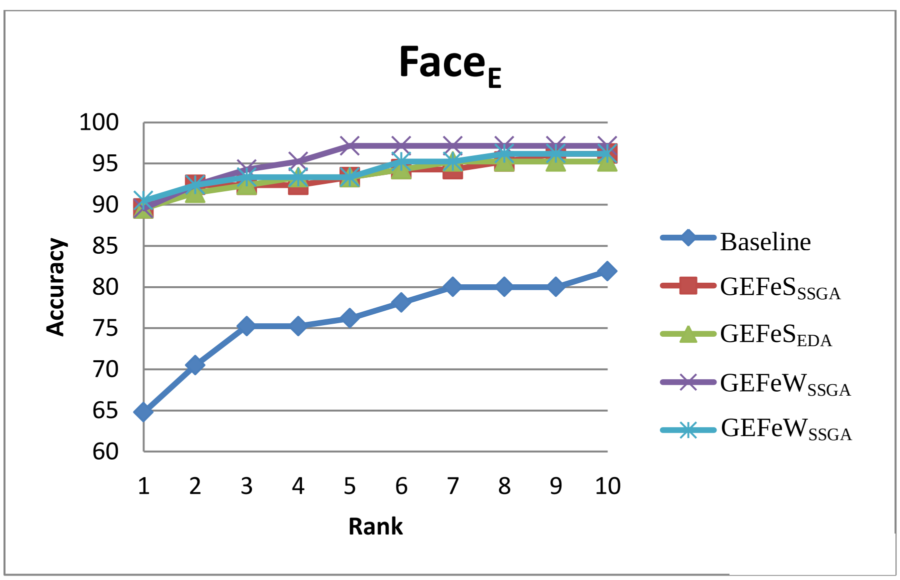

Figure 4.1. CMC Curves for GEFeS(Face$_E$) and GEFeW(Face$_E$).

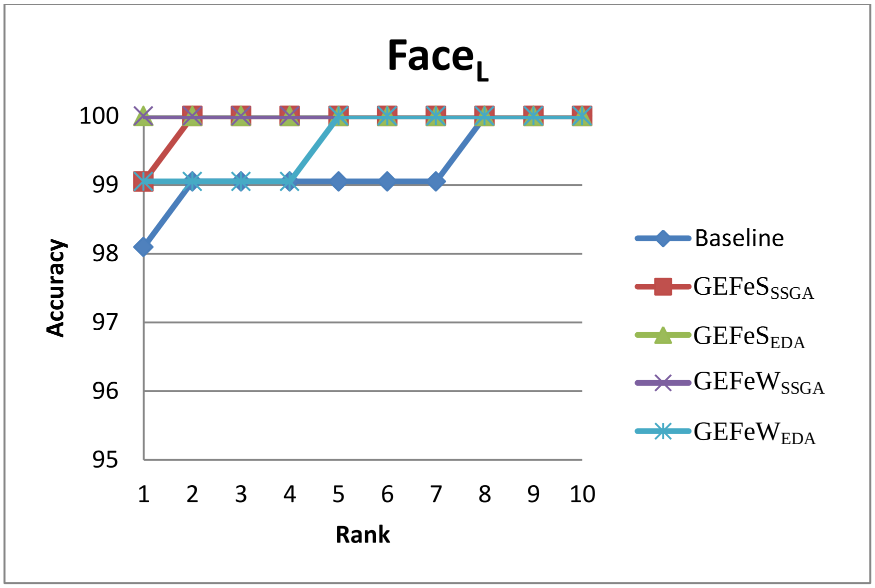

Figure 4.2. CMC Curves for GEFeS(Face$_L$) and GEFeW(Face$_L$).

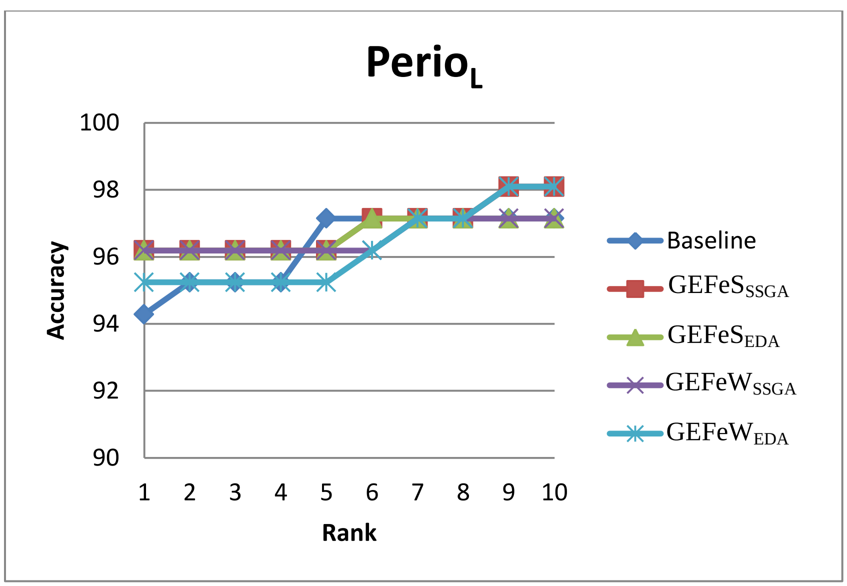

Figure 4.3. CMC Curves for GEFeS(Perio$_L$) and GEFeW(Perio$_L$).

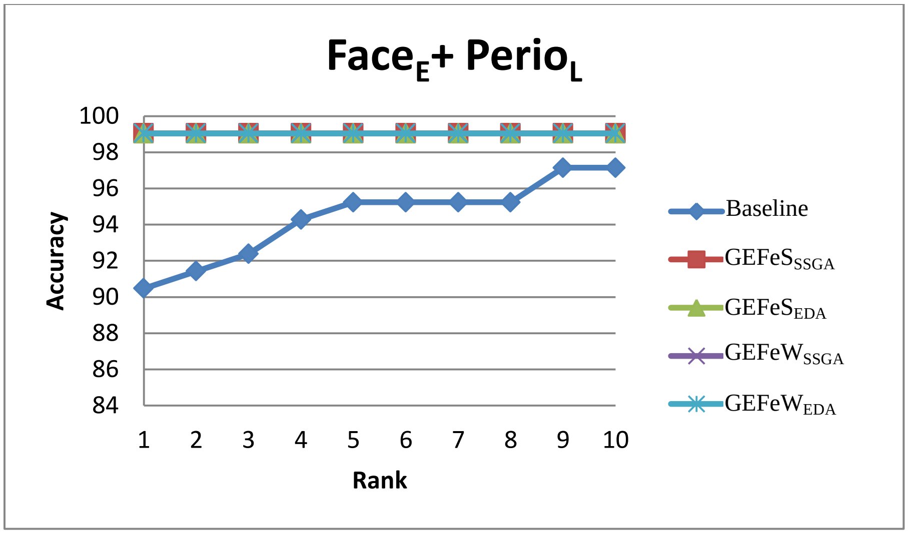

Figure 4.4. CMC Curves for GEFeS(Face$_E$, Perio$_L$) and GEFeW(Face$_E$, Perio$_L$).

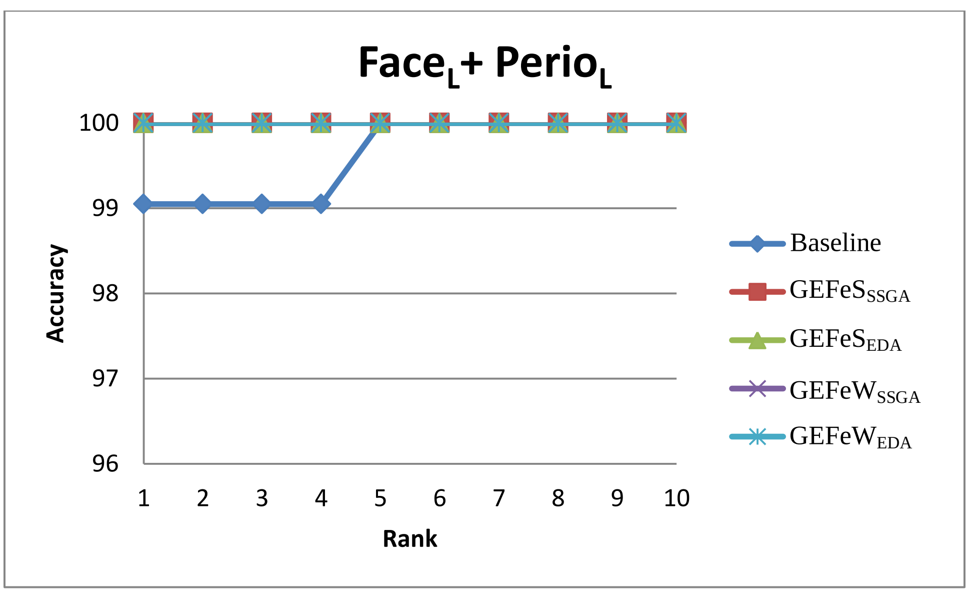

Figure 4.5. CMC Curves for GEFeS(Face$_L$, Perio$_L$) and GEFeW(Face$_L$, Perio$_L$).

CHAPTER 5

Hybrid Genetic & Evolutionary Feature Weighting and Selection (GEFeWS)

In Chapter 3, we presented Genetic & Evolutionary Feature Selection (GEFeS) and in Chapter 4, we presented a variant of GEFeS, known as Genetic & Evolutionary Feature Weighting (GEFeW). Our results showed that GEFeS performed better at reducing the dimensionality of the feature sets, while GEFeW performed better in terms of recognition accuracy. However, it is possible to combine these two techniques to further improve the performance of Genetic & Evolutionary Feature Selection. In this chapter, we present a GEFeS/GEFeW hybrid referred to as Genetic & Evolutionary Feature Weighting/Selection (GEFeWS) [9, 65].

Similar to GEFeS and GEFeW, GEFeWS evolves a population of real-valued candidate FMs. Values within the FMs that are less than 0.5 are set to 0, masking out the corresponding features as done by GEFeS. Otherwise, the values are used to weight the features as done by GEFeW.

GEFeWS was used to evolve FMs for face-only, periocular-only, and face + periocular templates. The templates within the probe and gallery sets were compared using the following weighted Manhattan distance formula:

$$wMD_3\left(h_j, h_l, fm_i\right) = \sum_{k=0}^{n-1} \left|h_{j,k} - h_{l,k}\right| q(\mu_{i,k}) \tag{24}$$

$$q\left(\mu_{i,k}\right) = \begin{cases} \mu_{i,k}, if\ \mu_{i,k} \geq 0.5 \\ 0, otherwise \end{cases} \tag{25}$$

where wMD_3 is the weighted Manhattan distance (the subscript *3* denotes our third technique, GEFeWS), h_j and h_l are two feature templates which are being compared, n is the original number of features, $\mu_{i,k}$ is the k^{th} feature of fm_i, and the function q represents the process of feature weighting/selection as performed by GEFeWS.

As in the previous chapters, the subject associated with the template within the gallery set with the smallest weighted Manhattan distance (smallest fused score for the multibiometric system) when compared to the probe was considered the match. In addition, each candidate FM was evaluated using Equation 19 presented in Chapter 3.

5.1 Experiments

To test the efficiency of GEFeWS as compared with GEFeS and GEFeW, the FRGC-105 Optimization Experiment was performed as described in Chapter 3. The performance of GEFeWS on the face-only, periocular-only, and face + periocular templates was compared to the performances of GEFeS, GEFeW, and the baseline methods presented in the previous chapters.

5.2 Results

For the FRGC-105 Optimization Experiment, GEFeWS was implemented using the X-TOOLSS SSGA and EDA. The parameters selected for the instances of GEFeWS were the same as those used for GEFeS and GEFeW. As with GEFeS and GEFeW, each instance of GEFeWS was run 30 times with a maximum of 1000 function evaluations allowed for each run.

The results of the performance of GEFeWS as compared with GEFeS and GEFeW are shown in Table 5.1. The first column represents the biometric modalities. The second column represents the methods that were compared. The third column records the average recognition accuracy and the fourth column records the average percentage of features used. The performances of the methods were separated into equivalence classes in terms of accuracy and the percentage of features used by performing ANOVA and t-tests.

5.2.1 Face-Only

5.2.1.1 $Face_E$

With respect to the Face-Only Eigenface results, the instances of GEFeWS performed better than the baseline method in terms of accuracy and used significantly fewer features. Comparing the performances of the methods in terms of accuracy, $GEFeWS_{EDA}$ was in the first equivalence class along with the instances of GEFeW. The performance of $GEFeWS_{SSGA}$ was in the second equivalence class along with the performances of the instances of GEFeS.

In terms of the percentage of features used, the performance of $GEFeWS_{EDA}$ was in the first equivalence class along with the performance of $GEFeS_{EDA}$, which used approximately 43% of the features. The performance of $GEFeS_{SSGA}$ was in the second equivalence class and the performance of $GEFeWS_{SSGA}$ was in the third equivalence class. The performances of $GEFeW_{SSGA}$ and $GEFeW_{EDA}$ were in the fourth and fifth equivalence classes respectively.

Table 5.1. FRGC-105 Optimization Experiment Results of GEFeS, GEFeW, and GEFeWS

Modalities	Method	Average Recognition Accuracy	Average % of Features Used
Face-Only	$Baseline_E$	65.76%	100.00%
	$GEFeS_{SSGA}(Face_E)$	86.13%	50.30%
	$GEFeS_{EDA}(Face_E)$	85.59%	42.86%
	$GEFeW_{SSGA}(Face_E)$	87.56%	87.16%
	$GEFeW_{EDA}(Face_E)$	87.81%	96.53%
	$GEFeWS_{SSGA}(Face_E)$	86.38%	51.71%
	$GEFeWS_{EDA}(Face_E)$	87.02%	43.35%
	$Baseline_L$	98.00%	100.00%
	$GEFeS_{SSGA}(Face_L)$	100.00%	43.59%
	$GEFeS_{EDA}(Face_L)$	99.71%	39.66%
	$GEFeW_{SSGA}(Face_L)$	99.37%	85.69%
	$GEFeW_{EDA}(Face_L)$	99.05%	94.99%
	$GEFeWS_{SSGA}(Face_L)$	100.00%	43.69%
	$GEFeWS_{EDA}(Face_L)$	99.75%	38.83%
Periocular-Only	$Baseline_L$	94.29%	100.00%
	$GEFeS_{SSGA}(Perio_L)$	95.14%	48.03%
	$GEFeS_{EDA}(Perio_L)$	95.87%	41.03%
	$GEFeW_{SSGA}(Perio_L)$	95.46%	86.22%
	$GEFeW_{EDA}(Perio_L)$	94.67%	95.78%
	$GEFeWS_{SSGA}(Perio_L)$	96.16%	45.39%
	$GEFeWS_{EDA}(Perio_L)$	95.75%	41.01%
Face + Periocular	$Baseline_{EL}(0.5, 0.5)$	90.77%	100.00%
	$Baseline_{EL}(0.11, 0.89)$	95.24%	100.00%
	$GEFeS_{SSGA}(Face_E, Perio_L)$	97.40%	48.18%
	$GEFeS_{EDA}(Face_E, Perio_L)$	96.70%	45.24%
	$GEFeW_{SSGA}(Face_E, Perio_L)$	98.98%	87.59%
	$GEFeW_{EDA}(Face_E, Perio_L)$	96.64%	97.40%
	$GEFeWS_{SSGA}(Face_E, Perio_L)$	98.48%	46.24%
	$GEFeWS_{EDA}(Face_E, Perio_L)$	98.10%	41.72%
	$Baseline_{LL}(0.5, 0.5)$	99.52%	100.00%
	$Baseline_{LL}(0.69,0.31)$	100.00%	100.00%
	$GEFeS_{SSGA}(Face_L, Perio_L)$	100.00%	45.16%
	$GEFeS_{EDA}(Face_L,Perio_L)$	100.00%	41.94%
	$GEFeW_{SSGA}(Face_L, Perio_L)$	100.00%	86.80%
	$GEFeW_{EDA}(Face_L, Perio_L)$	100.00%	95.37%
	$GEFeWS_{SSGA}(Face_L, Perio_L)$	100.00%	45.18%
	$GEFeWS_{EDA}(Face_L, Perio_L)$	99.94%	42.00%

5.2.1.2 *Face$_L$*

With respect to the Face-Only LBP results, the instances of GEFeWS achieved higher accuracies than the baseline method while using less than 50% of the features. Comparing the performances of the GECs in terms of accuracy, GEFeWS$_{SSGA}$ and GEFeS$_{SSGA}$ were in the first equivalence class, accurately recognizing all of the subjects for each of the 30 runs. The performances of GEFeWS$_{EDA}$ and GEFeS$_{EDA}$ were in the second equivalence class, GEFeW$_{SSGA}$ was in the third equivalence class, and GEFeW$_{EDA}$ was in the fourth equivalence class.

In terms of feature reduction, the performance of GEFeWS$_{EDA}$ was in the first equivalence class, using an average of 38.83% of the features. The performance of GEFeS$_{EDA}$ was in the second equivalence class, while the performances of GEFeS$_{SSGA}$ and GEFeWS$_{SSGA}$ were in the third equivalence class. The performances of GEFeW$_{SSGA}$ and GEFeW$_{EDA}$ were in the fourth and fifth equivalence classes respectively.

5.2.2 Periocular Only

For the Periocular-Only results, the instances of GEFeWS outperformed the baseline method in terms of accuracy and feature reduction. In addition, when compared to the other techniques in terms of accuracy, GEFeWS$_{EDA}$ performed the best, having a 96.16% average accuracy. The performances of GEFeWS$_{SSGA}$ and GEFeS$_{EDA}$ were in the second equivalence class, GEFeS$_{SSGA}$ and GEFeW$_{SSGA}$ were in the third equivalence class, and GEFeW$_{EDA}$ was in the fourth equivalence class.

In terms of the percentage of features used, the performances of GEFeWS$_{EDA}$ and GEFeS$_{EDA}$ were in the first equivalence class using only 41% of the features. The performance of $GEFeWS_{SSGA}$, $GEFeS_{SSGA}$, $GEFeW_{SSGA}$ and $GEFeW_{EDA}$ were in the second, third, fourth, and fifth equivalence classes respectively.

5.2.3 Face + Periocular

5.2.3.1 $Face_E$ + $Perio_L$

For the $Face_E$ + $Perio_L$ results, the instances of GEFeWS outperformed both of the baseline methods. Comparing the GECs in terms of accuracy, $GEFeW_{SSGA}$ still had the highest average accuracy. The performance of $GEFeWS_{SSGA}$ belonged to the second equivalence class while the performance of $GEFeWS_{EDA}$ belonged to the third equivalence class. The performances of $GEFeS_{SSGA}$ and $GEFeS_{EDA}$ were in the fourth equivalence, and the performance of $GEFeW_{EDA}$ was in the fifth equivalence class.

In terms of the percentage of features used, however, $GEFeWS_{EDA}$ performed the best. The performances of $GEFeS_{EDA}$ and $GEFeWS_{SSGA}$ were in the second equivalence class, $GEFeS_{SSGA}$ was in the third equivalence class, $GEFeW_{SSGA}$ was in the fourth equivalence class, and $GEFeW_{EDA}$ was in the fifth equivalence class.

5.2.3.2 $Face_L$ + $Perio_L$

For the $Face_L$ + $Perio_L$ system, the instances of GEFeWS outperformed the baseline methods. In addition, when compared to the other GECs in terms of accuracy, the performances of the instances of GEFeWS were in the first equivalence class along with the instances of GEFeS and GEFeW.

In terms of the percentage of features used, $GEFeS_{EDA}$ used the smallest percentage of features. The performance of $GEFeWS_{EDA}$ was in the second equivalence class. The performances of $GEFeS_{SSGA}$ and $GEFeWS_{SSGA}$ were in the third equivalence class. $GEFeW_{SSGA}$ was in the fourth equivalence class, and $GEFeW_{EDA}$ was in the fifth equivalence class.

5.3 Discussion of Results

Our results showed that GEFeWS is able to achieve higher recognition accuracies than using GEFeS alone, while using significantly fewer features to achieve approximately the same accuracies as using GEFeW. Our results suggest that GEFeWS would be the most appropriate technique to use to create the short-length templates to be used in a Gentile-style biometric recognition system.

To better visualize the identification performance of GEFeWS in comparison to the other techniques, the CMC curves for the best performing FMs for the FRGC-105 Optimization experiment are shown in the Figures 5.1 to 5.5.

Figure 5.1 shows the CMC curves for the Face-Only Eigenface results. At Rank 1, all of the GECs have an accuracy of approximately 90%, significantly outperforming the baseline method. At Rank 2, $GEFeWS_{SSGA}$ had the highest recognition accuracy. At Rank 3, $GEFeW_{SSGA}$ had the highest recognition accuracy; however, it is important to note that $GEFeW_{SSGA}$ also used the highest percentage of features. $GEFeWS_{SSGA}$ obtained accuracy only slightly lower that $GEFeW_{SSGA}$ while using approximately 50% of the features.

Figure 5.2 shows the CMC curves for the Face-Only LBP results. The instances of GEFeWS achieved 100% Rank 1 accuracies, while using less than 45% of the features.

Figure 5.3 shows the CMC curves for the Periocular-Only results. For Ranks 1-4, the instances of GEFeWS, along with the instances of GEFeS and $GEFeW_{SSGA}$, had the highest accuracies. At Rank 5, $GEFeWS_{SSGA}$ and the baseline method had the highest recognition accuracy. However, $GEFeWS_{SSGA}$ used less than 50% of the features.

Figures 5.4 and 5.5 show the CMC curves for the multibiometric results. The best FMs for each of our techniques significantly outperformed the baseline methods. For the $Face_E$ + $Perio_L$ system, the techniques achieved 99% Rank 1 accuracies. For the $Face_L$ + $Perio_L$ system, the techniques achieved 100% Rank 1 accuracies.

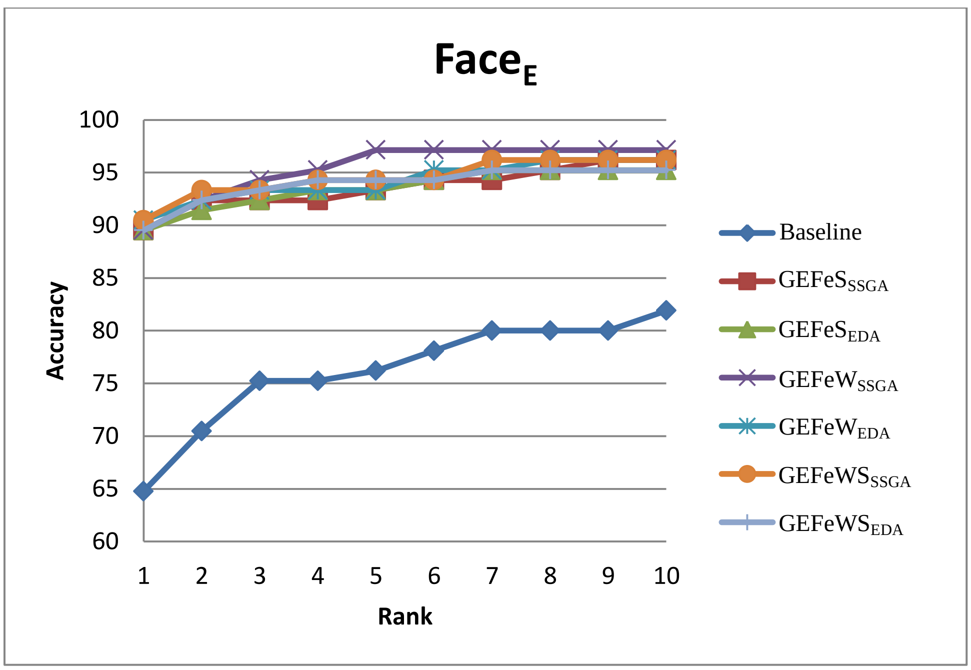

Figure 5.1. CMC Curves for GEFeS($Face_E$), GEFeW($Face_E$), and GEFeWS($Face_E$).

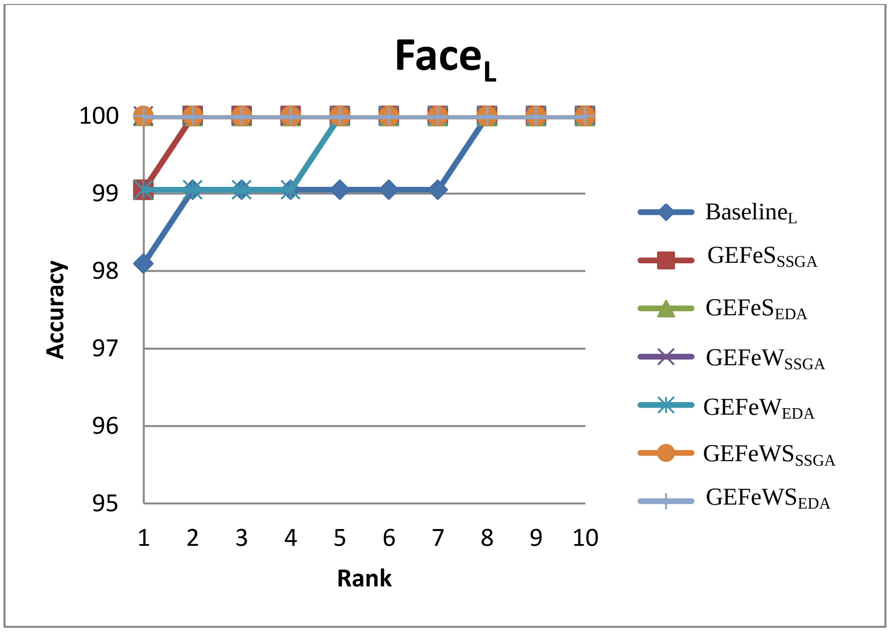

Figure 5.2. CMC Curves for GEFeS(Face$_L$), GEFeW(Face$_L$), and GEFeWS(Face$_L$).

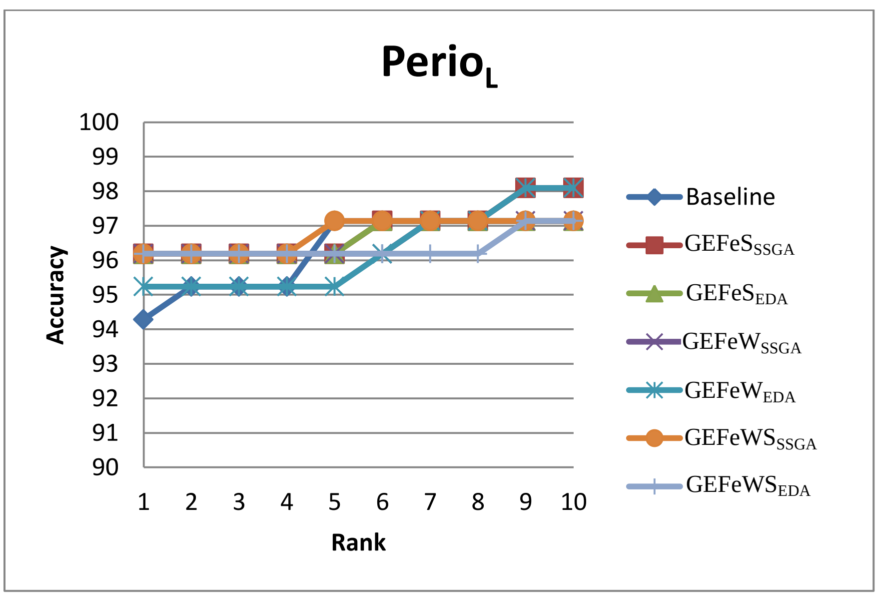

Figure 5.3. CMC Curves for GEFeS(Perio$_L$), GEFeW(Perio$_L$), and GEFeWS(Perio$_L$).

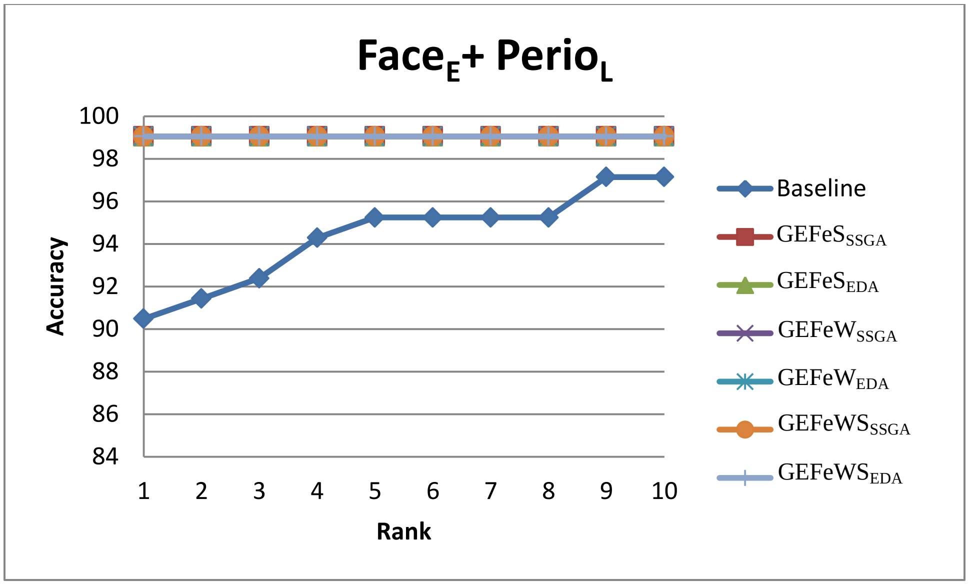

Figure 5.4. CMC Curves for GEFeS($Face_E$, $Perio_L$), GEFeW($Face_E$, $Perio_L$), and GEFeWS($Face_E$, $Perio_L$).

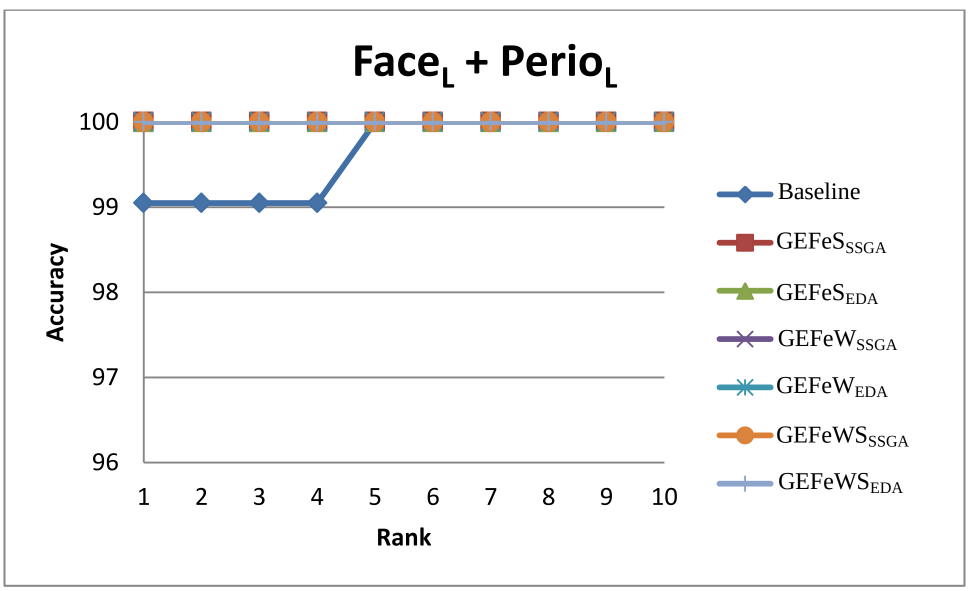

Figure 5.5. CMC Curves for GEFeS($Face_L$, $Perio_L$), GEFeW($Face_L$, $Perio_L$), and GEFeWS($Face_L$, $Perio_L$).

CHAPTER 6

GEFeWS-Machine Learning (GEFeWS$_{ML}$)

In the previous chapters, we addressed an optimization problem for the development of short-length templates for use in a Gentile-based recognition system. In this chapter, we extend the work presented in Chapter 5 and present a hybrid GEC known as Genetic & Evolutionary Feature Weighting/Selection – Machine Learning (GEFeWS$_{ML}$) [115]. GEFeWS$_{ML}$ is similar to GEFeWS with the exception that the machine learning concept of cross validation is incorporated in an effort to evolve FMs that generalize well to unseen subjects.

As mentioned in Section 1.4, in cross validation, the total set of available subjects is broken up into three sets: a training set, a validation set, and a test set. GEFeWS$_{ML}$, which is an instance of an EDA (because GEFeWS$_{EDA}$ performed better than GEFeWS$_{SSGA}$ in Chapter 5), works as follows. An initial population of Q real-valued candidate FMs is randomly generated. Each candidate FM is then evaluated, using Equation 19, based on its performance on a training set. The candidate FMs are also applied to a validation set, and the best performing candidate FM on the validation set, which will be referred to as *FM**, is retained. Next, the top 50% performing candidate FMs in the population are used to form a probability density function (PDF). The PDF is then sampled to create $(1-\alpha)Q$ offspring FMs, where α is the percentage of elites. Each offspring is evaluated and assigned a fitness based on its performance on the training set. In addition, the offspring are evaluated based on their performance on the validation set. The offspring's performance on the validation set is then compared to the performance of

*FM**. If its performance is better than *FM**, the offspring will become the new *FM**. A new population is then formed using αQ elites, and the $(1\text{-}\alpha)Q$ offspring. This process continues until a user-specified stopping condition is satisfied. When the stopping condition has been satisfied, the best performing FM in the population as well as *FM** are returned. Figure 6.1 provides a flowchart of the GEFeWS_{ML} learning process.

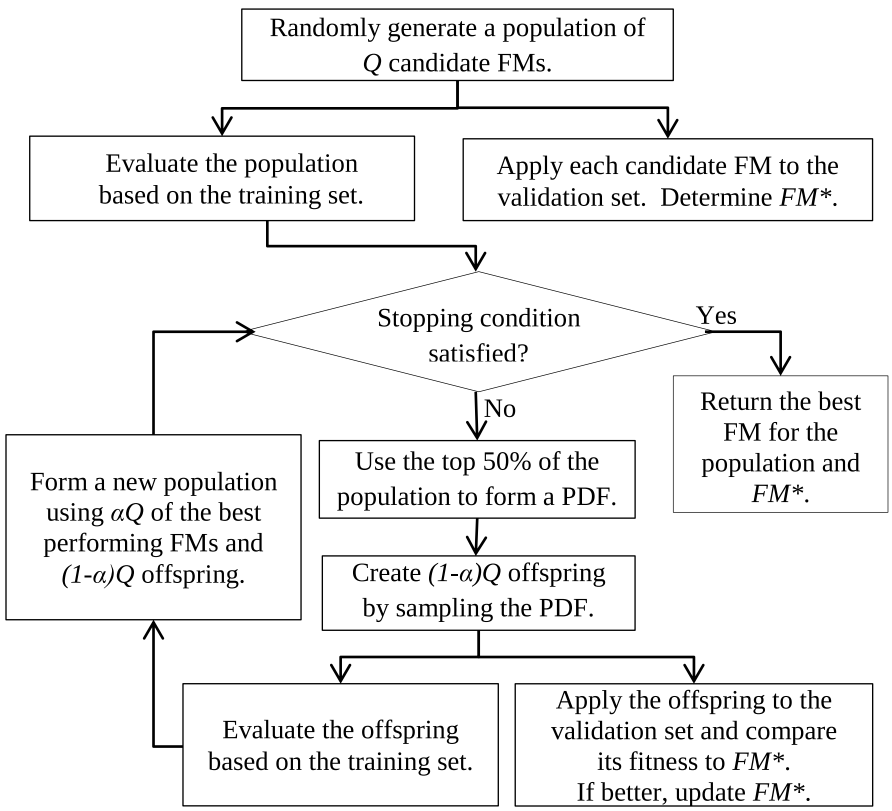

Figure 6.1. Flowchart of the GEFeWS_{ML} Learning Process.

6.1 Experiments

To examine the generalization ability of the evolved FMs, we used a cross validation strategy: a training set, a validation set, and a test set. For our experiment, FRGC-105 (described in Chapter 3) was used as the training set. An additional 204 subjects were selected from the FRGC database and were used to form our validation and test set. The validation set was formed using 105 of the selected subjects and will be referred to as the FRGC-105b dataset. The test set consisted of the remaining 99 subjects and will be referred to as the FRGC-99 dataset. For each of these datasets, one image of each subject was used to form the probe set and two additional images of each subject were used to form the gallery set. As before, the images selected were frontal views of the subjects with neutral facial expressions and the images were preprocessed as described in Chapter 3. For each selected image, the LBP method was used to extract 2124 (*36* patches × *59* bins) facial features and 2832 (*24* patches × *59* bins = *1416* features per periocular region) periocular features. Only the LBP method was used to extract features because the resulting LBP templates performed best in the previous experiment.

For our experiment, as done with GEFeWS, $GEFeWS_{ML}$ was used to evolve FMs for the FRGC-105 face, periocular, and face + periocular templates. As in the previous chapters, this will be referred to as FRGC-105 Optimization. The evolved FMs were then applied to the test set in order to evaluate how well they generalized to unseen subjects. This will be referred to as FRGC-99 Opt-Gen. In addition, the best performing FMs for the validation set, *FM**s, were applied to the test set in order to evaluate how well they generalized to unseen subjects. This will be referred to as FRGC-99 Val-Gen.

6.2 Results

The EDA instance of $GEFeWS_{ML}$ used a population size of 20 and always retained 5 ($\alpha = 0.2$) elites. $GEFeWS_{ML}$ was run 30 times with a maximum of 1000, 2000, and 4000 function evaluations allowed. At the end of each run, the best performing FM on the training set and the best performing FM on the validation set, *FM**, were returned. These FMs were then applied to FRGC-99.

The optimization and generalization performances are presented in Table 6.1. The first column represents the biometric modalities and the second column represents the methods that were compared. Note that for each method, the number of function evaluations allowed is denoted in parentheses. The FRGC-105 Optimization performances are represented in the third column, the FRGC-99 Opt-Gen performances are in the fourth column, and the FRGC-99 Val-Gen performances are in the final column. For the last three columns, the first number denotes the average recognition accuracy and the number in parentheses denotes the average percentage of features used.

Table 6.1. Optimization and Generalization Results for the FRGC Datasets

Modality	Method	**FRGC-105 Optimization** *Acc. (% feat)*	**FRGC-99 Opt-Gen** *Acc. (% feat)*	**FRGC-99 Val-Gen** *Acc. (% feat)*
Face Only	$GEFeWS_{ML(1000)}$	0.997 (38.3%)	0.974 (38.3%)	0.984 (45.5%)
	$GEFeWS_{ML(2000)}$	0.997 (35.1%)	0.966 (35.1%)	0.986 (45.5%)
	$GEFeWS_{ML(4000)}$	0.996 (34.4%)	0.975 (34.4%)	0.985 (45.0%)
Periocular Only	$GEFeWS_{ML(1000)}$	0.958 (40.7%)	0.876 (40.7%)	0.882 (46.4%)
	$GEFeWS_{ML(2000)}$	0.957 (37.4%)	0.870 (37.4%)	0.870 (45.3%)
	$GEFeWS_{ML(4000)}$	0.956 (36.7%)	0.872 (36.7%)	0.874 (46.0%)
Face + Periocular	$GEFeWS_{ML(1000)}$	1.00 (41.3%)	0.994 (41.3%)	0.994 (42.8%)
	$GEFeWS_{ML(2000)}$	1.00 (38.7%)	0.994 (38.7%)	0.994 (41.3%)
	$GEFeWS_{ML(4000)}$	1.00 (38.2%)	0.994 (38.2%)	0.994 (41.6%)

The performances of the $GEFeWS_{ML}$ methods were separated into equivalence classes based on accuracy and the percentage of features used by performing the ANOVA and t-tests. As explained in Chapter 4, for an ANOVA test, the performances of the methods were considered statistically different if the *p-value* < 0.05. For the t-test, the performances of two methods were considered statistically different if $t_{stat} > t_{crit}$. Methods that had higher recognition accuracies and used lower percentage of features were preferred.

6.2.1 Face-Only

With respect to the Face-Only FRGC-99 Opt-Gen results, the evolved FMs generalized well to the test set. In terms of the average recognition accuracy, there was not a statistically significant difference between the performances of $GEFeWS_{ML}$. However, in terms of feature usage, $GEFeWS_{ML(4000)}$ performed best and was in the first equivalence class. $GEFeWS_{ML(2000)}$ was in the second equivalence class, while $GEFeWS_{ML(1000)}$ was in the third equivalence classes.

Similarly, with respect to the FRGC-99 Val-Gen results, the best performing FMs on the validation set generalized well to the test set. When the performances of $GEFeWS_{ML}$ were compared in terms of accuracy and the percentage of features used, there was not a statistically significant difference between their performances.

Comparing the performances of Val-Gen and Opt-Gen, the Val-Gen performances were better in terms of accuracy. This result shows that cross validation improves the performance when generalizing to unseen subjects. However, in terms of the percentage of features used, the Val-Gen performances used more features than the Opt-Gen performances. This is most likely because more features may be needed for adequate generalization.

In summary, $GEFeWS_{ML(4000)}$ performed best for the Face-Only templates, using the fewest percentage of features while achieving accuracies that were practically the same as the other methods. In addition, in terms of accuracy, the FM*s performed better on the test set than the FM^{ts}s. However, the FM*s used more features than the FM^{ts}s, probably because more features may be required for adequate generalization.

6.2.2 Periocular-Only

With respect to the Periocular-Only FRGC-99 Opt-Gen results, the evolved FMs generalized well to the test set. Comparing the Opt-Gen performances in terms of accuracy, there was not a statistically significant difference. However, in terms of the percentage of features used, $GEFeWS_{ML(4000)}$ was in the first equivalence class,

$GEFeWS_{ML(2000)}$ was in the second equivalence class, and $GEFeWS_{ML(1000)}$ was in the third equivalence class.

Likewise, with respect to the FRGC-99 Val-Gen results, the best performing FMs on the validation set generalized well to the test set. In terms of accuracy, $GEFeWS_{ML(1000)}$ was in the first equivalence class, while $GEFeWS_{ML(2000)}$ and $GEFeWS_{ML(4000)}$ were both in the second equivalence class. In terms of feature usage, there was no statistical difference between the $GEFeWS_{ML}$ performances.

When the performances of FRGC-99 Opt-Gen and Val-Gen were compared, in terms of accuracy, there was only a statistical difference between the $GEFeWS_{ML(1000)}$ performances. For $GEFeWS_{ML(1000),}$ the Val-Gen performances were better statistically. In terms of feature usage, the Opt-Gen performances outperformed the Val-Gen performances.

In summary, for the Periocular-Only templates, $GEFeWS_{ML(4000)}$ performed best for FRGC-105 Optimization and FRGC-99 Opt-Gen. $GEFeWS_{ML(4000)}$ achieved recognition rates statistically equivalent to the other methods, while using significantly fewer features. Although for Val-Gen, $GEFeWS_{ML(1000)}$ performed best statistically, there may not be a practical difference between the performance of $GEFeWS_{ML(4000)}$.

6.2.3 Face + Periocular

With respect to the Face + Periocular FRGC-99 Opt-Gen results, the evolved FMs had an average recognition accuracy of 99.4%. Comparing the Opt-Gen performances in terms of accuracy, there was not a statistically significant difference. However, in terms of the percentage of features used, the performance of $GEFeWS_{ML(4000)}$ was in the first equivalence class, the performance of $GEFeWS_{ML(2000)}$ was in the second equivalence class, and the performance of $GEFeWS_{ML(1000)}$ was in the third equivalence class.

With respect to the FRGC-99 Val-Gen results, the best performing FMs on the validation set generalized well to the test set. Comparing the Val-Gen performances, there was not a statistically significant difference in terms of accuracy. However, in terms of feature usage, $GEFeWS_{ML(2000)}$ and $GEFeWS_{ML(4000)}$ were in the first equivalence class.

In addition, when the performances of Val-Gen and Opt-Gen were compared in terms of accuracy, there was not a statistically significant difference in their performances. However, in terms of the percentage of features used, the performances of Opt-Gen were statistically better.

In summary, for the fusion of the face and periocular feature templates, $GEFeWS_{ML(4000)}$ would also be the best method to use. Statistically, $GEFeWS_{ML(4000)}$ used the fewest percentage of features, while achieving practically the same accuracy as the other methods.

CHAPTER 7

Investigating the Value Preference Space for GEFeWS$_{ML}$

The methods presented in this dissertation have attempted to solve a multiobjective problem. They attempted to evolve FMs that (a) maximize the recognition accuracy and (b) minimize the number of features. However, the fitness function used to evaluate FMs placed more emphasis on the reduction of errors. Referring to Equation 19, the number of errors associated with a given FM was multiplied by 10. As a result, the GECs do not attempt to reduce the number of features until the number of errors has been minimized.

In this chapter, we investigate the relative weighting of each objective using a value preference structure [53]. We searched the value preference space in an attempt to analyze its impact in respect to optimization and generalization. In order to do this, we evaluated GEFeWS$_{ML}$ using the evaluation function as shown in Equation 26, where $\eta \in \{0.1, 0.2, \ldots, 1.0\}$, ε is the number of recognition errors that occurred when the candidate FM was applied to the probe and gallery templates, N is the number of subjects in the probe set, m is the number of features used by the candidate FM, and where n is the original number of features in the templates.

$$fit_i = \eta \frac{\varepsilon}{N} + (1 - \eta) \frac{m}{n} \tag{26}$$

7.1 Experiments

To examine the effect searching the value preference space has on the optimization and generalization ability of GEFeWS$_{ML}$, the following experiment was performed. As in Chapter 6, we employed a cross validation strategy. The FRGC-105 dataset was used as the training set, the FRGC-105b dataset was used as the validation set, and the FRGC-99 dataset was used as the test set. Note that only the LBP templates were used in this experiment because they performed best in our previous experiments.

GEFeWS$_{ML}$ was used to evolve FMs for the face, periocular, and face + periocular templates within the training set, FRGC-105. As in the previous chapters, we will refer to this process as FRGC-105 Optimization because we are attempting to optimize the recognition accuracy while reducing the number of features needed. The best performing FMs on the training set (FM^{ts}s) and the best performing FMs on the validation set (FM^{*}s) were then applied to the test set in order to evaluate how well they generalized to unseen subjects. As in Chapter 6, this process will be referred to respectively as FRGC-99 Opt-Gen and FRGC-99 Val-Gen.

7.2 Results

As in Chapter 6, GEFeWS$_{ML}$ was an instance of an EDA that used a population size of 20 and always retained 5 elites. Because GEFeWS$_{ML(4000)}$ performed best in Chapter 6, in this chapter GEFeWS$_{ML}$ was run 30 times with a maximum of 4000 function evaluations allowed. At the end of each run, the best performing FM on the training set, FM^{ts}, and the best performing FM on the validation set, FM^*, were applied to FRGC-99.

The results of applying GEFeWS$_{ML}$ to the face-only, periocular-only, and face + periocular templates are presented in Tables 7.1, 7.2, and 7.3. Within these tables, the first column denotes the value of η. The remaining columns present the performances of FRGC-105 Optimization, FRGC-99 Opt-Gen, and FRGC-99 Val-Gen respectively. For these columns, the first number denotes the average recognition accuracy and the average percentage of features used is denoted in parentheses.

The performances of the methods were separated into equivalence classes in terms of accuracy and the percentage of features used by performing ANOVA and t-tests. The performances of the methods that had higher recognition accuracies and used lower percentage of features were considered to be better.

7.2.1 Face-Only

With respect to the Face-Only FRGC-105 Optimization performances, in terms of accuracy, the performance of $\eta = 1.0$ was in the first equivalence class. The performances of the following η values were in the second equivalence class: 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9, while the performances of $\eta = 0.1$ and 0.2 were in the third equivalence class. In contrast, in terms of the percentage of features used, $\eta = 0.1$ was in the first equivalence class, while $\eta = 0.2$, 0.3, and 0.4 were in the second equivalence class. In the third equivalence class was the performances of $\eta = 0.5$ and 0.6, and in the fourth equivalence class was the performances of $\eta = 0.7$, 0.8, and 0.9. The performance of $\eta = 1.0$ was in the fifth equivalence class.

With respect to the FRGC-99 Opt-Gen performances, the FM^{ts}s generalized well to the unseen subjects within the test set. In terms of accuracy, the performances of the following η values were all in the first equivalence class: $\eta = 0.2$, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1.0, while the performances of $\eta = 0.1$ and 0.3 were in the second equivalence class. In terms of feature reduction, the equivalence classes were the same as those for FRGC-105 Optimization.

With respect to the FRGC-99 Val-Gen performances, the FM*s also generalized well to test set. In terms of accuracy, the performances of $\eta = 0.7$, 0.8, 0.9, and 1.0 were all in the first equivalence class, while the remaining η values were in the second equivalence class. However, in terms of the percentage of features used, as the value of η increased, so did the feature percentage. In the first equivalence class was $\eta = 0.1$, while $\eta = 0.2$ and 0.3 were in the second equivalence class. The performances of $\eta = 0.4$ to 1.0 were in the third to ninth equivalence classes respectively.

Finally, comparing the performances of the Opt-Gen and Val-Gen results, in terms of accuracy, the Val-Gen performances were statistically better than the Opt-Gen performances for $\eta = 0.6$, 0.8, and 0.9, while the Opt-Gen performances were better for $\eta = 0.4$. Although there was not a statistically significant difference better the performances for the other η values, the Val-Gen accuracies were higher. In contrast, in terms of feature reduction, the Opt-Gen performances were best for $\eta = 0.1$ to 0.9. This is most likely because more features may be needed for adequate generalization. There was not a statistically significant difference in the generalization performances for $\eta = 1.0$.

In summary, taking into consideration the two objectives we are attempting to optimize, $\eta = 0.4$ appears to be the best value to use for the Face-Only templates because the FMs achieved high recognition accuracies on the training set as well as the test set while using a low percentage of features.

Table 7.1. Value Preference Space for $GEFeWS_{ML}$: Face-Only Results

η	FRGC-105 Optimization *Acc. (% feat)*	FRGC-99 Opt-Gen *Acc. (% feat)*	FRGC-99 Val-Gen *Acc. (% feat)*
0.1	0.9879 (31.89%)	0.9660 (31.89%)	0.9667 (31.91%)
0.2	0.9905 (32.41%)	0.9690 (32.41%)	0.9694 (32.44%)
0.3	0.9952 (32.62%)	0.9609 (32.62%)	0.9620 (32.73%)
0.4	0.9949 (32.91%)	0.9707 (32.91%)	0.9697 (33.01%)
0.5	0.9952 (33.36%)	0.9744 (33.36%)	0.9751 (33.63%)
0.6	0.9956 (33.73%)	0.9731 (33.73%)	0.9771 (34.79%)
0.7	0.9975 (34.56%)	0.9795 (34.56%)	0.9815 (36.06%)
0.8	0.9978 (34.48%)	0.9751 (34.48%)	0.9832 (38.50%)
0.9	0.9971 (34.64%)	0.9707 (34.64%)	0.9879 (45.19%)
1.0	0.9997 (50.04%)	0.9818 (50.04%)	0.9842 (49.96%)

7.2.2 Periocular-Only

First, analyzing the performance of the Periocular-Only FRGC-105 Optimization results, higher η values achieved higher recognition accuracies. In terms of equivalence classes, the performance of η = 1.0 was in the first equivalence class, while the performances of η = 0.5 to 0.9 were in the second equivalence class. The performance of η = 0.4 was in the third equivalence class and the performances of η= 0.2 and 0.3 were in the fourth equivalence class. The performance of η = 0.1 was in the fifth equivalence class.

With respect to the FRGC-105 Optimization feature usages, lower η values resulted in the use of lower percentages of features. In terms of equivalence classes, η = 0.1 and η = 0.2 were in the first and second equivalence classes respectively. The performances of η = 0.3 and 0.4 were both in the third equivalence class, while the performance of $\eta = 0.5$ was in the fourth equivalence class. The performances of $\eta = 0.6$ and 0.7 were in the fifth equivalence class, and the performances of $\eta = 0.8$ and 0.9 were in the sixth equivalence class. The performance of $\eta = 1.0$ was in the seventh equivalence class.

Next, analyzing the Opt-Gen performances, in terms of accuracy, there was not a statistically significant difference in the performances of the η values. However, the equivalence classes for the feature usage were the same as those for FRGC-105 Optimization.

With respect to the Val-Gen performances, in terms of accuracy, the performances of $\eta = 0.1$, 0.3, 0.6, 0.7, 0.8, 0.9, and 1.0 were all in the first equivalence class. There was not a statistically significant difference in the performances of the other η values. In terms of feature usage, lower η values resulted in the use of fewer features. The equivalence classes were as follows: $\eta = 0.1$ was in the first equivalence class, $\eta = 0.2$ was in the second equivalence class, $\eta = 0.3$ and 0.4 were in the third equivalence class, and the performances of $\eta = 0.5$ to 1.0 were in the fourth to ninth equivalence classes respectively.

Finally, comparing the generalization performances in terms of accuracy, the Val-Gen performances were statistically better for $\eta = 0.5$ 0.6, 0.7, and 0.9, while the Opt-Gen performances were statistically better for $\eta = 0.3$. There was not a statistically significant difference in the performances of $\eta = 0.1$, 0.2, 0.4, 0.8, and 1.0. In contrast, in terms of feature usage, the Opt-Gen performances were better for $\eta = 0.2$ to 0.9 and there was not a statistically significant difference in the performances for η = 0.1 and 1.0. Again, this may be due to the need of more features for adequate generalization.

In summary, for the Periocular-Only templates, η = 0.4 would be the best value to use, considering the two objectives, for both optimization and generalization.

Table 7.2. Value Preference Space for $GEFeWS_{ML}$: Periocular-Only Results

η	**FRGC-105 Optimization** *Acc. (% feat)*	**FRGC-99 Opt-Gen** *Acc. (% feat)*	**FRGC-99 Val-Gen** *Acc. (% feat)*
0.1	0.9451 (34.10%)	0.8680 (34.10%)	0.8684 (34.10%)
0.2	0.9530 (34.55%)	0.8667 (34.55%)	0.8663 (34.48%)
0.3	0.9537 (35.01%)	0.8697 (35.01%)	0.8677 (35.09%)
0.4	0.9556 (35.23%)	0.8670 (35.23%)	0.8653 (35.38%)
0.5	0.9571 (35.66%)	0.8636 (35.66%)	0.8657 (36.14%)
0.6	0.9587 (36.23%)	0.8653 (36.23%)	0.8680 (37.27%)
0.7	0.9562 (36.54%)	0.8687 (36.54%)	0.8717 (38.34%)
0.8	0.9587 (37.38%)	0.8714 (37.37%)	0.8721 (42.14%)
0.9	0.9594 (37.63%)	0.8700 (37.63%)	0.8764 (46.02%)
1.0	0.9622 (50.22%)	0.8761 (50.22%)	0.8758 (50.32%)

7.2.3 Face + Periocular

First, comparing the FRGC-105 Optimization Face + Periocular performances, in terms of accuracy, the performances of η = 0.3 to 1.0 were all in the first equivalence class, while η =0.2 was in the second, and η=0.1 was in the third. In terms of feature reduction, the performances of η = 0.1 to 0.3 were all in the first equivalence class, the performances of η = 0.4 to 0.8 were in the second equivalence class, and the performances of η = 0.9 and 1.0 were in the third and fourth equivalence classes respectively.

With respect to the FRGC-99 Opt-Gen results, there was not a statistically significant difference in the η value performances in terms of accuracy; however, the equivalence classes for the feature usage were the same as for the FRGC-105 Optimization results.

Similarly, with respect to the FRGC-99 Val-Gen results, in terms of accuracy, there was not a statistically significant difference in the performances of the η values. However, in terms of feature usage, the equivalence classes were as follows: $\eta = 0.1$ to 0.3 were in the first equivalence class, $\eta = 0.4$ was in the second equivalence class, $\eta =$ 0.5 to 0.7 was in the third equivalence class, and the performances of $\eta = 0.8$, 0.9, and 1.0 were in the fourth, fifth, and sixth equivalence classes respectively.

When the performances of the Opt-Gen and Val-Gen results were compared in terms of accuracy, there was not a statistically significant difference. In terms of feature usages, there was not a statistically significant difference between the performance of $\eta =$ 0.1, 0.4, and 1.0. However, for the other η values, the Opt-Gen performances were better.

In summary, $\eta = 0.3$ would be the best value to use to create FMs that perform well on the training and test sets because its performance was in the first equivalence class in terms of accuracy and feature usage for the optimization and generalization performances.

Table 7.3. Value Preference Space for GEFeWS$_{ML}$: Face + Periocular Results

η	FRGC-105 Optimization *Acc. (% feat)*	FRGC-99 Opt-Gen *Acc. (% feat)*	FRGC-99 Val-Gen *Acc. (% feat)*
0.1	0.9949 (37.22%)	0.9896 (37.22%)	0.9896 (37.23%)
0.2	0.9981 (37.26%)	0.9902 (37.26%)	0.9902 (37.29%)
0.3	0.9994 (37.53%)	0.9926 (37.53%)	0.9923 (37.56%)
0.4	1.0000 (37.80%)	0.9929 (37.80%)	0.9929 (37.81%)
0.5	1.0000 (38.09%)	0.9926 (38.09%)	0.9933 (38.20%)
0.6	1.0000 (38.16%)	0.9929 (38.16%)	0.9923 (38.49%)
0.7	1.0000 (38.20%)	0.9909 (38.20%)	0.9926 (38.94%)
0.8	1.0000 (38.20%)	0.9946 (38.20%)	0.9943 (39.97%)
0.9	1.0000 (38.44%)	0.9923 (38.44%)	0.9926 (41.04%)
1.0	1.0000 (50.07%)	0.9943 (50.07%)	0.9963 (50.09%)

7.3 Discussion of Results

To highlight the effect varying the value of η has on the average accuracy and percentage of features used, the Pareto fronts for the FRGC-99 Val-Gen performances were plotted in Figures 7.1, 7.2, and 7.3. Within each figure, the average performance for each η value is plotted in the objective space, where the x-axis represents the average percentage of features used and the y-axis represents the average error rate. Within each of these figures, one can notice that as the value of η increase, so does the average percentage of features used. However, for generalization, η does not seem to correlate well with the reduction of the average error rates.

In addition, the performance of the η values that were determined to be best for each biometric modality was compared to the performances obtained in Chapter 6. The results showed that for each biometric modality, the best performing η value outperformed the previously presented results, using significantly fewer features while performing statistically the same in terms of accuracy.

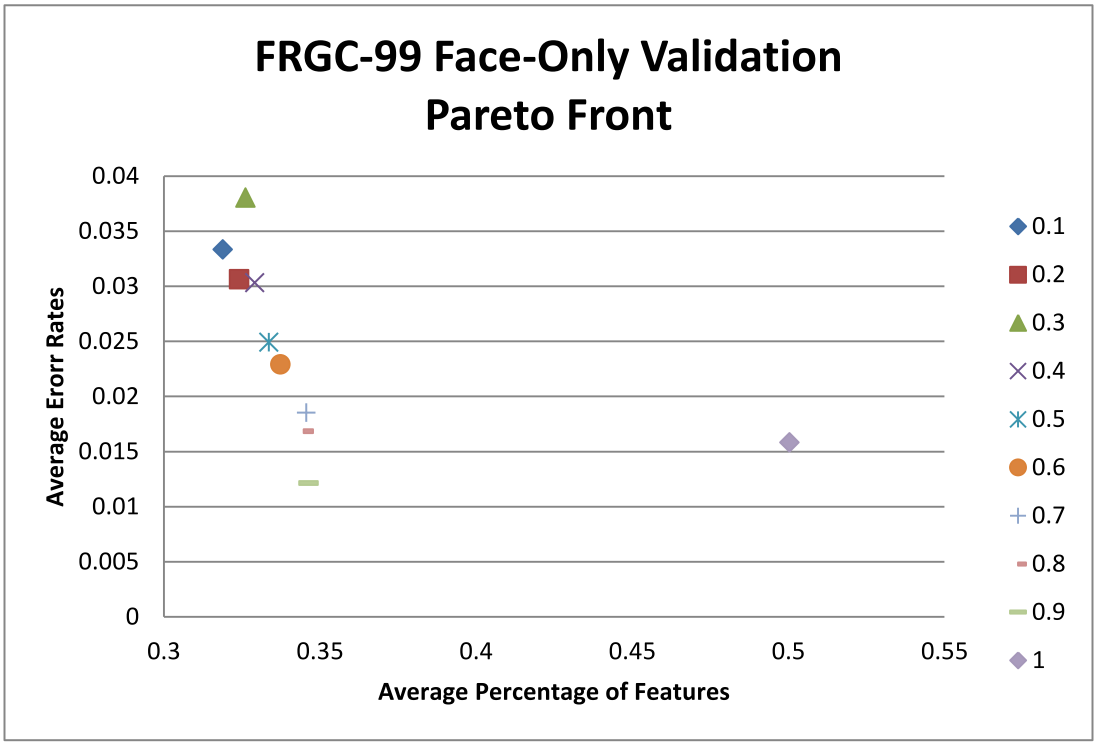

Figure 7.1. Pareto Front for Face-Only Val-Gen

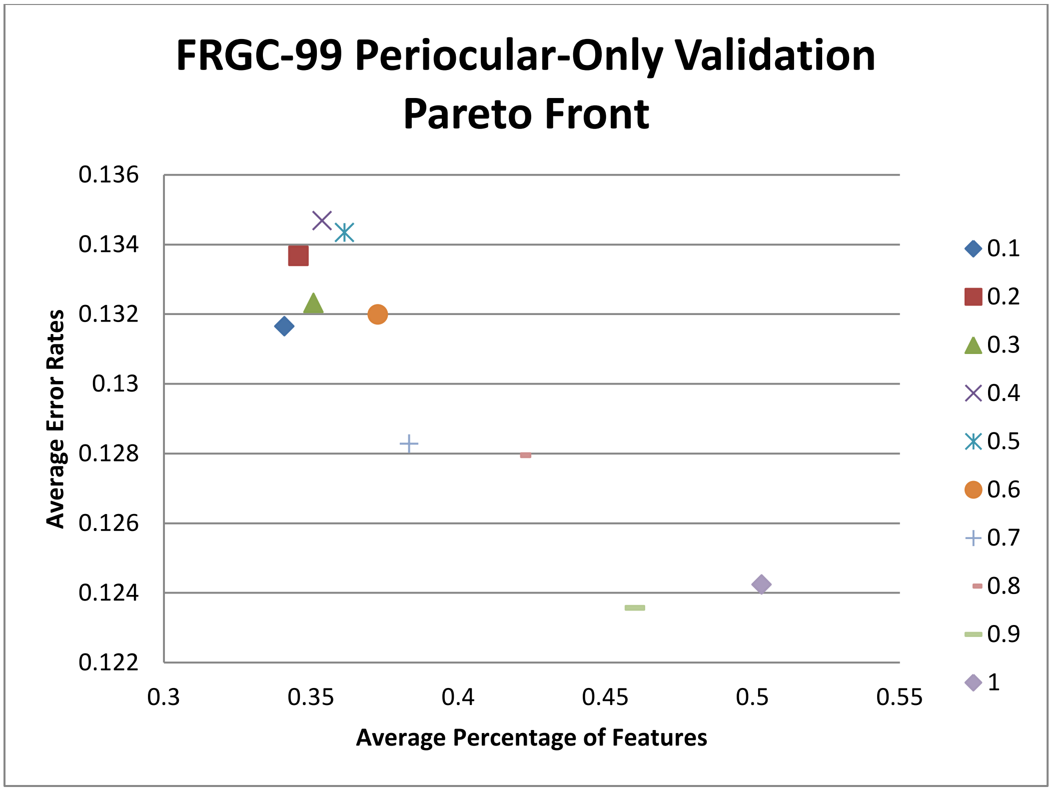

Figure 7.2. Pareto Front for Periocular-Only Val-Gen.

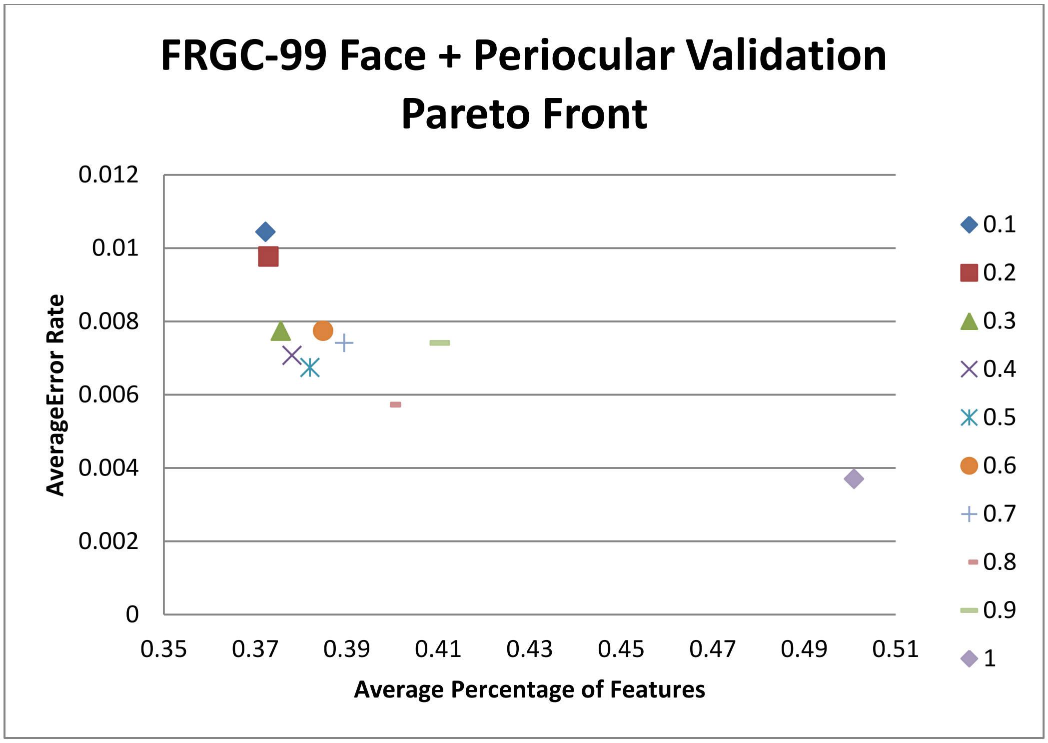

Figure 7.3. Pareto Front for Face + Periocular Val-Gen.

CHAPTER 8

Analysis

In this chapter, we provide an analysis of the FMs evolved for the Eigenface and LBP facial templates in an attempt to learn which eigenvectors were determined to be the most useful as well as which areas of the face are most discriminative for recognition. We also provide an analysis of the advantages and disadvantages of using our proposed techniques in comparison to conventional biometric systems.

8.1 Feature Analysis

First, we analyzed the FMs evolved by $GEFeWS_{EDA}$ for the Eigenface facial features. We then analyzed the FMs returned by $GEFeWS_{ML(4000)}$ for the LBP facial features. These FMs were chosen for analysis because they resulted in the best performance in terms of accuracy and feature reduction.

8.1.1 Eigenface Features

Figure 8.1 shows the average percentage of usage of each Eigenface feature for the FMs evolved by $GEFeWS_{EDA}$. From this figure, we can see that the eigenfaces that correspond to the highest eigenvalues are used the lowest percentage of the time. This supports the research of Swets and Weng [107] who stated that the eigenvectors with the highest eigenvalues do not necessarily correlate to the most discriminative features. In fact, our research shows that combinations of the eigenvectors achieve higher recognition rates than the feature selection method typically used within the biometrics community.

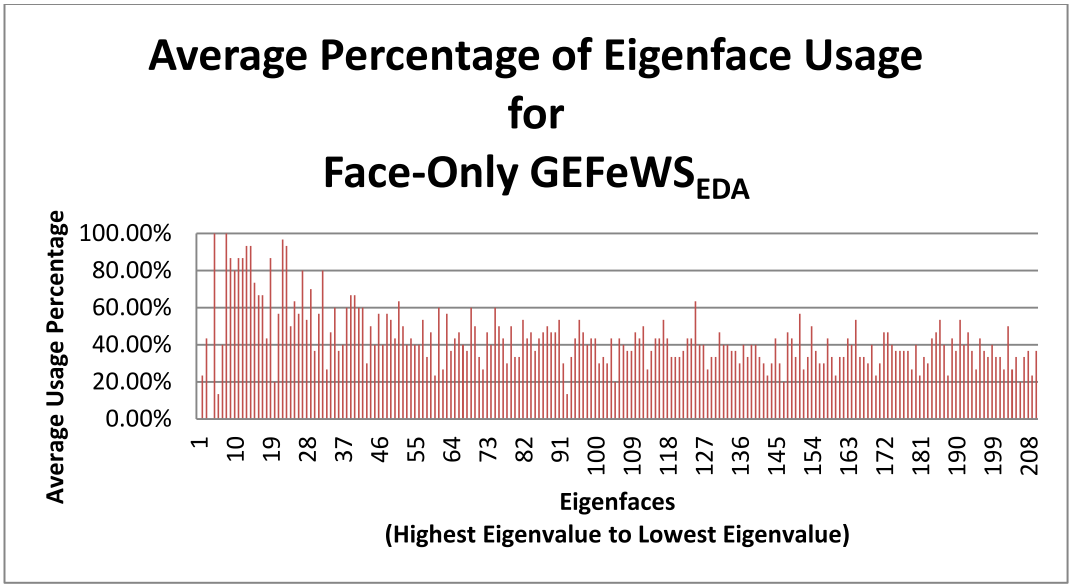

Figure 8.1. Average Percentage of Eigenface Usage for Face-Only $GEFeWS_{EDA}$ FMs.

8.1.2 LBP Features

Figure 8.2 shows a sample facial image segmented into 36 patches as done for our LBP feature extraction. We computed the average percentage of features used within each patch by the best performing FMs on the training set, $FM^{ts}s$, and the best performing FMs on the validation set, $FM^{*}s$, returned by $GEFeWS_{ML(4000)}$.

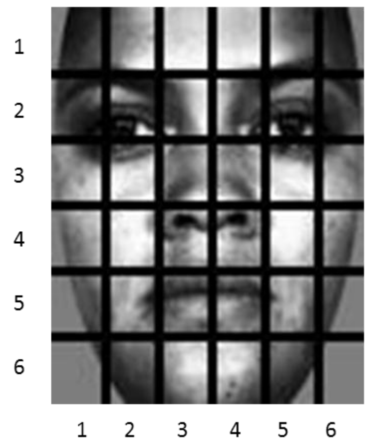

Figure 8.2. A Sample Face Image Divided Into 36 Patches.

Figure 8.3 shows the average patch usage for the FM^{ts}s and Figure 8.4 shows the average patch usage for the FM^*s. For the FM^{ts}s, the patches within the periocular region were used the highest percentage of the time. As before mentioned, the FM^*s used a higher percentage of features in comparison to the FM^{ts}s, therefore, the patch usage percentages were higher in Figure 8.4. In addition, the regions correlated to the highest average patch usage of the FM^* is different from the FM^{ts}s. Besides the periocular region, the FM^*s also included the information from the nose and mouth region. This may be due to the differences in the training and validation datasets such as image quality, facial expressions, and pose of the individuals.

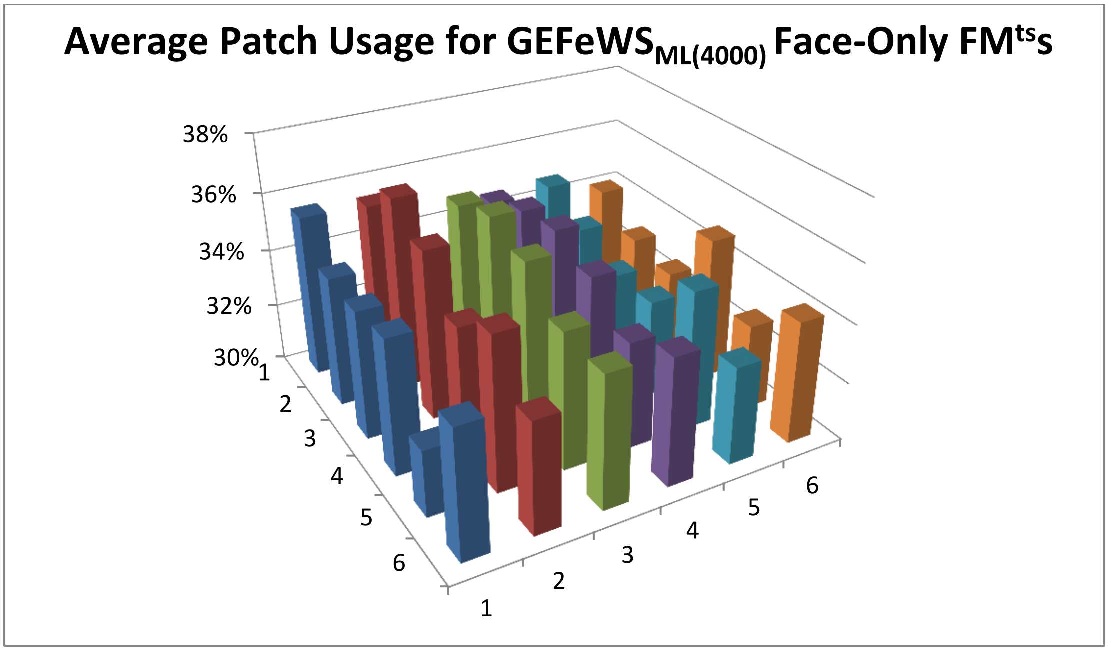

Figure 8.3. Average Patch Usage for GEFeWS$_{ML(4000)}$ Face-Only FM^{ts}s.

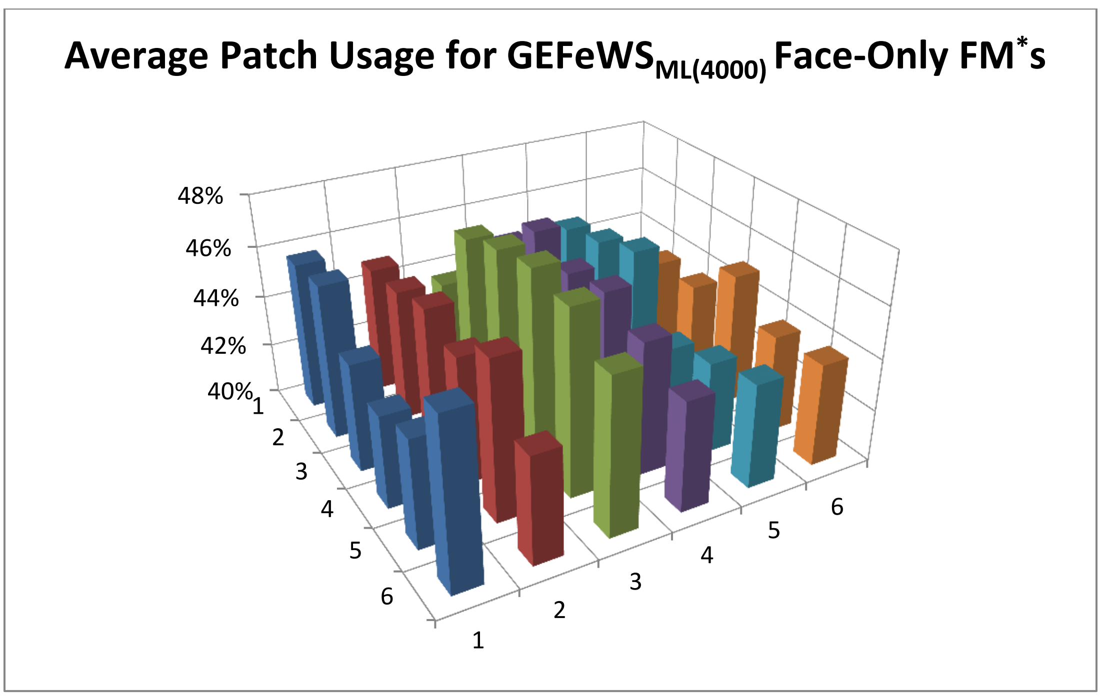

Figure 8.4. Average Patch Usage for GEFeWS$_{ML(4000)}$ Face-Only FM*s.

8.2 Comparison: Conventional vs. Hierarchical Biometric System

As before mentioned, the original objective of our work was to evolve short-length biometric templates that can be used in a 'Gentile-style' [74] recognition system. This recognition system would use a reduced feature set size in an effort to reduce the total number of feature checks required. In Section 3.1, we presented how to compute the number of feature checks performed by a conventional biometric system and a 'Gentile-style' system. We also presented the savings gained by using the hierarchical biometric system instead of the conventional biometric system. In this section, we first compare the performance of these two systems with respect to time, we then compare the implementation costs of these systems.

8.2.1 Time Complexity

To analyze the performance of our techniques, we computed the computational complexity, in terms of time, of our best performing technique, $GEFeWS_{ML}$, on the face + periocular templates. This analysis was performed on an Intel® Xeon® E5430 Processor, which had a 2.66 GHz clock speed.

First, we computed the average time (of 1000 runs), t, to compare one biometric feature. Our results showed that 0.0074 ms or 7.4×10^{-6} seconds were required to do so. Next, we computed the time required to recognize N subjects using a conventional and hierarchical system, where the number of original features, n, is 4956. The time complexity for a conventional system is computed using Equation 27, where γ_c is the number of features required for the conventional recognition system (described in Section 3.1). The time complexity for a hierarchical system was computed using Equation 28, where γ_c is the number of features required for the conventional recognition system (also described in Section 3.1), $m = 0.38n$ (average percentage of feature usage of GEFeWS$_{ML}$), and where $r = 0.1N$ (as in [75]).

$$time_c = \gamma_c t = Nnt \quad (27)$$

$$time_h = \gamma_h t = (Nm + rn)t \quad (28)$$

The time complexity of these two systems, computed in terms of seconds, are shown in Table 8.1, where the first column represents the number of subjects, the second column presents the average time complexity of a conventional system, and the last column presents the average time complexity of our hierarchical system. These results prove that implementing a hierarchical system using our reduced-length biometric templates would perform faster than a conventional biometric system.

Table 8.1. Time Complexity of a Hierarchical and Conventional System

# of Subjects	Conventional System (secs)	Hierarchical System (secs)
1	0.0366744	0.01760164
100	3.66744	1.760164
500	18.3372	8.80082
1000	36.6744	17.60164
5000	183.372	88.0082
10000	366.744	176.0164
50000	1833.72	880.082
100000	3667.44	1760.164
500000	18337.2	8800.82
1000000	36674.4	17601.64

To further analyze the time complexity of these two systems, we computed the expected speedup, Equation 29, of using our hierarchical system over the conventional system.

$$Speedup = \frac{time_c}{time_h} \tag{29}$$

Our results, as depicted in Figure 8.5, showed that our hierarchical system performs approximately 2 times faster than the conventional recognition system, while achieving better recognition accuracies.

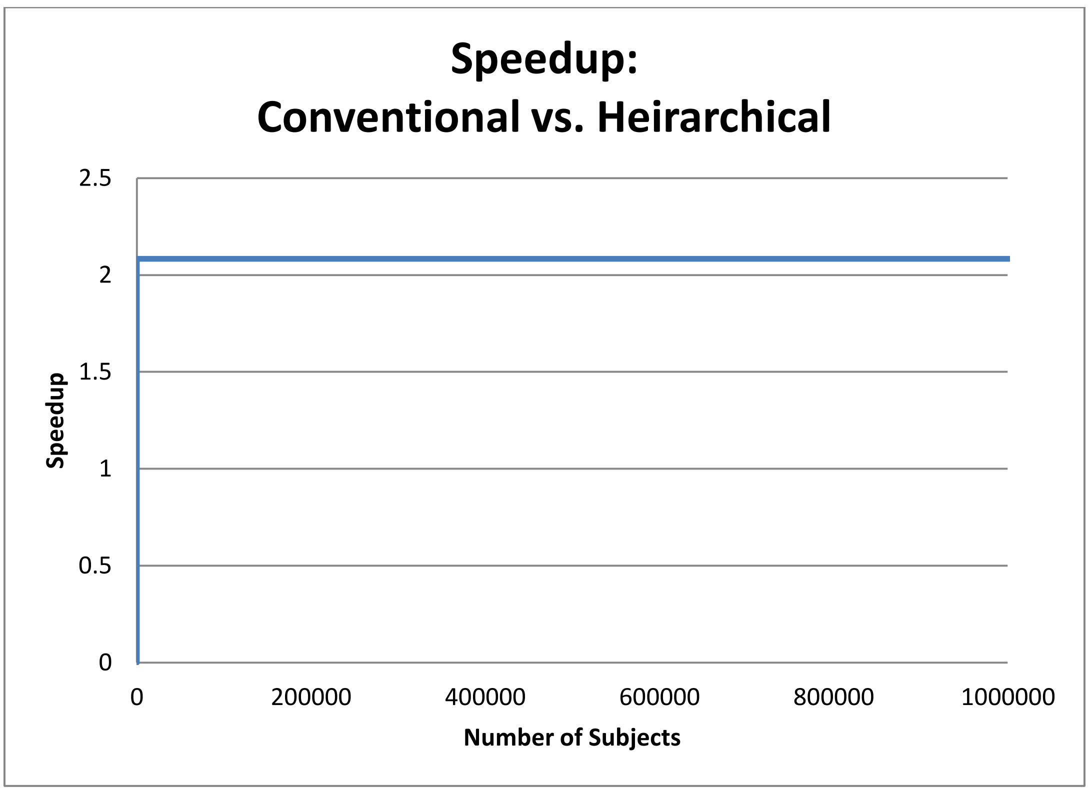

Figure 8.5. Speedup Chart.

8.2.2 Implementation Issues

Depending on the needs and complexity of an access control system, a biometric system can be described as a stand-alone system or networked system [114]. Each of these systems has their own advantages and disadvantages, and by implementing our techniques, we believe we can alleviate some of these issues.

For a stand-alone system, the entire biometric process is performed locally: enrollment of users, storage of the biometric templates, comparison of a probe and gallery templates, and the overall decision (e.g. allowing or denying an individual access). The advantage of a stand-alone system is that the operations may be fast and convenient for a user, since the required tasks are all performed in one location. We have proven that by using our techniques, these operations will be even faster. However, the major disadvantage of this system is that the biometric templates are stored locally, making the entire system vulnerable to being stolen.

For networked systems, a number of biometric sensors are connected. One advantage of such a system is that the system can be monitored from a central location, thus more secured biometric databases. Another advantage is that if the sensor is stolen, no information about the identity of the users of the system will be obtained. One disadvantage of this type of system is that if a large number of sensors are working simultaneously and/or the size of the resulting biometric templates are large, the speed of the system may be significantly reduced. One possible way to alleviate this traffic is to use our reduced dimensionality templates for recognition. Our results have shown that they achieve recognition accuracies that were practically the same as using the original templates.

CHAPTER 9

Conclusions

In conclusion, we have presented three new GEB techniques for multibiometric recognition. These three techniques attempted to create short-length biometric templates that could be used in a Gentile-style hierarchical recognition system [74]. The first technique we introduced was GEFeS, which evolved subsets of the most salient combinations of features in an effort to increase accuracy while decreasing the overall number of features needed for recognition. Our results showed that GEFeS was able to use less than 50% of the extracted features to achieve higher recognition accuracies than the baseline methods. Our second technique, GEFeW, evolved weights for the biometric templates. GEFeW performed better than the baseline methods in terms of accuracy and the percentage of features used. However, it used significantly more features than GEFeS. Our third technique, GEFeWS, was a hybrid of GEFeS and GEFeW. GEFeWS achieved higher recognition accuracies than GEFeS, and used significantly fewer features to achieve approximately the same accuracies as using GEFeW. Therefore, GEFeWS was considered the best technique to use if we were to implement the hierarchical system.

Our next objective was to evolve FMs that not only performed well on the training set, but also generalized well to unseen instances. To do so, we introduced $\text{GEFeWS}_{\text{ML}}$, which was similar to GEFeWS with the exception that the machine learning concept of cross validation was incorporated. Our best performing method, $\text{GEFeWS}_{\text{ML}(4000)}$, used less than 50% of the features to achieve high recognition accuracies on the test set. Our results also showed that the feature masks evolved via the validation set performed better in terms of accuracy than those evolved via the training set.

The final objective of this dissertation was to investigate the relative weighting of our two objectives (i.e. maximize the recognition accuracy and minimize the number of features) using a value preference structure. By varying the weights assigned to our objectives, we were able to suggest values that would result in the best optimization and generalization performances for face, periocular, and face + periocular recognition. In addition, these suggested weights resulted in FMs that used significantly fewer features than the previously reported results.

CHAPTER 10

Recommendations

For future work, it would be interesting to see if, using the analysis presented in Chapter 8, we could reverse engineer LBP feature extractors (FEs), similar to those evolved by Shelton et al. [18], that obtain higher recognition accuracies than the baseline method. The resulting FEs would extract features only from those patches that were determined to be the most useful by $GEFeWS_{ML}$. We believe that, similar to $GEFeWS_{ML}$, these reverse engineered FEs will use significantly fewer features and will result in higher recognition rates due to the extraction of features only from discriminative regions.

In addition, in this research there was not a lot of difference between the sizes of our training, validation, and test sets. Therefore, one should evaluate what effect varying the sizes of these datasets would have on the generalization performance of $GEFeWS_{ML}$. Furthermore, the datasets used in this research consisted of snapshots of individuals taken in a controlled setting within a short period of time. It would be interesting to see if our GEB applications could perform well on a longitudinal database, such as MORPH [36], in which the images of individuals were acquired over an extended period of time and collected in an uncontrolled setting. Additionally, by performing training on datasets consisting of images extracted from multiple databases, we believe that we can evolve FMs that would perform well to any face, due to the diversity that would be present in the training set. This would lead to a significant advancement in the biometrics community due to creation of universal FMs that could be further analyzed to identify the most discriminative regions for recognition, which could result in the discovery of new biometric modalities.

Finally, although the applications presented in this dissertation were used for the recognition of human faces and periocular biometrics, these applications should not be limited to this field. There are opportunities for the use of these applications for recognition of other biometric traits, as well as the recognition of other species and objects.

REFERENCES

[1] A.K. Jain, P. Flynn, and A. Ross (eds.), *Handbook of Biometrics*, Springer, 2007.

[2] A. Ross, “An Introduction to Multibiometrics”, In *Proceedings of the 15th European Signal Processing Conference (EUSIPCO)*, Poznan, Poland, September 2007.

[3] R. M. Ramadan, and R. F. Abdel-Kader, “Face Recognition Using Particle Swarm Optimization-Based Selected Features,” In *International Journal of Signal Processing, Image Processing and Pattern Recognition*, Vol. 2, No. 2, June 2009.

[4] J. Galbally, J. Fierrez, M. Freire, and J. Ortega-Garcia, "Feature Selection Based on Genetic Algoirthms for On-Line Signature Verification." 2007.

[5] D. Kumar, S. Kumar, and C.S. Rai, "Feature selection for face recognition: a memetic algorithmic approach." *Journal of Zhejanga University Science A*, Vol. 10, no. 8, pp. 1140-1152, 2009.

[6] D.E. Goldberg, *Genetic Algorithms in Search, Optimization & Machine Learning*, Addison-Wesley Publishing Company, Inc., Reading, Massachusetts, 1989.

[7] J. Adams, D.L. Woodard, G. Dozier, P. Miller, K. Bryant, and G. Glenn, “Genetic-based type II feature extraction for periocular biometric recognition: less is more,” In *Proc. Int. Conf. on Pattern Recognition,* 2010.

[8] A. Alford, K. Bryant, T. Abegaz, G. Dozier, J.Kelly, J. Shelton, L. Small, J.Williams, and D. L. Woodard, “Genetic & Evolutionary Methods for Biometric Feature Reduction”, (2011) *Special Issue on: "Computational Intelligence in Biometrics: Theory, Methods and Applications"*, Guest Editor: Qinghan Xiao, *International Journal of Biometrics*, 2011.

[9] P. J. Phillips, P.J. Flynn, T. Scruggs, K. W. Bowyer, J. Chang, K. Hoffman, J. Marques, J. Min, and W. Worek, “Overview of face recognition grand challenge,” in *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, 2005.

[10] P.E. Miller, A.W. Rawls, S.J. Pundlik, D.L. Woodard. "Personal identification using periocular skin texture". *SAC 2010: Proceedings of the 2010 ACM symposium on Applied Computing*. New York, NY, USA: ACM, 2010.

[11] D. Woodard, S. Pundlik, J. Lyle, and P. Miller, “Periocular region appearance cues for biometric identification”. In *CVPR Workshop on Biometrics,* 2010.

[12] J.R. Lyle, P. E. Miller, S. J. Pundlik, and D. L. Woodard, “Soft Biometric Classification Using Periocular Region Features”, In *IEEE 4th International*

Conference on Biometrics Theory, Applications, and Systems, Arlington, Virginia, Sept. 27 – Sept. 29, 2010.

[13] S. Marcel, Y. Rodriguez and G. Heusch, “On The Recent Use of Local Binary Patterns for Face Authentication”, *International Journal of Image and Video Processing – Special Issue on Facial Image Processing*, 2006.

[14] T. Ojala, M. Pietikainen, and D. Harwood, “A comparative study of texture measures with classification based on feature distributions”, *Pattern Recognition*, vol. 29, pp. 51-59, 1996.

[15] T. Ojala, M. Pietikäinen, and T. Mäenpää. “Multiresolution Gray-scale and Rotation Invariant Texture Classification with Local Binary Patterns”. In *Proceedings of IEEE Trans. Pattern Analysis and Machine Intelligence*, 24(7): 971-987.

[16] G. Dozier, A. Homaifar, E. Tunstel, and D. Battle. "An Introduction to Evolutionary Computation" (Chapter 17), *Intelligent Control Systems Using Soft Computing Methodologies*, A. Zilouchian & M. Jamshidi (Eds.), pp. 365-380, CRC press, 2001.

[17] P. Larrañaga and J. A. Lozano. *Estimation of Distribution Algorithms: A new tool for evolutionary computation*. Springer, 2002.

[18] J. Shelton, G. Dozier, K. Bryant, L. Small, J. Adams, K. Popplewell, T. Abegaz, A. Alford, D. L. Woodard, and K.Ricanek, “Genetic and Evolutionary Feature Extraction via X-TOOLSS”, to appear in *The 8th Annual International Conference on Genetic and Evolutionary Methods (GEM)*, 2011.

[19] J. Ortega-Garcia, J. Fierrez-Aguilar, D. Simon, J. Gonzalez, M. Faundez-Zanuy, V. Espinosa, A. Satue, I. Hernaez, J.-J. Igarza, C. Vivaracho, C. Escudero, and Q.-I. Moro, "MCYT baseline corpus: a bimodal biometric database," *IEEE Proc. Vis. Image Signal Process.*, vol. 150, no. 6,pp. 395-401, December 2003.

[20] AT&T Laboratories Cambridge, “ORL Face Database”, http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html.

[21] “The Extended Yale Face Database B”, http://vision.ucsd.edu/~leekc/ExtYaleDatabase/ExtYaleB.html.

[22] K.P. Dahal, K.C. Tan, and P.I. Cowling, “Evolutionary Scheduling”, *Springer Berlin /Heidelberg*, pp. 317-330, 2007.

[23] D. Fogel. *Evolutionary Computation: Toward a New Philosophy of Machince Intelligence*, IEEE Press, 1995.

[24] A.P. Engelbrecht, *Genetic Algorithms, in Computational Intelligence: An Introduction*, John Wiley & Sons, Ltd, 2007.

[25] S. Nolfi and D. Floreano, *Evolutionary Robotics:The Biology, Intelligence and Technology of Self-Organizing Machines*. MIT Press, 2000.

[26] P.J. Bentley, *Evolutionary design by computers*, San Francisco: Morgan Kaufmann, 1999.

[27] T. Bäck and H.-P. Schwefel, "An overview of evolutionary algorithms for parameter optimization", *Evolutionary Computation*, Vol. 1, No. 1, Pages 1-23, 1993.

[28] G. Dozier, D. Brown, H. Hou, and J. Hurley, "Vulnerability Analysis of Immunity Based Intrusion Detection Systems Using Genetic and Evolutionary Hackers," *Journal of Applied Soft Computing*, Elsevier, Volume 7, Issue 2, Pages 547-553, March 2007.

[29] Y. Wang, T. Tan, and A.K. Jain, "Combining face and iris biometrics for identity verification", in *Proceedings of the 4th international conference on Audio- and video-based biometric person authentication (AVBPA)*, 2003.

[30] T. Ahonen, A. Hadid, and M. Pietikinen, "Face Description with Local Binary Patterns: Application to Face Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 12, pp. 2037-2041, Dec. 2006.

[31] C. Darwin, *The origin of species*, London: John Murray, 1872.

[32] L. Davis, *Handbook of genetic algorithms*, Van Nostrand Reinhold, New York, 1991.

[33] J. Kennedy and R. C. Eberhart, with Y. Shi, *Swarm Intelligence*, Morgan Kaufmann, 2001.

[34] T. M. Mitchell, *Machine Learning*, McGraw-Hill Companies, Inc., 1997.

[35] G.B. Fogel, and D.W. Corne (eds.), *Evolutionary Computation in Bioinformatics*. Morgan Kaufmann, 2002.

[36] K. Ricanek Jr and T. Tesafaye, " MORPH: A Longitudinal Image Database of Normal Adult Age-Progression", *Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition*, pp. 341-345, April 10-12, 2006.

[37] T. Back, *Evolutionary Algorithms in Theory and Practice*, Oxford University Press, Inc., New York, 1996.

[38] J.H. Holland, *Adaptation in Natural and Artificial Systems*, The University of Michigan Press, 1975.

[39] S. Haykin, *Neural Networks: a Comprehensive Foundation*, 2nd Edition, Prentice-Hall, Inc., New Jersey, 1999.

[40] J.-S. R. Jang, C.-T. Sun, and Z. Mizutani, *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Prentice-Hall, Inc. , New Jersey, 1997.

[41] P.D. Wasserman, *Neural Computing*. Van Nostrand Reinhold, New York, 1989.

[42] M. Negnevitsky, *Artificial Intelligence: A Guide to Intelligent Systems*, 2nd Edition, Addison-Wesley, 2005.

[43] T. Abegaz, G. Dozier, K. Bryant, J. Adams, K. Popplewell, J. Shelton, K. Ricanek, and D. L. Woodard, "Hybrid GAs for Eigen-Based Facial Recognition", *Proceedings of the 2011 IEEE Workshop on Computational Intelligence in Biometrics and Identity Management*, Paris, France, April 11-15, 2011.

[44] J. Han and M. Kamber. *Data Mining: Concepts and Techniuqes*. Morgan Kaufmann Publishers, San Francisco, CA, 2001.

[45] A. Alford, C. Hansen, G. Dozier, K. Bryant, J. Kelly, J. Adams, T. Abegaz, K. Ricanek, and D.L. Woodard, "GEC-Based Multi-Biometric Fusion, in *Proceedings of IEEE Congress on Evolutionary Computation (CEC)*, 2011.

[46] J. Daugman, "How Iris Recognition Works", *IEEE Transactions on Circuits and Sysems for Video Technology*, Vol. 14, No. 1, pp. 21-30, Jan. 2004.

[47] J. Daugman, "Probing the Uniqueness and Randomness of IrisCodes: Results From 200 Billion Iris Pair Comparisons", *Proceedings of the IEEE,* Vol. 94, No. 11, Nov. 2006 .

[48] K. Hollingsworth, K. Bowyer, and P. Flynn, "All Iris Code Bits are Not Created Equal", *Proceedings of the 2007 IEEE Conference on Biometrics: Theory, Applications, and Systems*, September 2007.

[49] G. Dozier, K. Frederiksen, R. Meeks, M. Savvides, K. Bryant, D. Hopes, and T. Munemoto, "Minimizing the Number of Bits Needed for Iris Recognition via Bit Inconsistency and GRIT", *Proceedings of the IEEE Workshop on Computational Intelligence in Biometrics Theory, Algorithms, and Applications*, 2009.

[50] A.K. Jain and A. Ross, “Multibiometric Systems”, *Communications of the ACM - Multimodal interfaces that flex, adapt, and persist,* Volume 47, Issue 1, January 2004.

[51] A. Jain, K. Nandakumar, and A. Ross, “Score Normalization in Multimodal Biometric Systems”, Pattern Recognition, Vol. 38, no. 12, pp. 2270–2285, Dec. 2005.

[52] J. Branke, K. Deb, K. Miettinen, and R. Slowinski (Eds.), *Multiobjective optimization: interactive and evolutionary approaches*, Berlin: Springer-Verlag, 2008.

[53] P.L. Yu, “Multiple Criteria Decision Making: Five Basic Concepts”, *Handbooks in Operations Research and ManagementScience,* Vol 1 (Optimization), pp. 663-699, G.L. Nemhauser et al. Eds. Elsevier Science Publishers B.V. (North-Holland).

[54] G. Dozier, S. McCullough, A. Homaifar, E. Tunstel, and L. Moore, “Multiobjective evolutionary path planning via fuzzy tournament selection”, *Proceeding of the 1998 IEEE Conference on Evolutionary Computation,* pp. 684-689, 1998.

[55] J. González-Rodríguez, D. Toledano and J. Ortega-García, “Voice Biometrics”, *Handbook Of Biometrics*, Springer, 2008.

[56] B. Bhanu and J. Han, “Match Score Level Fusion of Face and Gait at a Distance”, *Human Recognition at a Distance In Video,* Springer-Verlag, 2011.

[57] J. Phillips, H. Moon, S. Rizvi, and P. Rauss, “The FERET Evaluation Methodology for Face Recognition Algorithms,” *IEEE Trans. Pattern Anal. and Mach. Intel.*, vol. 22, no. 10, pp. 1090–1104, October 2000.

[58] A.S. Georghiades, P.N. Belhumeur, and D.J Kriegman, “From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose", *IEEE Trans. Pattern Anal. Mach. Intelligence,* Vol. 23, No. 6, pp. 643-660, 2001.

[59] L. Spacek, Essex face database, http://cswww.essex.ac.uk /allfaces/index.html, 2000.

[60] C. Sanderson and K.K. Paliwal, “Information fusion and person verification using speech and face information”, Research Paper IDIAP-RR 02-33, IDIAP, 2002.

[61] A. Ross and A. Jain, “Information fusion in biometrics”, *Pattern Recognition,* Volume 24, Issue 13, September 2003, pp. 2115-2125.

[62] Y. Wang, T. Tan, and A.K. Jain, "Combining face and iris biometrics for identity verification", in *Proceedings of the 4th International Conference on Audio- and Video-based Biometric Person Authentication (AVBPA)*, 2003.

[63] K. Popplewell, A. Alford, G. Dozier, K. Bryant, J. Kelly, J. Adams, T. Abegaz, K. Purrington, and J. Shelton, "A Comparison of Genetic Feature Selection and Weighting Techniques for Multi-Biometric Recognition", in *Proceedings of ACM SouthEast (ACMSE) Conference*, 2011.

[64] A. Alford, K. Popplewell, G. Dozier, K. Bryant, J. Kelly, J. Adams, T. Abegaz, J. Shelton, K. Ricanek, and D.L. Woodard, "A Comparison of GEC-Based Feature Selection and Weighting for Multimodal Biometric Recognition", in *Proceedings of IEEE Congress on Evolutionary Computation (CEC)*, 2011.

[65] A. Alford, K. Popplewell, G. Dozier, K. Bryant, J. Kelly, J. Adams, T. Abegaz, and J. Shelton, "GEFeWS: A Hybrid Genetic-Based Feature Weighting and Selection Algorithm for Multi-Biometric Recognition", in *Proceedings of the 22nd Midwest Artificial Intelligence and Cognitive Science Conference (MAICS)*, Kennesaw, GA, March 24-26, 2011.

[66] T. Abegaz, "Genetic and Evolutionary Feature Selection and Weighting for Face Recognition", Thesis submitted to North Carolina A&T State University.

[67] T. Abegaz, G. Dozier, K. Bryant, J. Adams, K. Popplewell, J. Shelton, K. Ricanek, and D. L. Woodard, "Hybrid GAs for Eigen-Based Facial Recognition", *IEEE Symposium Series in Computational Intelligence (SSCI 2011)*, 2011.

[68] T. Abegaz, G. Dozier, K. Bryant, J. Adams, J. Shelton, K. Ricanek, and D. L. Woodard, "SSGA & EDA Based Feature Selection and Weighting for Face Recognition", in *Proceedings of IEEE Congress on Evolutionary Computation (CEC)*, 2011.

[69] T. Abegaz, G. Dozier, K. Bryant, J. Adams, B. Baker, J. Shelton, K. Ricanek, and D. L. Woodard, "Genetic-Based Selection and Weighting for LBP, oLBP, and Eigenface Feature Extraction", in *Proceedings of the 22nd Midwest Artificial Intelligence and Cognitive Science Conference (MAICS)*, Kennesaw, GA, March 24-26, 2011.

[70] X-TOOLSS (eXploration Toolset for Optimization Of Launch and Space Systems). http://nxt.ncat.edu/, May 3, 2011.

[71] M. L. Tinker, G. Dozier, and A. Garrett, "X-TOOLSS--eXploration Toolset for Optimization Of Launch and Space Systems", http://xtoolss.msfc.nasa.gov/, 2011.

[72] K. Ramirez-Gutierrez, D. Cruz-Perez, J.Olivares-Mercado, M. Nakano-Miyatake, and H. Perez-Meana, "A Face Recognition Algorithm using Eigenphases and Histogram Equalization", *International Journal Of Computers*, Issue 1, Volume 5, 2011.

[73] G.R. Iversen and N. Norpoth, *Analysis of Variance*, Sage University Papers Series on Quantitiative Applications in the Social Sciences, 07-001, Thousand Oaks, CA: Sage, 1976.

[74] J.E. Gentile, J.E., N. Ratha, and J. Connell, "An Efficient, Twostage Iris Recognition System", In *Proceedings of the IEEE 3rd International Conference on Biometrics: Theory, Applications, and System (BTAS)*, 2009.

[75] W.H. Press, S.A. Teukolsky, W.T. Vetterling, and B.P. Flannery, *Numerical Recipes in C*, 2nd edition, Cambridge: Cambridge University Press, 1992.

[76] A.K. Jain, R. Bolle, and S. Pankanti, "Introduction to Biometrics", In Jain, A.,Bolle, R., and Pankanti, S. (Eds.), *Biometrics. Personal Identification in Networked Society.* Norwell, MA: Kluwer Academic Publishers, pp. 1–41.

[77] R.T. Marler and J.S. Arora, "Survey of multi-objective optimization methods for engineering", in : *Struct Multidisc Optim 26*, pp. 369-395, 2004.

[78] A.K. Jain, A. Ross, and S. Prabhakar, "An Introduction to Biometric Recognition", In *IEEE Transactions on Circuits And Systems for Video Technology*, Volume (14), Issue (1): pp: 4-20, 2004.

[79] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal of Cognitive Neuroscience*, vol. 3 no. 1 pp. 76-81, Winter 1991.

[80] Y.V. Lata, C. K. B. Tungathurthi, H. R. M. Rao, A. Govardhan, and L. P. Reddy, "Facial Recognition using Eigenfaces by PCA". In *International Journal of Recent Trends in Engineering*, Vol. 1, No. 1, pp. 587-590, May 2009.

[81] K. Fukunaga, "Introduction to statistical pattern recognition," Academic Press, 1990.

[82] M. Kirby and L. Sirovich, "Application of the Karhumen Loeve Procedure for the characterization of human-faces," *IEEE Trans. Pattern Anal. And Mach. Intell.*, Vol.12, No.1 pp.103-108, 1990.

[83] I. Jolliffe, "Principal Component Analysis", *Encyclopedia of Statistics in Behavioral Science*, 2005.

[84] L.J.P. van der Maaten, E.O. Postma, and H.J. van den Herik, “Dimensionality reduction: A comparative review”, Online Preprint, Elsevier, 2008.

[85] M.A. Turk and A.P. Pentland, “Face Recognition Using Eigenfaces”, in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, , Maui, Hawaii, USA, pp. 586-591, 3-6 June 1991.

[86] S. Z. Li and A. K. Jain, *Encyclopedia of Biometrics*, Volume 1, Springer, 2009.

[87] F. Camastra and A.Vinciarelli, “Machine learning for audio, image and video analysis: theory and applications”, Springer, 2008.

[88] T. Mäenpää, and M. Pietikäinen, “Texture analysis with local binary patterns”, In: C. Chen, P. Wang (eds.) *Handbook of Pattern Recognition and Computer Vision*, ch.1, pp. 197–216. World Scientific, Singapore (2005).

[89] T. Mäenpää, *The local binary pattern approach to texture analysis – extensions and applications*, Ph.D. Thesis, Infotech Oulu and Department of Electrical and Information Engineering, University of Oulu, 2003.

[90] J. Xu, M. Cha, J. L. Heyman, S. Venugopalan, R. Abiantun, and M. Savvides, “Robust local binary pattern feature sets for periocular biometric identification,” in *IEEE Int. Conf. on Biometrics: Theory, Applications, and Systems*, pp. 1–8, Sept 2010.

[91] C. Shan and T. Gritti, “Learning discriminative LBP-histogram bins for facial expression recognition”, In *Proc. British Machine Vision Conference*, 2008.

[92] D. Mazumdar, S. Mitra, S. Mitra, “Evolutionary-rough feature selection for face recognition,” *ACM Journal on Transactions on Rough Sets XII*, LNCS 6190, Springer-Verlag Berlin Heidelberg, pp.117-142, 2010.

[93] H.K. Ekenel and B. Sankur, “Feature selection in the independent component subspace for face recognition”, *Pattern Recognition Letters*, Volume 25, Issue 12, September 2004, Pages 1377-1388, ISSN 0167-8655, 10.1016/j.patrec.2004.05.013.

[94] C. Liu and H. Wechsler, “Evolutionary Pursuit and Its Application to Face Recognition”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 6, pp.570-582, June 2000.

[95] M.A. Tahir, A. Bouridane and F. Kurugollu, “Simultaneous feature selection and feature weighting using hybrid tabu search/K-nearest neighbor classifier”, *Pattern Recognition Letters 28*, pp. 438–446, 2007.

[96] A.K. Jain, R.P.W. Duin, and J. Mao, "Statistical pattern recognition: A review," *IEEE Trans. PAMI*, vol. 22, no. 1, Jan. 2000.

[97] Y. Lei and H. Liu, "Feature Selection for High-Dimensional Data: A Fast Correlation-Based Filter Solution", in *Proceedings of the Twentieth Internationl Conference on Machine Learning (ICML-03)*, Washington, DC, 2003.

[98] S.M.S. Ahmad, "A Hybrid Feature Weighting and Feature Selection Approach in an Attempt to Increase Signature Biometrics Accuracy", in *Proceedings of the International Conference on Electrical Engineering and Informatics*, Institut Teknologi Bandung, Indonesia, pp. 184-187, June 17-19, 2007.

[99] M. Dash and H. Liu, "Feature selection for classification," *Intell. Data Anal. 1*, pp. 131–156, 1997.

[100] I.-S. Oh, J.-S. Lee, and B.-R. Moon, "Hybrid Genetic Algorithms for Feature Selection", *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 26, no.11, Nov. 2004.

[101] I. Bichindaritz, *Computational Intelligence in Healthcare 4: Advanced Methodologies, Volume 4*, Springer, pp. 408, 2010.

[102] L. S. Burrell, O. L. Smart, G. Georgoulas, E. Marsh, and G. J. Vachtsevanos, "Evaluation of Feature Selection Techniques for Analysis of Functional MRI and EEG", in *International Conference on Data Mining*, Las Vegas, Nevada, 2007.

[103] T. Chin and D. Suter, "A study of the eigenface approach for face recognition", Technical report, Monash University, 2004.

[104] P. Langley, "Selection of relevant features in machine learning", In: *Proceedings of the AAAI Fall Symposium on Relevance*, pp.1–5, 1994.

[105] J. E. Gentile, N. Ratha, and J. Connell, "SLIC: Short-length iris codes," in *Proc. IEEE 3rd International Conference on Biometrics: Theory, Applications, and Systems*, 2009. BTAS '09, pp.1-5, 28-30 Sept. 2009.

[106] B. Baker, K. Bryant, and G. Dozier. "GESLIC: Genetic and Evolutionary-Based Short-Length Iris Codes". In *Proceedings of ACM SouthEast (ACMSE) Conference.* 2011.

[107] D. L. Swets and J. Weng, "Using discriminant eigenfeatures for image retrieval," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 18, No. 8, pp. 831-836, 1996.

[108] A. Jain, L. Hong, and S. Pankanti, “Biometric Identification,” Commun. ACM, vol. 43, no. 2, Feb. 2000.

[109] A. Ross and A.K. Jain, “Multimodal Biometrics: An Overview,” *Proc. 12th European Signal Processing Conf.*, pp. 1221-1224, 2004.

[110] A.K. Jain, "Biometric recognition: how do I know who you are?," Proceedings of the IEEE 12th Signal Processing and Communications Applications Conference, 2004 , pp. 3- 5, 28-30 April 2004.

[111] A.K. Jain, “Biometric recognition: overview and recent advances”, In: *Lecture Notes in Computer Science: Progress in Pattern Recognition, Image Analysis And Applications*, vol. 4756, Berlin: Springer; pp. 13–19, 2007.

[112] A. Ross, K. Nandakumar, and A. K. Jain, Handbook of Multibiometrics (International Series on Biometrics), Springer-Verlag New York, Inc., Secaucus, NJ, 2006.

[113] L. Hong and A. Jain, “Integrating Faces and Fingerprints for Personal Identification”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 20, No. 12, 12 December 1998.

[114] R. Newman, “Security and Access Technologies”, *Security and Access Control Using Biometric Technologies*, Boston: Course Technology, pp. 249-284, 2010.

[115] A. Alford, C. Steed, M. Jeffrey, D. Sweet, J. Shelton, L. Small, D. Leflore, G. Dozier, K. Bryant, T. Abegaz, J.C. Kelly, K.. Ricanek, “Genetic & Evolutionary Biometrics: Hybrid Feature Selection and Weighting for a Multi-Modal Biometric System”, *Proceedings of IEEE SoutheastCon 2012*, Orlando, FL., March 15-18, 2012.