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Genetic And Evolutionary Feature Selection And Weighting For Face Recognition

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GENETIC AND EVOLUTIONARY FEATURE SELECTION AND WEIGHTING FOR FACE RECOGNITION

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BIOGRAPHICAL SKETCH

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LIST OF ABBREVIATIONS

EBGM	Elastic Bunch Graph Matching
CMC	Cumulative Match Characteristic
FR	Face Recognition
FRGC	Face Recognition Grand Challenge
FRR	False Reject Rate
GM	Genetic Algorithm
GEC	Genetic & Evolutionary Computation
GEFeS	Genetic & Evolutionary Feature Selection
GEFeW	Genetic & Evolutionary Computation Feature Weighting
IDA	Independent Component Analysis
LBP	Local Binary Pattern
LDA	Linear Discriminate Analysis
PCA	Principal Component Analysis

ABSTRACT

Tamirat, Abegaz. GENETIC AND EVOLUTIONARY FEATURE SELECTION AND WEIGHTING FOR FACE RECOGNITION. **(Advisor: Gerry Dozier)**, North Carolina Agricultural and Technical State University.

In this thesis, we have investigated the hybridization of genetic-based feature selection (GEFeS), genetic-based feature weighting (GEFeW) and LBP-based face recognition techniques. The results indicate that feature selection and weighting enhances the overall performance of LBP-based face recognition techniques. In addition, the results show that GEFeS reduces the number of features needed by approximately 50% while obtaining significant improvement in the accuracy. GEFeS improves the accuracy from 70.36 to 96.62 (in the case of LBP-GEFeS) and from 70.71 to 96.43 (in the case of oLBP-GEFeS) respectively.

CHAPTER 1

INTRODUCTION TO BIOMETRICS

The term biometrics refers to measuring and analyzing both the physiological (such as face, iris, periocular regions, hand geometry, etc.) and behavioral (such as hand gestures and expressions) characteristics for identification (one-to-many matching) and/or verification (one-to-one matching) purposes [1]. Biometric-based Identification/ Verification techniques have emerged as more promising options for recognizing individuals than authenticating individuals based on passwords, PINs, smart cards, plastic cards, tokens, keys and so forth [2]. Passwords and PINs are hard to remember and can be stolen or guessed. Cards, tokens, and keys can be misplaced, forgotten, purloined or duplicated. Magnetic cards can become corrupted and rendered unreadable. However, an individual's biological traits cannot be misplaced, forgotten, or stolen [2].

The mechanism of selecting methods of acquisition of a biometric characteristic varies from application to application and must not put the health, safety, or welfare of individuals in danger [2, 3]. A variety of methods and techniques are available to be used to automatically identify or verify the claimed identity of individuals [4]. Popular biometric modalities include face, iris, periocular, heartbeat, fingerprint, hand geometry, voice, face, retina scans, iris scans, bio-signatures, etc [4]. Among these diverse types of biometrics, face recognition is one that is widely used for identification and/or verification of individuals.

The human face, which possesses both physiological and behavioral characteristics, is an extremely complex visual stimulus that articulates identity, emotion, race/ethnicity, age, and gender of an individual [4]. Humans are pre-wired from birth for face recognition (FR) [3, 4]. The human brain is highly adapted for recognizing faces. It is also far better than computers at compensating for changes in lighting, facial hair growth, weight changes, and aging [4]. Although humans perform the tasks of FR in an effortless manner, the automation of this task has been a difficult problem and has required research in a wide area of diverse fields of study, from cognitive psychology to psychophysical psychology to pattern recognition [4, 5]. For FR using pattern recognition, we can formulate the problem as: Given an input face image (probe) and a Dataset of face images of known individuals (gallery), "How can we identify or verify the identity of the person?" Automating FR is useful for several application areas such as passport verification, entrance control, criminal investigation, and surveillance, to name a few [4, 5].

To explain the applications of FR technology, we can categorize the real world applications as Identification, Verification, and Watch list [6]. Identification is a closed universe application that ranks the gallery by similarity to the probe (query image). It can be used for criminal identification. Verification is a one-to-one process and open universe application where a person presents his/her identity like badge or passport. The system determines if the claimed identity is correct. It can be used for immigration control and airport/seaport security. A Watch list based application is an open universe, one-to-many application where a person's live image is compared to each face image in the list. It is of importance for intelligence agencies and police departments, for example for searching for known terrorists.

FR has a number of benefits over other biometric methods such as fingerprint, retina, and iris recognition, due to its natural passive recognition. Almost all of the other biometric techniques require some voluntary, invasive actions. FR has tremendous benefits for covert use such as surveillance for intelligence agencies, military and police departments. In addition, it is non-intrusive, which means it doesn't require physical interaction with the user. In addition, FR can be used in conjunction with other biometrics such as perocular, iris, heartbeat, fingerprint, and gait recognition. This technique is referred to as Multibiometric (Biometric Fusion). Multibiometric systems can consolidate the information presented by multiple sensor, multi-sample, multi-instance, multi-algorithm, multimodal, and hybrids of two or more types of sources of information to enhance the performance.

Face recognition generally follows the following steps: Image Sensing, Face Detection, Face Normalization, Feature Extraction, Feature Selection, and Classification. In Image sensing, sensor is used to capture the face of individuals. Most current FR systems are based on face images captured in the visible light spectrum [7]. However, recently, as indicated in Woodard et al.[8], researchers have started using NIR (Near-infrared) to capture the face images of individuals because different snapshots of the same individual taken under visible spectrum may, because of different illumination, actually show more difference than snapshots of different persons [9]. Face Detection is used to provide location, size and shape information about individual faces. A good face detection algorithm is paramount to a successful FR system. Although, this work does not focus on detection, the interested reader can review the following for robust detection in still and video images [9]. Detected faces may vary in size, colors, pose, etc. Face Normalization is used to homogenize these variations. It consists of two important tasks: Geometric and Photometric adjustment of a face image. The objective of Geometric normalization is to adjust the pose, size, and shape of the face, while photometric normalization is used to adjust the illumination among various images.

Feature Extraction is used to extract those features of a face that result in high discriminatory power [10]. It should be capable of capturing the relevant data in a manner which is invariant to pose, expressions, or illumination. Feature extraction techniques are roughly classified into holistic and local approaches [10, 11]. There are a number of algorithms that utilize the holistic approach [11, 12]. Independent Component Analysis (ICA) [11, 12], Linear Discriminant Analysis (LDA) [12, 13], and Eigenface, which uses Principal Component Analysis (PCA) [13, 14, 15] are techniques that utilize the holistic approach. Among these, the most widely used is the Eigenface. Holistic approaches usually suffer from environmental variations in practice [15]. The local approaches, such as Elastic Bunch Graph Matching (EBGM) [16] and Local Binary Pattern (LBP) [17], extract information from local facial features to distinguish faces, and have the advantage of robustness to environmental changes. For thesis, we will investigate the use of LBP and overlapping-LBP (oLBP) feature extraction. We will apply Genetic-Based feature selection and weighting on the extracted features sets obtained by LBP and oLBP.

Feature Selection techniques are basically used to select a subset of the features obtained from feature extraction based on some optimization principle. The ideal feature selection technique removes those features that are useless and keeps those that have high discriminatory power. A number of feature selection techniques have been developed and roughly could be categorized as Enumeration Algorithms [18], Sequential Algorithms [18, 19], and Genetic Algorithms [20, 21, 22, 23, 24, 25]. Enumeration Algorithms generally guarantee the optimal solution by evaluating all possible subsets of the features and choosing the best among the features. Though this works for very small sized feature space, it is computationally infeasible when the size of the feature sets is large. Sequential Search Algorithms try to divide the feature set U into X and Y where X denotes the selected features and Y denotes the remaining ones. Based on some criteria, it tries to select the least significant features from subset X and move those features into subset Y, while selecting the most significant features from Y and move them into subset X, and repeats the process.

Classification is used to provide the similarity measure among different face representation to determine individual identity by classifying the features. Given a set of gallery image T, we can then determine the identity of the probe set T_p by finding which gallery image is most closely positioned to the probe. One technique is to find the distance among the faces. There are several methods of measuring the distance for classification purpose [26]. However, the most commonly used distance metrics for face classification are the Manhattan (L1) and Euclidian (L2) [27]. The Manhattan and the Euclidian distance are given by Equation 1.1 and 1.2 respectively

$$d_{L1}(x; y) = |x, y| \tag{1.1}$$

$$d_{L1}(x; y) = ||x, y|| \tag{1.2}$$

Genetic & Evolutionary Computation (GEC) [28, 29] is a subfield of Artificial and Computational intelligence inspired by natural selection. A Genetic Algorithm (GA) [28, 29] is a GEC that uses the principle of simulated evolution to select those features based on survival of the fittest principle. The basic concept behind Genetic & Evolutionary Computing is to find an optimal (or near optimal) solution for a specific problem. A GA works as follows, initially, a number of individuals candidate (solutions) are generated to form an initial population. Each individual is then evaluated and assigned a fitness value received from an evaluation function specific to the problem at hand. Parents are then selected based on their fitness. Children (also in the form of candidate solutions) are produced from the selected parents. Survivors are selected from the previous generation and combined with the offspring to form the next generation. This evolutionary process is continued until one of the following conditions is met: the discovery of a satisfactory solution, detection that no feasible solution exists, reaching a user-specified threshold, or after a user-specified number of function evaluations.

Genetic & Evolutionary Feature Selection (GEFeS) [30, 31, 32] and weighting (GEFeW) use the basic concept of GEC for selecting and weighting those features that are relevant for biometric recognition systems. In addition, GECs help to minimize the features by improving the accuracy. This allows one to realize the biometric authentication for real time applications due to the fact that reducing the number of features minimizes the computation time and storage requirements.

This thesis makes two contributions to the field of biometrics. The first contribution is to answer the question of how overlapping blocks/patches affect LBP feature extraction for FR. The assumption is that overlapping blocks might increase the recognition accuracy of the LBP based face recognition algorithm since overlapping will increase the data redundancy and redundancy will in turn enhance the performance of the algorithm. This thesis will add more credibility to the impact of block overlapping on recognition performance of the LBP FR algorithm. The second contribution is the application of GEC feature selection and weighting to reduce the number of features required for recognition purposes while attempting to improve the recognition accuracy.

The rest of the thesis is organized as follows. In Chapter 2, LBP feature extraction techniques will be presented. In Chapter 3, a detailed description of genetic search will be presented. Chapter 4 presents the GEFeS and GEFeW. In Chapter 5, the feature extraction experiments and results will be presented. In chapter 6, a detailed description of the Genetic & Co-Evolutionary feature selection and feature weighting experiments and the result will be presented. And finally, in Chapter 7, a Conclusion and insight to future work will be provided.

CHAPTER 2

TECHNIQUES FOR FEATURE EXTRACTION

2.1 Local Binary Pattern (LBP) method

LBP is a feature extraction technique that labels the pixels of input images (both the gallery and the probe) by making a neighborhood threshold of each pixel with the gray value of the center. In other words, the neighborhood pixels' gray values are evaluated with the gray value of the center to generate a binary code that describes the local texture feature. LBP has become a widely used method for feature extraction for various application domains because of its simplicity, high discriminatory power, and invariance to both scale and illumination [33, 34, 35]. It has already been used in several applications including visual inspection, image retrieval, remote sensing, biomedical image analysis, environmental modeling, and motion analysis [36, 37,38].

LBP was first developed by Ojala et al [39, 40]. A number of extensions have been added to the original LBP method since then and a lot of research is being done to improve its accuracy and robustness. LBP is defined a 3 by 3 neighborhood (see Figure 2.1) giving 8 bit codes by taking 8 sampling points of pixels around the central pixel. Formal representation of the LBP is given by Equation 2.1

$$\mathrm{LBP}(\mathrm{x_c,y_c}) = \sum_{p=0}^{7} 2^p s(\mathrm{i_p,i_c}) \tag{2.1}$$

where p is the sampling point of the neighbors around the central pixel i_p and i_c are the gray-level values at the center and at a given point p on the circle , and s(d) is

$$\begin{cases} 1 \; if \; d \geq 0 \\ 0 \; otherwise \end{cases}$$

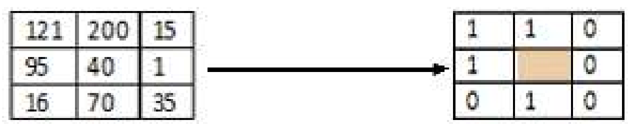

Figure 2.1. The Original LBP Operator

As can be referred from Equation 2.1, there is $2^p=2^8$ quantization that ranges from $(00000000)_2$ to $(11111111)_2$. One drawback of this approach is the length of the feature vector which would be 256 bins representing 2^8 patterns which indeed slows down the recognition speed, especially for a larger Dataset. The other drawback is that only those patterns that contribute to the distinguishing power are needed, especially for pattern recognition problems, since the objective is to extract those distinguishing features for a given input. Two important extensions to the original approach are proposed to allow neighborhoods of different size, since the original LBP uses only 8 neighborhoods and minimize the quantization by using only uniform patterns among all   possible patterns. Figure 2.2 shows variable sampling points using the uniform pattern. Varying the sampling points is very useful in dealing with textures at different scales.

As can be seen in Figure 2.2, the uniform pattern considers a circle of radius R from the center pixels and P sampling points are taken on the circle and compared with the central pixel. It is similar to the original LBP. However, it uses only those patterns which have at most one 0-1 and one 1-0 transition when viewed as a circular bit string. This method considers only uniform patterns to construct the histogram with 2^P bins; it uses only P (P-1) +3 possible uniform patterns as bins where P is the number of sampling points. For instance, for 8 sampling points we have 8(8-1) +3 =59 bins, for 12 sampling points we have 12(12-1) +3=135 bins, and for 16 sampling points we have 16(16-1)+3=243 bins.

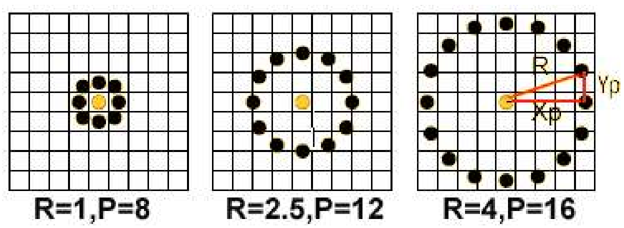

Figure 2.2. Circular neighborhood with variable radius

Suppose the coordinates of the center pixel is (x_c and y_c) then the coordinates of the P sampling point (x_p and y_p) on the circle with radius R where $x_p = x_c + Rcos(2\prod p/P$and $y_p = y_c + Rsin(2\prod p/P$. To compare a given pattern for uniformity, one possible method is to differentiate patterns in which a pattern gets '0' value where there are no transitions, a value of '1'on places where there is a transition from 0 to 1, and a pattern gets ‘-1’ on places where there is a transition from 1 to 0. The sum of the absolute values of this new vector is the number of transitions in the original pattern. It can be represented by the pseudo code fragment shown in Figure 2.3.

```
Pattern=0
If no transition: pattern=pattern+0
If transition is from 0 to1: pattern=pattern+1
If transition is from 1 to 0: pattern=pattern+|-1|
If pattern<3 : uniform
Else non-uniform
```

Figure 2.3. The sample code pattern determination.

Figure 2.4 shows all 58 possible patterns to be used as bins in the construction of the histogram using 8 sampling points. The 59th bin is used to account for all non-uniform patterns. Each pattern will be counted its respective bin in the construction of a histogram. Uniformity is a very important concept in the LBP technique, representing primitive structural information about the spot, line end, edge, corner, etc. These patterns represent discriminatory features that can be used for distinguishing individual images for recognition purpose

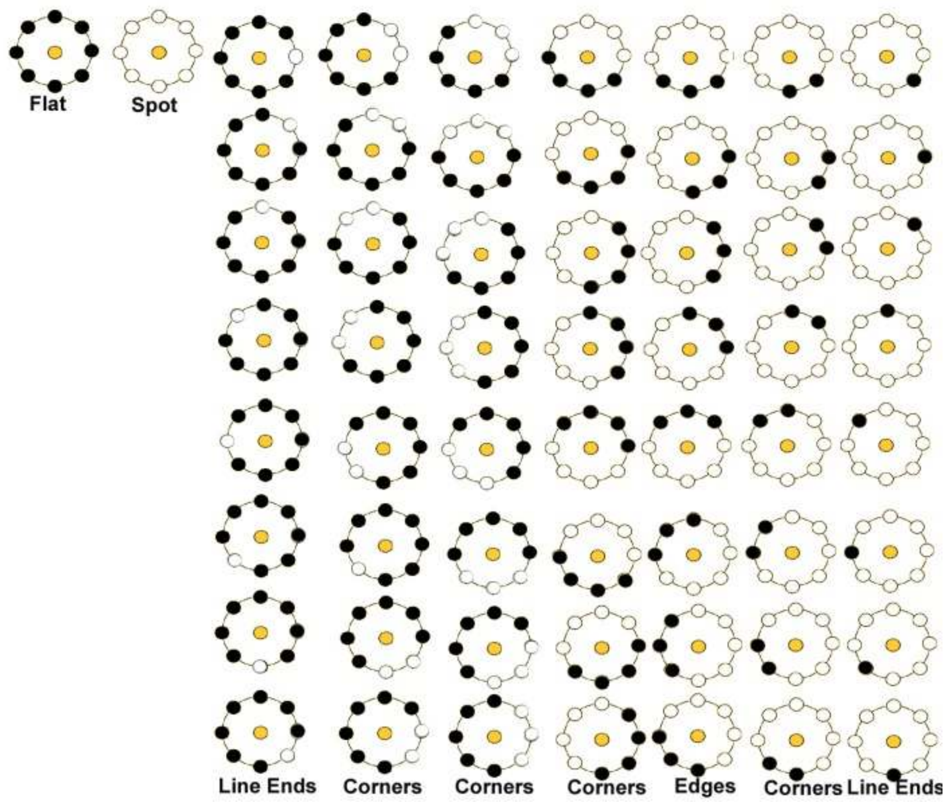

Figure 2.4. The 58 patterns representing uniform patterns.

2.2 Overlapping LBP (oLBP)

For LBP based feature extraction, an image is first divided into several patches from which local binary patterns are extracted to produce histograms from all non-border pixels. The histogram obtained from each patch is concatenated to construct the global feature histogram that represents both the micro-patterns and their spatial location. In other words, the histograms contain description of the images on three different levels of localities. The first one indicates that the labels for histograms contain information about the pattern on a pixel level. Second, the summation of the labels obtained in the patch level produce the information on a regional level. Third, the histograms at the regional level are concatenated to produce the global descriptor of the image.

For each patch, local binary patterns are extracted from non-border pixels. When logically partitioning the images into the patches, both the external and the internal borders are ignored. As the number of patches increases, the number of pixels excluded as border increases. In LBP patches are treated as separate images and it is by design not possible to compute LBP for border pixels since they do not have the required P neighbors to form a neighborhood. However, excluding the borders, especially for LBP with a significant number of patches, may have an impact on the overall performance of the algorithm. The purpose of this research to investigate whether including the internal border pixels by overlapping patches has an impact on the performance of LBP.

In order to consider a given pixel as part of LBP features, the pixel should have neighbor pixels equal to the number of sampling points. So both the internal and external borders are excluded due to the basic methodology of LBP that computes local binary patterns only for the non-border pixels. As the number of patches increase, the number of border pixels to be excluded increase. Therefore, excluding the border pixels, especially the internal borders created by the logical partitioning of the input image into an arbitrary number of patches, may be significant. It is possible to include those internal borders created due to the logical partition of the image by overlapping the patches by one pixel value. By performing the overlap, it is possible to retain the same number of features, while allowing those internal border pixels to contribute to the overall feature representation.

Three possible overlaps were investigated: horizontal, vertical, and horizontal & vertical. The horizontal overlap is used to include those border pixels found in the left and right side of a patch. The vertical overlap is used to include those border pixels found at the top and bottom of a given patch. The horizontal & vertical overlap includes those borders at the left, right, top, and bottom of a given patch. In addition, it is also possible to overlap the patches with an arbitrary number of pixels so that, by overlapping pixels, data redundancy is increased. There exists a small amount of research [41] that investigates such overlapping. In this research, the authors of [41] found that overlapping blocks have significantly improved accuracy. However, this work was performed on a Dataset of Corel Images which have no relationship with biometric systems.

CHAPTER 3

OVERVIEW OF GEC

Conceptually, Genetic and Evolutionary Computation (GEC) searches for good solutions to problems by testing a large number of candidate solutions (Chromosomes) [42]. A typical GEC starts with the generation of an initial population of chromosomes, then each chromosome is evaluated using a fitness (objective) function designed for a specific problem domain. Parents are selected from the existing chromosomes based on their fitness values. Then reproduction operators (either crossover, mutation, or both) are applied to the parents to produce new chromosomes. Based on their fitness values, survivors are selected from the current generation combined with the newly produced offspring to form the new population for the next generation. This general framework is represented in Figure 3.1.

A Genetic Algorithm (GA) is generally used to deal with the optimization of search problems by a pair P=(c, f) where c is the set of all candidate solutions and f is the fitness function [42]. A typical GA can be characterized in terms of eight basic attributes: The first attribute is the Genetic Representative of a Candidate Solution. There are two types of representations: real coded which directly represents variables of problems with the values themselves and binary coded, which encodes each variable into a binary string.

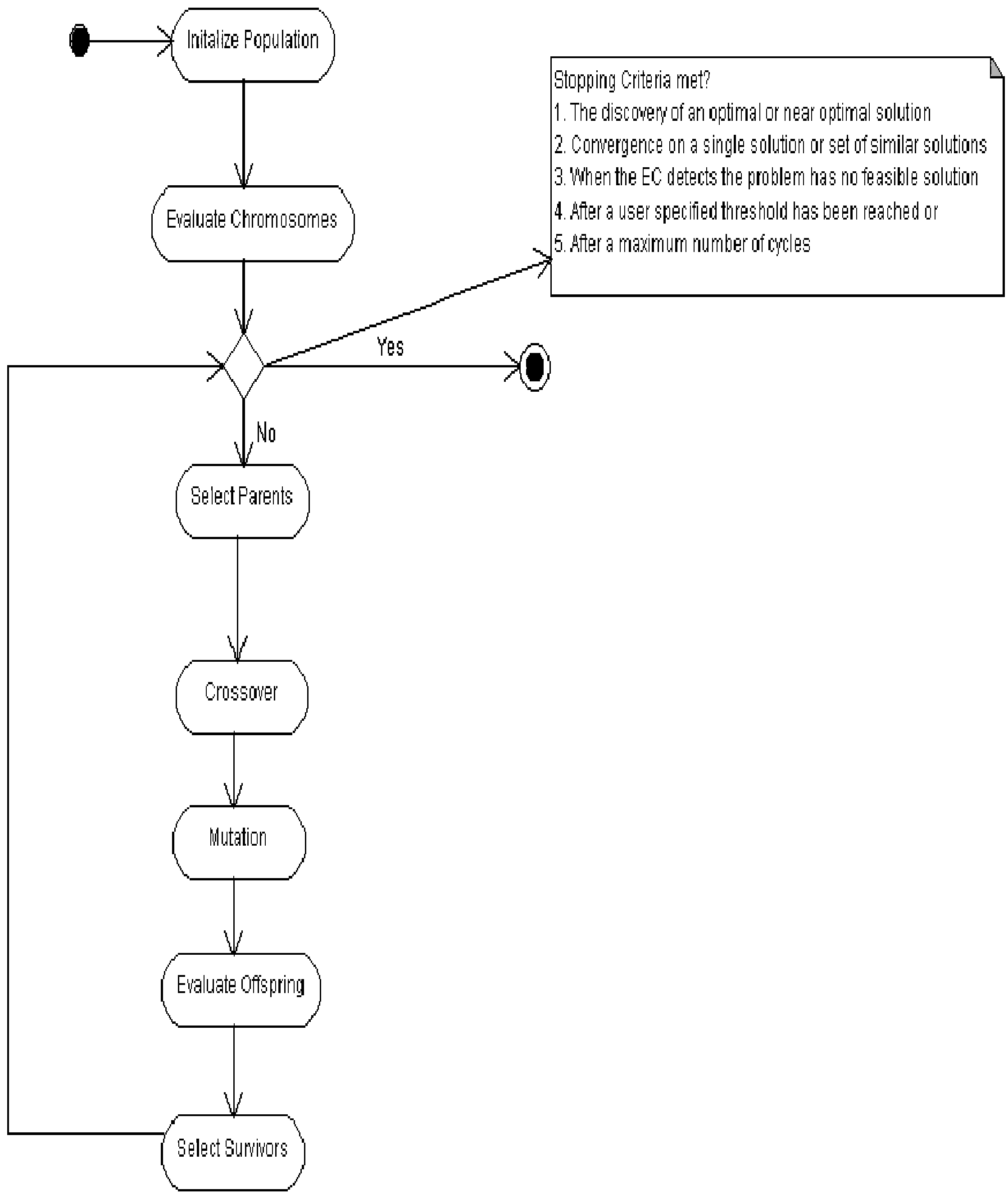

Figure 3.1. Framework of a typical GA

The second attribute is the Population Size. It represents the number of individuals allowed in the population maintained by the GA. It is important to take into consideration the various factors for choosing the population size. If the population size is too large then the GA tends to take longer to converge upon a solution, whereas a smaller population size leads to premature convergence upon a sub-optional solution. One reason for premature convergence is that there may not be enough diversity in the population to allow the GA to escape from local optima. A third attribute is the Evaluation Function. This function evaluation is used simply to calculate an individual's fitness. The fitness indirectly determines the probability of an individual surviving to the age of reproduction and successfully reproducing.

The fourth attribute is the Genetic Operators, which includes recombination (crossover) and mutation. Natural selection is the process of allowing individuals to procreate or die based on their relative fitness. Crossover (recombination) operators exchange information among parents. Typical GA crossover operators are single-point, two-point, and uniform crossover [43].   Mutation operators are essential to the prevention of premature convergence.. There are two commonly used terms in Mutation: Mutation usage rate and mutation range. Mutation usage rate indicates how often children are mutated. For example, a mutation usage rate of 0.2 indicates that 20% of all children must undergo mutation. The mutation range provides a window from the current valve (obtained value after recombination) that the new value will be mutated.

The fifth attribute is the Selection Algorithm**,** which is a component that selects individuals to become parents [43]. The most common selection algorithm is

Tournament Selection. Tournament Selection works as follows: The fittest individual is selected from a randomly selected group of individuals. The size of the group is commonly called the tournament size. A tournament size of two is commonly used in practice.

Generational and steady state [44] are the two commonly used types of evolution. They differ mainly in the replacement of strategy used. The generational GA creates a number of children equal to the current population and replaces all of the parents with the offspring. The steady state GA algorithm selects two parents and creates one or more (usually two)offspring which will replace the worst fitness among the parent population, even if the offspring itself has worse fitness values than the worst fitness the among the current generation.

CHAPTER 4

GEC-BASED FEATURE SELECTION AND WEIGHTING

4.1 Face Recognition Datasets

FR can be performed in either a frontal or profile view. There are a number of FR algorithms that have been developed by researchers in computer vision research. In full frontal view as described in [45], the nose doesn't play a significant role as compared to eyes and mouth for example. In dealing with the profile view however, the nose is one of the fudical points (face-specific points) that require extreme interest. The shape and length of the nose are just some of the features that are explored for profile based FR. There are a number of FR feature extraction methods developed by researchers in computer vision research. In general, we can make a rough classification of the research approaches to FR algorithms into part-based, holistic/appearance-based and a synthesis based methods. This chapter briefly discusses the FR feature extraction methods reported in the literature that are closely related to the work presented in this thesis.

Faces are highly deformable and complex structures that often differ due to a number of factors including pose, expression, lighting, and aging. The development of algorithms that are robust to these variations requires reasonable and sufficient datasets of images that consider the controlled variations of these aforementioned factors. Along with the development of FR algorithms, various Datasets have been constructed for evaluating the performance of FR methods.

There are many face Datasets available for researchers in the face recognition community; Face Recognition Technology (FERET) [46, 47], Face Recognition Grand Challenge (FRGC) [48, 49], Yale [50], Pose, Illumination, and Expression (PIE) [51], Morph[52], and BioID [53] are some examples of face datasets that are publicly available for researchers [54]. However, the most widely used dataset are FERET and FRGC.

For the research presented in this thesis, a subset of the FRGC dataset was selected with a consideration that it encompasses various ethnic origins with frontal images neutral and with facial expressions. A total of 280 images were used for probe and 560 images were selected for the gallery. The images had passed the preprocessing stages [55] such as eye rotation alignment, histogram equalization, masking resizing (each with 225 by 195), and conversion of the images into grayscale.

4.2 LBP based Feature Extraction

For LBP based feature extraction for face recognition purpose, we first need to logically divide the image into smaller regions. The most common technique is to divide the images into k^2, where k is an integer. However, one can divide the face image into any arbitrary regions with any kind of shape. There is no heuristics that suggests how many number of patches needed for a specific application such as FR.

We have devised two sets of experiments using the LBP based face recognition technique.. The objective of the first experiment is to determine whether including the middle border pixel has an impact on the recognition performance. To accomplish this, we have logically partitioned the 195 by 225 sized face image into 36 blocks and applied a uniform LBP operator with a radius of 1 and 8 pixel sampling point. The importance of portioning the face image into blocks is to produce spatial information on a specific region and concatenating the regional histogram to obtain the global feature of the face image. So every block consists of P(P-1) +3 bins where p(p-1) are the bins for the patterns with two transitions, 2 bins for the patterns with 0 transitions (00000000, 11111111) and 1 bin for all non-uniform patterns. We computed the total features vector to be 2124 using the formula B (P (P-1)+3) ,where B is the number of blocks and P is the sampling points.

In order to include the inner border pixels, we logically overlapped the blocks into horizontally, vertically, and both vertically and horizontally with one pixel. Sample of the non-overlapped and horizontally overlapped blocks are shown in Figure 4.1 A, B respectfully.

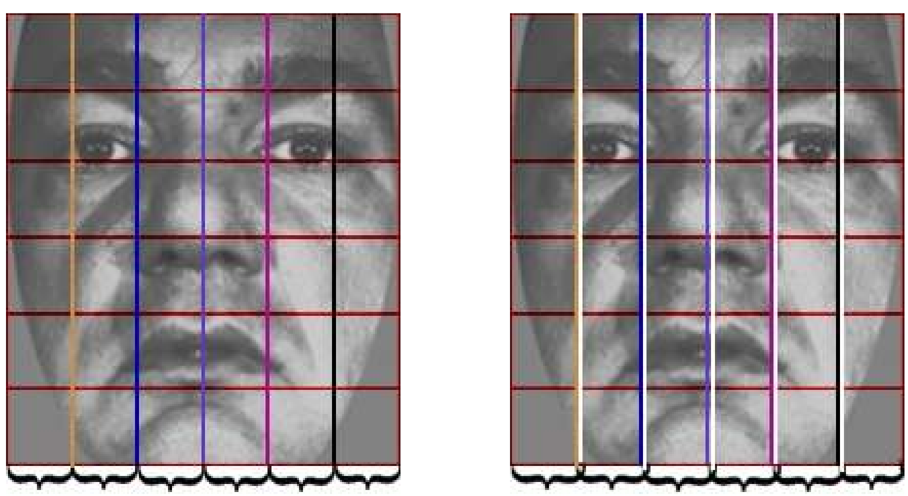

Figure 4.1. (A) left non-overlapped (B) right 1 pixel horizontal overlaps

In addition to overlapping the patches to include the inner border pixel, we have also logically partitioned the blocks (see Figure 4.2) vertically, horizontally, and both vertically and horizontally with pixel value of 2, 4, 8, and 16. The motivation for such partitioning experiment is that overlapping the blocks increases data redundancy and redundancy in turn increases the accuracy.

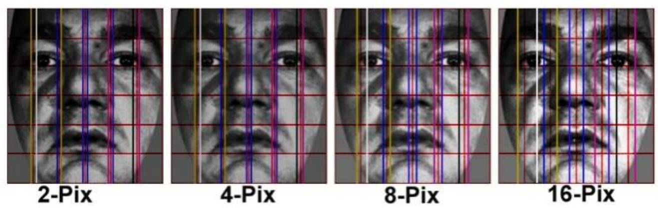

Figure 4.2. Horizontal overlapping of patches with 2, 4, 8, and 16

4.3 Genetic & Evolutionary Feature Selection and Weighting

The GEFeS and GEFeW are designed for filtering out the most discriminatory features used for recognition among subjects [55, 56]. GEFeS and GEFeW are instances of a Steady-State Genetic Algorithm (SSGA) [58,59] with a population size of 20, Mutation Rate of 1.0, and Mutation range of 0.2. The objective of this second experiment was to see the impact of applying feature selection and weighting on the LBP-based extracted features in an effort to improve accuracy while reducing the number of features relevant for face recognition. For the second experiment, consider the following feature matrix shown in Figure 4.3 which is extracted for and used as input for the GE feature selection and weighting experiment.

$$\begin{bmatrix} 0 & 50 & 70 & 1 & 4 & 9 \\ 14 & 6 & 7 & 12 & 6 & 0 \\ 2 & 1 & 5 & 14 & 70 & 14 \end{bmatrix}$$

Figure 4.3. Sample Feature matrix

Furthermore consider also the matrix shown in Figure 4.4 as a candidate real-coded feature mask. For GEFeS a masking threshold value of 0.5 is used to create a binary coded candidate feature mask.

$$\begin{bmatrix} 0.11 & 0.7 & 0.2 & 0.9 & 0.3 & 0.6 \\ 0.4 & 0.29 & 0.6 & 0.7 & 0.44 & 0.51 \\ 0.39 & 0.82 & 0.71 & 0.8 & 0.4 & 0.9 \end{bmatrix}$$

Figure 4.4. Real-Coded Feature Mask

The masking threshold determines which feature to select or not. If the real number generated is less than the threshold (0.5 in this case), then the value corresponding to the real generated number is set to 0 in the candidate feature mask (it is set to 11 otherwise). Figure 4.5 shows the candidate binary coded feature mask matrix obtained from the real numbers generated in and the masking threshold value is applied on the real numbers to obtain the binary representation

$$\begin{bmatrix} 0 & 50 & 70 & 1 & 4 & 9 \\ 14 & 6 & 7 & 12 & 6 & 0 \\ 2 & 1 & 5 & 14 & 70 & 14 \end{bmatrix} \begin{bmatrix} 0.11 & 0.7 & 0.2 & 0.9 & 0.3 & 0.6 \\ 0.4 & 0.29 & 0.6 & 0.7 & 0.44 & 0.51 \\ 0.39 & 0.82 & 0.71 & 0.8 & 0.4 & 0.9 \end{bmatrix}$$

$$\Downarrow$$

$$\begin{bmatrix} 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 & 1 \end{bmatrix}$$

Figure 4.5. Binary-Coded Candidate Feature Mask

When comparing the candidate feature mask with the feature matrix, if a position corresponding to the feature matrix value in the candidate feature mask is 0 then that feature value will be masked out (or removed) from being considered in the distance computation. Figure 4.6 shows the result of the features applied to a feature matrix.

$$\begin{bmatrix} 0 & 50 & 70 & 1 & 4 & 9 \\ 14 & 6 & 7 & 12 & 6 & 0 \\ 2 & 1 & 5 & 14 & 70 & 14 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 & 1 \end{bmatrix}$$

$$\Downarrow$$

$$\begin{bmatrix} 0 & 50 & 0 & 1 & 0 & 9 \\ 0 & 0 & 7 & 12 & 0 & 0 \\ 0 & 1 & 5 & 14 & 0 & 14 \end{bmatrix}$$

Figure 4.6. The resulting Feature matrix after Feature Masking

For GEFeW, the real-coded candidate feature mask is used to weight features within the feature matrix. The matrix shown in Figure 4.7 is the result of multiplication of the he real-coded candidate feature mask with each feature to provide weighted feature value. If the number generated is 0 (or approximately equal to 0) the feature value is 0, this means that the feature is considered as masked. So for GEFeW, the threshold value by default is 0. The fitness returned by the evaluation function is the number of recognition errors encountered after applying the feature masking multiplied by 10 plus the fraction of features used.

$$\begin{bmatrix} 0 & 50 & 70 & 1 & 4 & 9 \\ 14 & 6 & 7 & 12 & 6 & 0 \\ 2 & 1 & 5 & 14 & 70 & 14 \end{bmatrix} \begin{bmatrix} 0.11 & 0.7 & 0.2 & 0.9 & 0.3 & 0.6 \\ 0.4 & 0.29 & 0.6 & 0.7 & 0.44 & 0.51 \\ 0.39 & 0.82 & 0.71 & 0.8 & 0.4 & 0.9 \end{bmatrix}$$

$$\Downarrow$$

$$\begin{bmatrix} 0 & 35 & 14 & 0.9 & 12 & 9 \\ 5.6 & 17.4 & 42 & 0.84 & 2.64 & 0 \\ 0.78 & 0.82 & 3.55 & 11.2 & 28 & 12.6 \end{bmatrix}$$

Figure 4.7. The resulting Weighted Feature matrix

CHAPTER 5

FEATURE EXTRACTION EXPERIMENTS AND RESULTS

5.1 Feature Extraction experiment

Three snapshots for each subject, one for probe and two for constructing the gallery with a total of 840 images were used. All the 560 gallery images were used as training dataset with two snapshots of the images in the probe set. For both LBP and oLBP, we have extracted 2124 features for each image since we have used 36 patches and LBP pixel sampling point of 8 with radius 1. This resulted in 59 bins for each patch. Multiplying the number of patches with the number of bins resulted in 2124 feature values.

5.2 Feature Extraction experimental result

The experimental results for overlapping the inner border of patches with 1 pixel, with the intent to include the internal border pixels, are shown in Table 5.1. The results indicate that for vertical and both vertical and horizontal overlapping of the LBP- based algorithm inclusion of the internal boarder by overlapping has no impact on performance. However, horizontal overlapping slightly improves the accuracy. As show in Table 5.2, the experiment on overlapping the blocks with 4, 8, and 16 pixels with the assumption that overlapping blocks might increase the recognition accuracy of the LBP based face recognition algorithm. The reason is that overlapping blocks increase the data redundancy and redundancy in turn enhance the performance of the algorithm did not improve the performance.

Table 5.1. Result of the LBP baseline and 1pixel overlapping

Experiment	% Accuracy
Non-Overlapping	70.36
Horizontal (1 pixel overlap)	70.71
Vertical (1 pixel overlap)	70.36
Horizontal &Vertical (1 pixel overlap)	70.36

As can be seen from Table 5.2 for some overlaps, there is degradation in the performance as compared with the baseline. These two results indicate that including the internal borders by overlapping the patches by 1, 2, 4, 8, and 16 pixel values horizontally, vertically, and both (horizontally and vertically) does not provide a conclusive amount of improvement. A number of reasons can be given for this. One possible reason is that giving more weight to those patches that contain higher discriminatory features can improve the performance while giving less weight to those with discriminatory features degrade the performance. Similar explanation can be given for patches that contain lesser discriminatory features. Detailed presentations of the Cumulative Match Characteristic (CMC) of the LBP and oLBP experimental results are shown in the Appendix.

Table 5.2. LBP Overlapped with 2, 4, 8, and 16 Pixels

oLBP Experiment	**% Accuracy (2 pixel overlap)**	**% Accuracy (4pixel overlap)**	**% Accuracy (8 pixel overlap)**	**% Accuracy (16 pixel overlap)**
Horizontal	70.36	70.00	68.57	69.29
Vertical	70.36	70.00	69.69	69.69
Vertical & Horizontal	70.00	69.69	68.93	67.14

This gives us a clue on how to give weight to those patches with high discriminatory features at the feature level by overlapping instead of giving a mere integer value as weight for those patches with a high discriminatory feature at the score level which is a common current practice. Table 5.3 shows the experimental result of the LBP baseline and the oLBP best performing experimental set. As can be seen from the Table 5.3 the oLBP algorithm perfumed well as compared to LBP. Both have the same number of features.

Table 5.3. Result of the LBP and oLBP experiments

Experiment	**Number of features used**	**% Accuracy**
LBP (Baseline)	2124	70.36
oLBP(overlapping best)	2124	70.71

CHAPTER 6

GEFeS & GEFeW EXPERIMENT AND RESULT

6.1 Feature Selection experiment

The inputs for these experiments were the extracted features using the LBP, and oLBP (overlapping Patches) on the subset of the FRGC dataset. 280 subjects were used for oLBP and LBP based feature extraction experiments. Using 2124 features were used to produce the percentage accuracy of 70.36 and 70.71 in both the average & the best accuracy for LBP and oLBP best experiments respectively.

GEFeS and GEFeW are designed for filtering out the most discriminatory features used for recognition among subjects For our experiment, two instances of SSGA were used: The LBP-GEFeS, and oLBP-GEFeW. These instances all have a population size of 20, Gaussian mutation rate of 1 and mutation range of 0.2. Furthermore they were each run a total of 30 times with a maximum of 1000 function evaluations.

6.2 GEFes and GEFeW experimental results

GEFeS and GEFeW were applied on the features extracted via the LBPand oLBP methods. Four SSGA instances: LBP-GEFeS, LBP-GEFeW, oLBP-GEFeS, and LBP-GEFeW were compared. ANOVA and t-Tests were used to divide the four SSGAs and the LBP methods into corresponding equivalence classes based on accuracy.

The results show that when using 100 percent of the features, the maximum accuracy obtained for the baseline LBP was 70.36%. Even if the oLBP performs slightly better than the baseline, it still uses 100% features to provide the accuracy result of 70.71%. As can be seen in Table 6.1 applying the GEFeS on the feature set extracted by the standard LBP significantly improves accuracy from a 70.36 to 96.62 average. This shows that GEFeS is actually masking out those features which are less relevant for recognition purpose. This improvement in accuracy comes also with a reduction in the number of features used for recognition. The percentage of features used for GEFeS is 48.12. In other words, less than 50% of the features are needed to improve the accuracy by more than 25%.

Similarly, applying the feature set extracted via GEFeS to oLBP improves the accuracy from 70.71% to 96.43% . Both LBP-GEFEs and oLBP-GEFeS fall in the same equivalence class with respect to accuracy. However, the percentage of features used by LBP and oLBP is 47.85, 48.12 respectively. Table 6.1 shows, the overall comparison of the six methods used in this experiment.

Comparing the GEFeS for the baseline, there is a significant reduction of feature usage by GEFES. It reduces the feature approximately by half. Please refer the Appendix for CMC curve of the best accuracy result from each run with a given rank. For feature weighting using GEC, both applying GEFeW on LBP and oLBP resulted in worse performance than the corresponding GEFeS methods. This indicates that masking out features based on the binary-coded feature masks has better performance than applying GEC feature weighting.

Table 6.1. Feature Selection and Weighting experiments on LBP and oLBP

Experiment	% Feature Used	Average Accuracy	Best Accuracy
LBP (Baseline)	100	70.36	70.36
oLBP	100	70.71	70.71
LBP-GEFeS	48.12	96.62	97.14
LBP-GEFeW	87.82	95.33	95.71
oLBP-GEFeS	47.95	96.43	96.79
oLBP-GEFeW	87.81	95.33	96.07

In addition, GEFeW used a 87% of the features to obtain the recorded accuracy. This shows that GEFeW is not a better option in feature reduction than GEFeS . However, applying the GEFeW on the baseline LBP and on oLBP improves the performance significantly from 70.36 and 70.71 to 92.5 % and 92.3 respectively. One again, the overall result indicates that LBP-GEFeS and oLBP-GEFeS fall into the same equivalent class in terms of accuracy. Among them it is the oLBP-GEFeS that provides the smallest % of features (47.954%) followed by LBP-GEFeS with 48.12% feature usage.

CHAPTER 7

CONCLUSION AND FUTURE WORK

Including the internal borders by overlapping the patches by 1, 2, 4, 8, and 16 pixel values horizontally, vertically, and both (horizontally and vertically) does not provide a conclusive amount of improvement. This can be explained as giving more weight for those patches containing high discriminatory features improves the accuracy. On the contrary, if more weight is given to those patches which contain less discriminatory feature will degrade the performance. If one knew which patches to make redundant by overlapping and ignoring those with less discriminatory features one could improve the accuracy. However, we have seen from the result that there is improvement in performance for some overlaps, no change for some, and degradations for the others. The performance improvement can be explained by the fact that more weight is given to patches with higher discriminatory features by data redundancy (overlapping) leading to better performance just like giving more weight to that specific patch. Similarly, the degradation in performance could be explained by the fact that more weight (by data redundancy) is given to those patches with lesser discriminatory features resulting in performance degradation.

The experimental results of applying feature selection and weighting using the concept of GEC on LBP, and oLBP shows that GEFeS and GEFeW enhances the overall performance of the LBP based feature extraction. Among the LBP based algorithms, LBP-GEFeS and oLBP-GEFeS are in the same equivalence class in terms of accuracy. Both performed well in terms of reducing the number of features and in producing a significant improvement in accuracy.

The results show that GEFeS reduces the number of features needed by approximately 50% while obtaining significant improvement in the accuracy. GEFeS improves the accuracy significantly from 70.36 to 96.62 for LBP-GEFeS and from 70.71 to 96.43 for oLBP-GEFeS respectively. The reduction of the features will allow one to embed the biometric features into small smart devices, making it usable for real time systems.

Based on the experimental results, we can conclude that GEFeS and GEFeW are very useful for LBP based face recognition. For future work, we would like to extend our experiments to include LBP with different parameters (radius and sample pixel point) and other algorithms such as the Fisherface, and ICA approaches.

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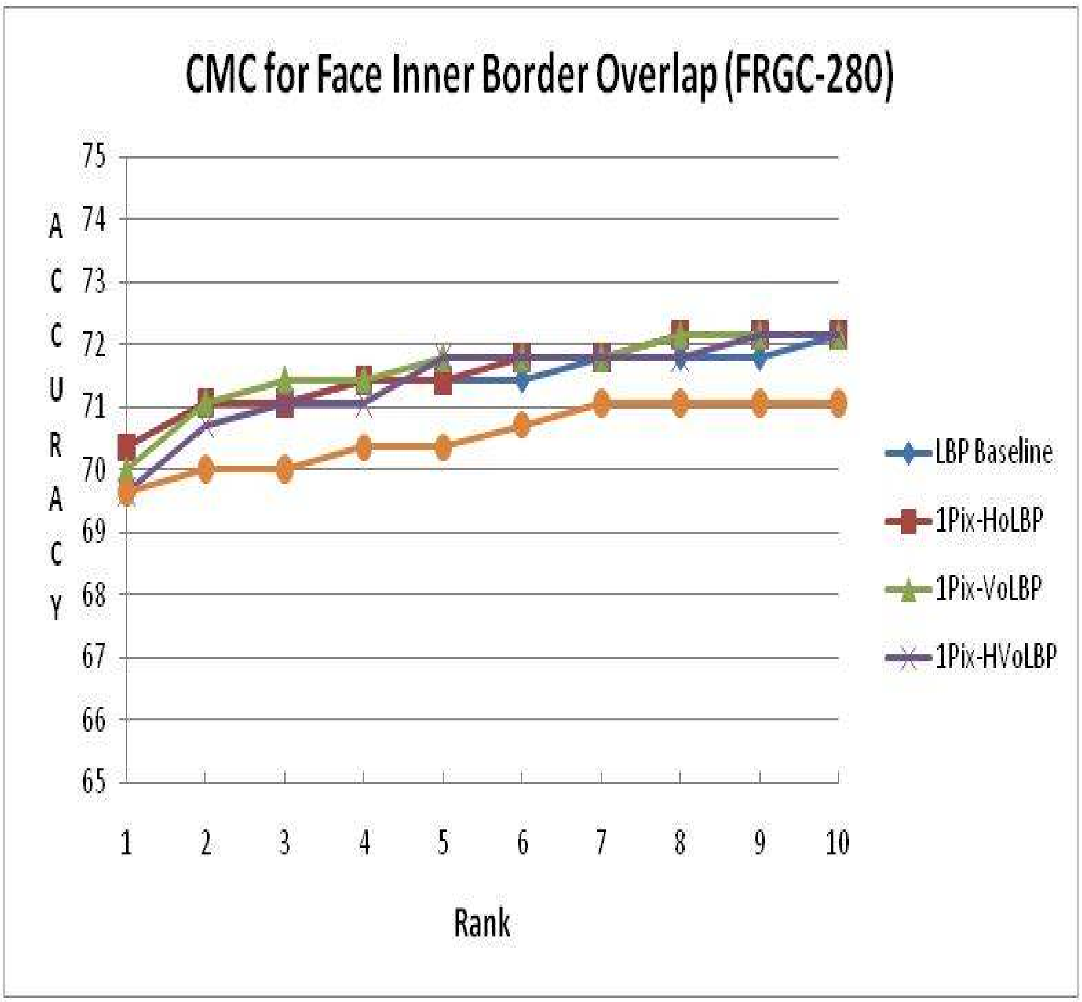
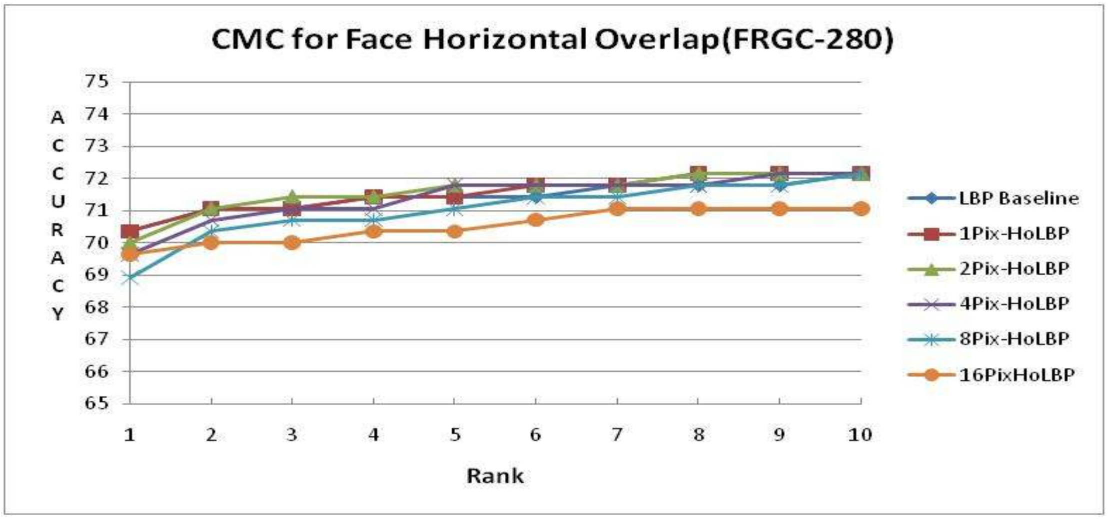
APPENDEX

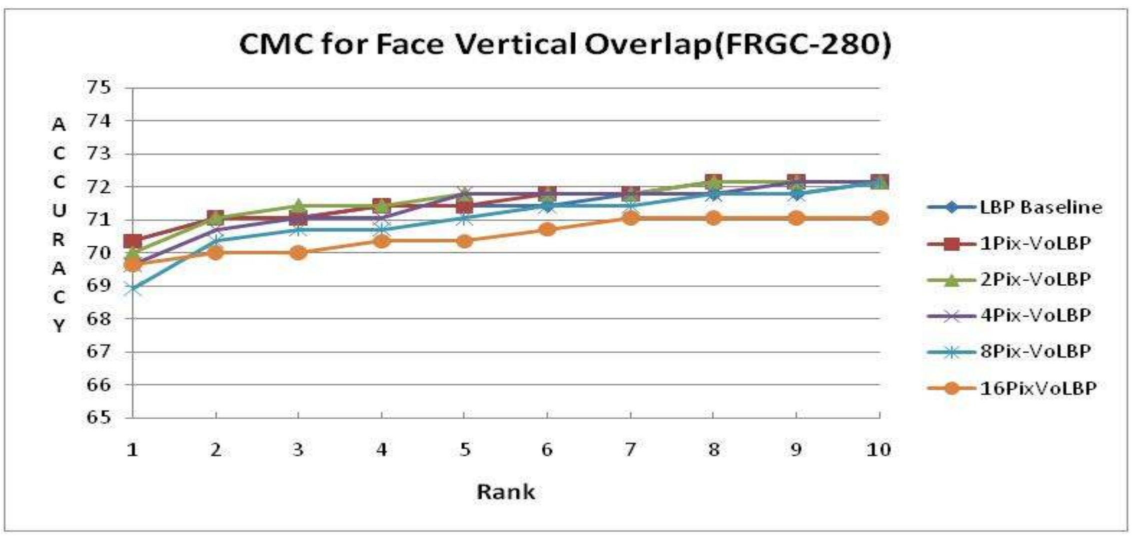
CUMULATIVE MATCH CHARACTERISTIC



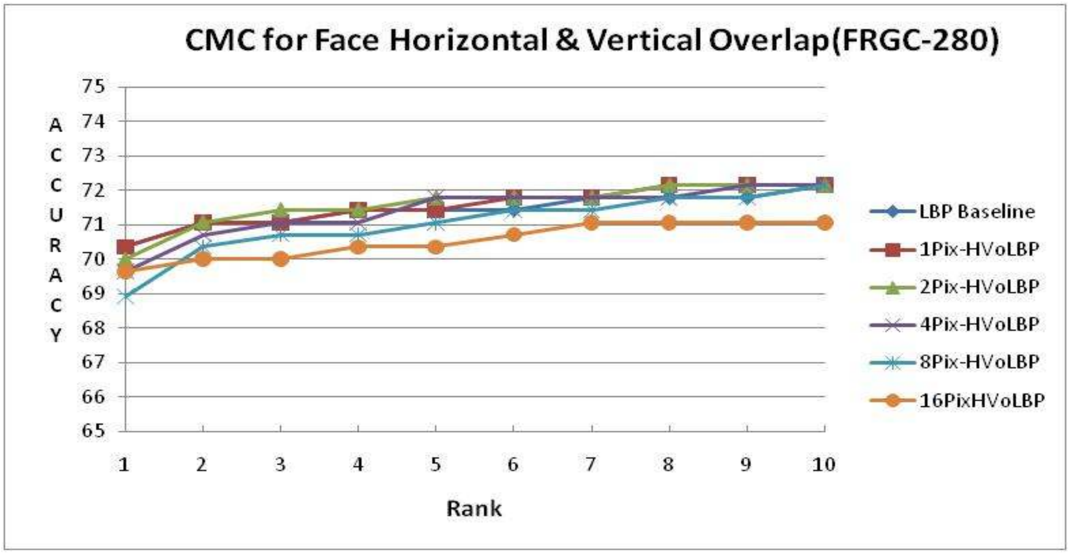
Comparison of LBP baseline with all 1-pixel LBP overlaps (oLBP)



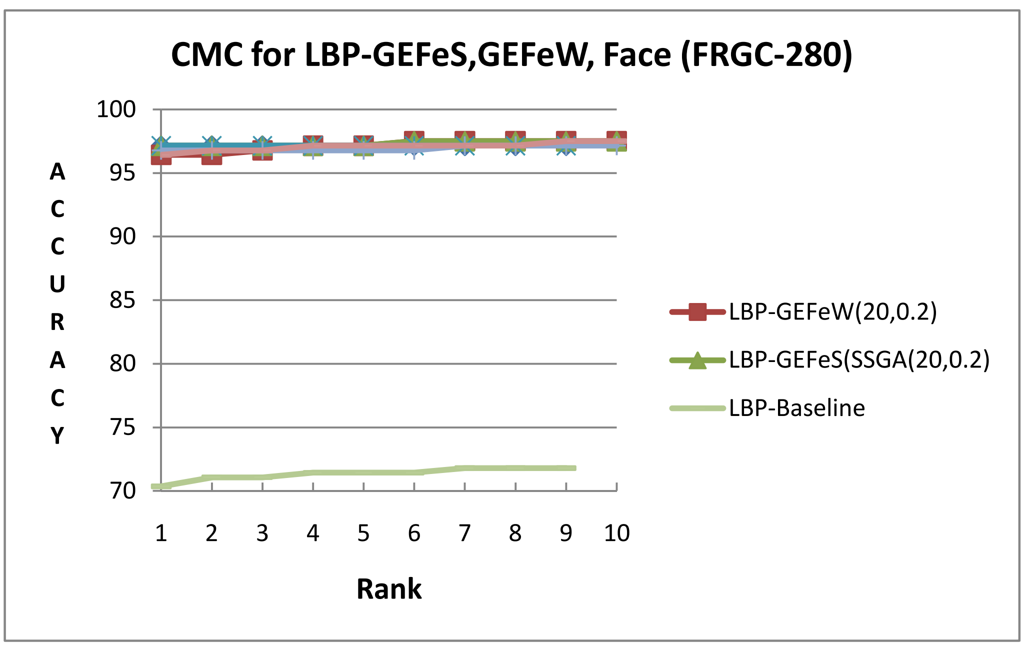
Comparisons of results for LBP 2, 4,8,16 horizontal overlaps



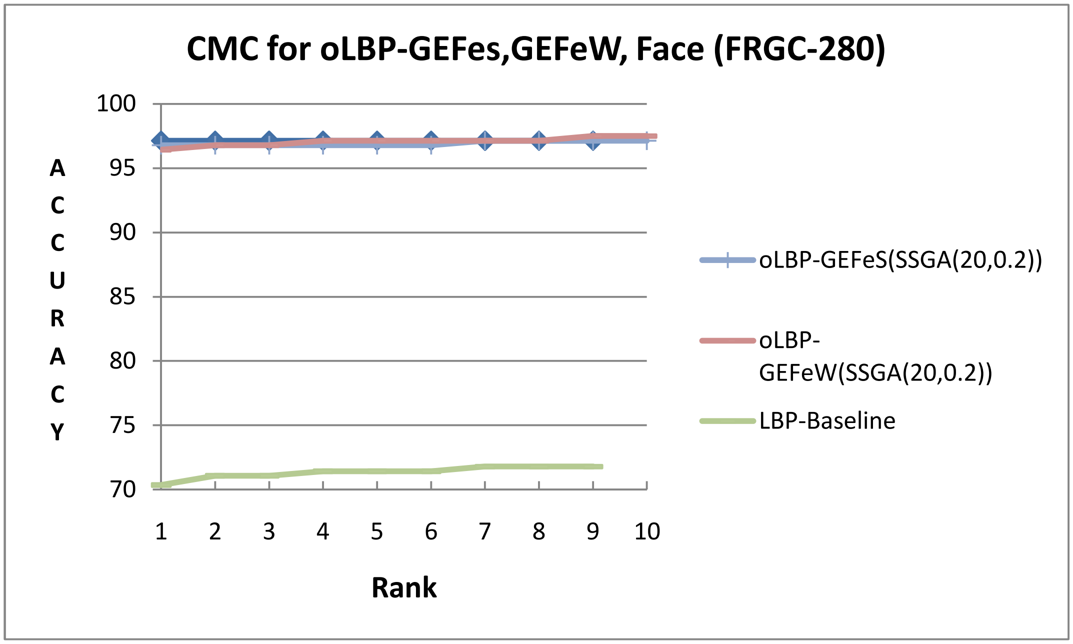
Comparisons of results for LBP 2, 4,8,16 vertical overlaps



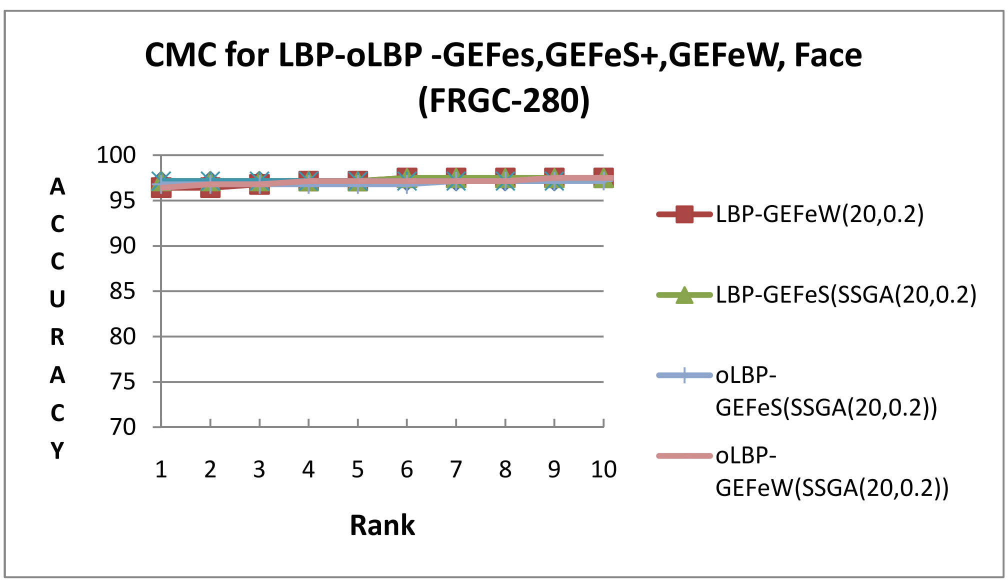
Results for LBP 2, 4,8,16 horizontal & vertical overlaps



CMC for the best accuracy result of the LBP Experiment



CMC for the best accuracy result of the oLBP Experiment



CMC for LBP and oLBP best Experiment