Fusion of Face and Iris Biometrics for Person Identity Verification

Maryam Eskandari

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Prof. Dr. Elvan Yılmaz
Director

I certify that this thesis satisfies the requirements as a thesis for the degree of Doctor of Philosophy in Computer Engineering.

Prof. Dr. Işık Aybay
Chair, Department of Computer Engineering

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Doctor of Philosophy in Computer Engineering.

Asst. Prof. Dr. Önsen Toygar
Supervisor

Examining Committee

1. Prof. Dr. Gözde Bozdağı Akar
2. Prof. Dr. Aytül Erçil
3. Assoc. Prof. Dr. Hasan Demirel
4. Asst. Prof. Dr. Önsen Toygar
5. Asst. Prof. Dr. Ahmet Ünveren

ABSTRACT

This thesis focuses on fusion of multiple biometric systems in different fusion levels especially score level fusion and feature level fusion. Generally, multimodal biometrics based systems aim to improve the recognition accuracy using more than one physical and/or behavioral characteristics of a person. In fact, fusion of multiple biometrics combines the strengths of unimodal biometrics to achieve improved recognition accuracy. This thesis improves the recognition accuracy by proposing different schemes in score level fusion, feature level fusion, decision level fusion and combination of different fusion levels such as score and feature level fusions.

Face and iris biometrics are used to obtain a robust recognition system by using several feature extractors, score normalization and fusion techniques in four different proposed schemes. Global and local feature extractors are used to extract face and iris features separately as unimodal system and then the fusion of these modalities is performed on different subsets of face and iris image databases. Subpattern-based PCA (spPCA), modular PCA (mPCA) and Local Binary Patterns (LBP) methods are used as local feature extractors. Beside these local methods, global feature extractors such as Principal Component Analysis (PCA) and subspace Linear Discriminant Analysis (LDA) are also used to compare the performance of global feature extractors on face and iris images separately. On the other hand, Libor Masek's iris recognition system is employed on iris images in some schemes to extract iris features. In order to enhance the recognition accuracy of unimodal and multimodal systems in some proposed schemes, Particle Swarm Optimization (PSO) is also implemented as feature selection procedure in reducing the dimension of feature vectors and subsequently improving the recognition performance.

The performance of different schemes is validated on several datasets using recognition accuracy and Receiver Operator Characteristics (ROC) analysis. These schemes are based on Weighted-Sum Rule, Sum-Rule, Product-Rule along with Tanh and Min-Max normalization in matching score level fusion. Additionally, Face-Feature Vector Fusion (Face-FVF) or Iris-Feature Vector Fusion (Iris-FVF) with and without PSO feature selection method are used in feature level fusion. Moreover, Majority voting is employed in decision level fusion. The datasets to perform the experiments are selected from ORL, FERET, BANCA, CASIA, UBIRIS and CASIA-Iris-Distance databases. In addition, combination of different databases is used to have different conditions in terms of illumination and pose.

Keywords: multimodal biometrics, face recognition, iris recognition, feature extraction, information fusion, Particle Swarm Optimization, match score level fusion, feature level fusion, decision level fusion.

ÖZ

Bu tezde, özellikle skor düzeyi ve öznitelik düzeyi olmak üzere değişik kaynaşım teknikleri kullanılarak birden fazla biyometriğin birleştirilmesine odaklanılmıştır. Genel olarak birden fazla biyometriğe dayalı sistemler, bir insanın fiziksel veya davranış özelliklerini kullanarak, insan tanıma performansını artırmayı amaçlar. Aslında birden fazla biyometriği birleştirirken, her bir biyometriğin güçlü yönleri birleştirilerek daha iyi tanıma performansı elde etmeye çalışılır. Bu tez, skor düzeyi kaynaşım, öznitelik düzeyi kaynaşım, karar düzeyi kaynaşım ve skor ve öznitelik düzeyi kaynaşım teknikleri gibi değişik kaynaşım tekniklerinin kombinasyonunu önererek tanıma performansını geliştirir.

Güçlü bir tanıma sistemi elde etmek için önerilen dört değişik yöntemde; yüz ve iris biyometrikleri, birçok öznitelik çıkartıcı yöntem, skor normalizasyonu ve kaynaşım teknikleri kullanılmıştır. Bütünsel ve yerel öznitelik çıkarıcı yöntemler, yüz ve iris özniteliklerini ayrı ayrı tek bir sistem olarak çıkarmak için kullanılmış ve daha sonra bu sistemler değişik yüz ve iris veritabanı altkümeleri kullanılarak birleştirilmiştir. Alt-Örüntüye Dayalı PCA (spPCA), modüler PCA (mPCA) ve Yerel İkili Örüntü (LBP) metotları yerel öznitelik çıkarıcılar olarak kullanılmıştır. Bu yerel yöntemlerin yanında, yüz ve iris resimleri üzerinde ayrı ayrı bütünsel öznitelik çıkarıcı yöntemlerin performansını karşılaştırmak için bütünsel Ana Bileşenler Analizi (PCA) ve alt-uzay Doğrusal Ayırtaç Analizi (LDA) yöntemleri kullanılmıştır. Öte yandan, iris özniteliklerini çıkarmak için bazı yöntemlerde iris resimleri üzerinde Libor Masek iris tanıma sistemi kullanılmıştır. Önerilen bazı yöntemlerde, tekli ve çoklu sistemlerin performansını artırmak için, Parçacık Sürü Optimizasyonu (PSO) uygulanmıştır. PSO yöntemi, öznitelik düzeyi kaynaşımı uygulanırken öznitelik vektörlerinin boyutunu azaltmak ve dolayısıyla tanıma performansını artırmak için kullanılmıştır.

Farklı yöntemlerin performansı birçok veritabanı üzerinde tanıma performansı ve Alıcı İşletim Karakteristik (ROC) analizi kullanılarak gösterilmiştir. Bu yöntemler Ağırlıklı-Toplam Kuralı, Toplam Kuralı, Çarpan Kuralı, Tanh ve Enaz-Ençok normalizasyonudur ve eşleşen skor düzeyi kaynaşım yöntemiyle kullanılmışlardır. Ek olarak, Yüz-Öznitelik Vektör birleştirmesi (Yüz-FVF) veya İris-Öznitelik-Vektör birleştirmesi (İris FVF), PSO öznitelik seçme yöntemiyle birlikte veya ayrı olarak öznitelik düzeyi kaynaşımda kullanılmıştır. Ayrıca, karar düzeyi kaynaşım yöntemi olarak Majority Voting yöntemi denenmiştir. Deneyler, ORL, FERET, BANCA, CASIA, UBIRIS ve CASIA-Iris-Distance veritabanları üzerinde yapılmıştır. Farklı veritabanları da birleştirilerek, farklı ışıklandırma ve poz değişimleri içeren ve yeterli sayıdaki bireylerin değişik resimlerini barındıran veritabanları elde edilmiştir.

Anahtar Kelimeler: Çoklu biyometrik, yüz tanıma, iris tanıma, öznitelik çıkarma, bilgi kaynaşımı, Parçacık Sürü Optimizasyonu, eşleşen skor düzeyi kaynaşım, öznitelik düzeyi kaynaşım, karar düzeyi kaynaşım.

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LIST OF ABBREVIATIONS

PCA	Principal Component Analysis
ssLDA	Subspace Linear Discriminant Analysis
spPCA	Subpattern-based Principal Component Analysis
mPCA	Modular Principal Component Analysis
LBP	Local Binary Patterns
FVF	Feature Vector Fusion
FERET	Face Recognition Technology
DWT	Discrete Wavelet Transform
DCT	Discrete Cosine Transform
SVM	Support Vector Machine
HE	Histogram Equalization
MVN	Mean-Variance Normalization
EER	Equal Error Rate
TER	Total Error Rate
ROC	Receiver Operator characteristics
FAR	False Acceptance Rate
FRR	False Rejection Rate
GAR	Genuine Acceptance Rate
PSO	Particle Swarm Optimization
AAM	Active Appearance Modeling

Chapter 1

INTRODUCTION

1.1 Biometric Systems

A biometric system aims to recognize individuals by making use of unique physical and behavioral characteristics of biometric traits based on pattern recognition techniques and statistical methods [1]. Nowadays, biometric systems are becoming a trend in many different places with high security needs such as airports, buildings that require high security for entrance, ATM machines, government and civilian applications, etc. The main advantage of biometrics systems over traditional security methods based on "*what you know*" such as passwords and PINs or "*what you have*" such as keys, magnetic cards and identity documents that can be forgotten, shared, lost, stolen, or copied is the difficulty to share, forget, steal and forge.

The general structure of a biometric system is categorized into two different modes namely *identification* and *verification* [2]. In *identification* mode, recognizing an individual is based on comparing the biometric information with the registered clients in a database. This mode is considered as one-to-many comparisons to establish the identity of the individual. In fact the system performs a comparison between the person's biometrics and all the biometrics templates stored in a database. On the other hand, *verification* mode, that is known as *authentication* as well, concentrates on verifying a user claimed identity to be confirmed by comparing the biometric information submitted by the user with the stored template in a database in a one-to-one comparison process.

Generally, two types of biometric traits can be considered in different applications, *anatomical* and *behavioral* traits [3]. *Anatomical* trait involves iris, face, ear, hand, retinal scan, DNA, palmprint or fingerprint. Speech, handwriting, signature, gait or keystroking are some examples of *behavioral* traits. It is needed to state that some biometric traits such as voice can be viewed as combination of both *anatomical* and *behavioral* traits [2, 3]. From one point of view, the voice can be considered as physical features such as vibration of vocal cords and vocal tract shape and from another point of view it is based on *behavioral* features such as the state of mind of the person who speaks. *Anatomical* characteristics involve measuring a part of body at some point in time to recognize the individual. On the other hand, *behavioral* characteristics are acquired and specifically learned over time using a special effort with the need of realization. Usually, time variability of *anatomical* traits is less compared to *behavioral* traits. Figure 1 depicts some examples of several biometric traits.

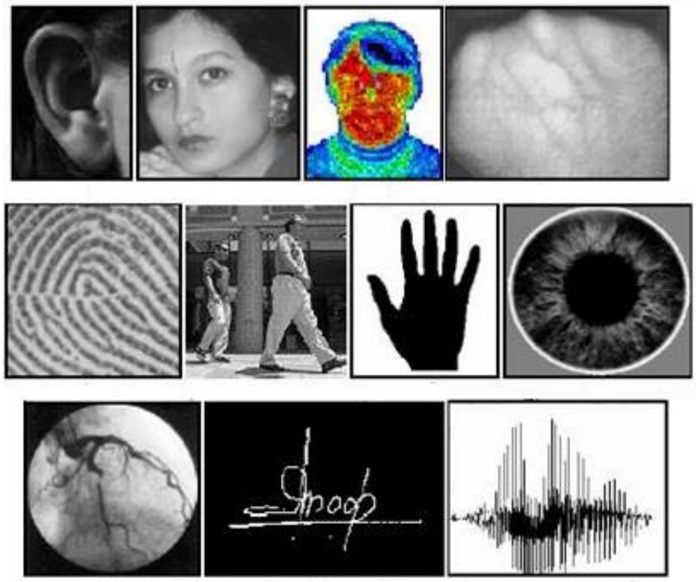

Figure 1. Different Biometric Traits.

In general, any human characteristic, either *anatomical* or *behavioral,* can be considered as a biometric identifier with satisfying the following requirements and properties [2, 3].

- **Permanence:** the characteristic should represent robustness over a period of time.
- **Distinctiveness (uniqueness):** sufficient variation of the characteristic should exist.
- **Availability (universality):** the characteristic processing should be done using the whole population.
- **Accessibility (collectability):** the characteristic should be accessed easily.
- **Performance:** it is referred to the factors that may affect the accuracy, efficiency, speed and resource requirements of a biometric system.
- **Acceptability:** it is referred to the fact that the characteristic taken from the population should be accepted by the population.
- **Circumvention**: represents the ability of the system against potential threats and attacks.

Analyzing different modalities based on aforementioned properties shows the fact that each biometrics has its strengths and limitations. Some of them have high distinctiveness, as an example iris and some others may concentrate more on accessibility without sufficient distinctiveness such as face. Therefore, no single biometric modality alone is able to meet all the desired and preferred conditions to improve the robustness and strength of all authentication applications.

1.2 Biometrics History: An Overview

Generally, the origin of “biometrics” comes from the Greek words “bio” (life) and “metrics” (to measure) [4]. In fact, biometric is used to identify physical and/or behavioral features of individuals based on statistical measurements. The idea of using different parts of body to identify human beings goes back to ancient times. In ancient Babylon, merchants recorded the trading transactions sealed deals with fingerprints on clay tablets around two thousand years ago [5]. Employing thumbprints and fingerprints on clay tablets as signatures to seal the official documents was common by Chinese in the 3rd century B.C. On the other hand, various official document papers dated in Persia bore fingerprint impressions in the 14th century A.D. [6, 7].

In the 14th century, the Portuguese writer Jo˜ao de Barros used stamped children’s palm print and footprints on paper for identification purposes against Chinese merchants [8]. In the 19th century, the French police and anthropologist Alphonse Bertillon developed an anthropometric system, known as Bertillonage [9], to fix the problem of identification of convicted criminals. His scientific human identification system was built on the assumption that the body of people do not change in basic characteristics. Bertillon‘s identification system consists five primary measurements of body parts such as head length; head breadth; length of the middle finger and the length from elbow to end of middle finger. The length of the little finger and the eye color were also recorded by the system. Recently new methods of biometrics are used in many applications to allow authorized person to enter a restricted place and to identify or verify a person.

1.3 Unimodal Biometric Systems

The increasing demand related to reliable verification and authentication schemes is an obvious evidence to pay more attention on biometrics at the places with high security needs. Biometric recognition systems use physical and/or behavioral characteristics that are unique and cannot be lost or forgotten [1]. Face, iris, fingerprint, speech, handwriting and other characteristics [1] can be used in a unimodal or multimodal system for reliable and secure identification of human beings. Performance of unimodal system is affected by different factors such as lack of uniqueness, non-universality and noisy data [10]. For instance, variations in terms of illumination, pose and expression lead to degradation of face recognition performance [10]. Performance of iris recognition can be degraded in non-cooperative situations [11].

In this study, we used two modalities namely face and iris. In the past few years, one of the most attractive areas for biometric schemes was face recognition. Many researches and plenty of algorithms were implemented for face recognition. On the other hand, one of the most reliable and secure biometric recognition systems is the iris recognition which remains stable over the human lifetime [1, 12, 13]. Since an iris has much pattern information and is invariable through a lifetime [14], it has higher accuracy rate compared to other biometric recognition systems [14].

Focus of this section is on face biometric system and iris biometric system employed in this study respectively. Face and iris unimodal biometric systems are described in two different subsections including the strategy and structure that each modality is used to recognize human being.

1.3.1 Face Biometric System

In the past few years, one of the most attractive areas for biometric schemes was face recognition. Many researches and plenty of algorithms were implemented for face recognition. Face image preprocessing, training, testing and matching are common processing steps used as face recognition steps. Face detection, resizing the face images, histogram equalization (HE) and mean-and-variance normalization (MVN) [15] can be applied on the face images as preprocessing techniques in order to reduce illumination effects on the images. The facial features are then extracted in the training stage. In testing stage, the aim is to obtain the feature vector for the test image using the same procedure applied in the training stage. Finally in the last step, Manhattan distance measurement has been used between training and test face feature vectors to compute the matching scores. The details of algorithms applied in face recognition steps are explained in chapter 2.

1.3.2 Iris Biometric System

One of the most reliable and secure biometric recognition systems is the iris recognition which remains stable over the human lifetime [1, 12, 13]. Iris image preprocessing, training, testing and matching are the stages for iris recognition process. For iris image preprocessing step, Libor Masek MATLAB open-source code [16] is used to detect the irises. This source code is a publicly available library for iris recognition written in MATLAB which is widely used in recent iris unimodal systems and face-iris multimodal systems [10, 17]. The detected iris region is normalized to a fixed dimension rectangular form (20 x 240). Resizing, HE and MVN are some other levels applied for prepossessing step. The same strategy as in face recognition is used for training and testing steps. In matching step, Manhattan distance measurement and Hamming distance measurement is used between training and test iris feature vectors to compute the matching scores. The details of algorithms applied in iris recognition steps are explained in chapter 2.

1.4 Multimodal Biometric Systems

Multimodality is able to solve problems related to unimodal biometrics that affect the performance of systems such as damages, lack of uniqueness, non-universality, and noisy data [10]**.** Recently, the accuracy of the biometric systems has been improved using fusion of multimodal biometrics. This approach extracts information from multiple biometric traits in order to overcome the limitations of single biometric trait [10]. Because of many similar characteristics of face and iris, fusion of these two modalities has led to an unprecedented interest compared to other biometric approaches [18].

In general, information fusion of several multimodal biometric systems can be performed at four different levels: sensor level, feature level, matching score level and decision level [10, 19]. Matching score fusion level is more popular among all fusion levels because of the ease in accessing and combining the scores. In this fusion method, different matchers may produce different scores such as distances or similarity measures with different probability distributions or accuracies [20]. In order to fuse the match scores, normalization is needed since the produced matching scores from different modalities are not homogenous. Therefore normalization on matched scores transforms the different matchers into a common domain and range to avoid of degradation in fusion accuracy [21].

Three different categories have been proposed for score fusion techniques: *Transformation-based score fusion, Classifier-based score fusion* and *Density-based score fusion* [20]. In *Transformation-based score fusion,* normalization of matching scores is needed before fusing due to incompatibility of different modalities feature set. *Classifier-based score fusion* treats the scores from different classifiers as a feature vector, in fact each matching score is considered as an element of feature vector [10]. In *Density-based score fusion,* base of work is on the likelihood ratio test and an explicit estimation of genuine and imposter match score densities is needed that leads to increasing of implementation complexity [20].

In sensor level fusion, the data obtained from different biometric sensors should be compatible thus this kind of fusion is applied rarely [22]. Feature level fusion considers concatenation of original feature sets of different modalities that may lead to high dimension vectors and noisy or redundant data, consequently affects the recognition accuracy [23]. In decision level fusion, results from multiple algorithms are combined to achieve a final fused decision. In fact information integration can be done when each biometric matcher individually decides on the best match based on the input presented to it [23].

Produced matching scores from face and iris images usually are not homogeneous, therefore normalization on matched scores is needed to transform the different matchers into a common domain and range in order to avoid degradation in fusion accuracy [21]. Performance of different kinds of normalization techniques such as z-score, minmax and tanh has been studied on multimodal biometric systems based on face, fingerprint and hand geometry in [21]. Focus of this study for normalization is on tanh and minmax techniques to normalize the matched score from face and iris to [0, 1] range.

One of the simplest normalization techniques is minmax normalization, since finding the maximum (max) and the minimum (min) values of the scores are straightforward for shifting them (minimum and maximum scores) to 0 and 1, respectively [21]. Original distribution of scores is preserved in this method, although there is an exceptional case for a scaling factor, in order to transform all scores into [0, 1] range. Transformation from distance scores into similarity scores is done using subtraction of minmax normalized score from matched scores [21]. Minmax normalization technique is calculated as

$$s_k^{'} = \frac{s_k - \min}{\max - \min} \tag{1.1}$$

where s_k is a set of matching scores for $k=1, 2 \ldots n$.

Tanh estimator is another normalization method which has been applied on matching scores in this study. This robust and efficient method was introduced by Hampel et al. [24] and works very well for noisy training scores. Tanh normalization technique also transforms the matched scores into [0, 1] range. Tanh normalization is based on the following equation

$$s_k^{'} = \{\tanh(0.01(\frac{s_k - \mu_{GH}}{\sigma_{GH}})) + 1\} \tag{1.2}$$

where μ_{GH} is the mean and σ_{GH} is the standard deviation of the genuine score distribution [21].

Details of different schemes at matching score level, feature level, decision level and also combination of different fusion levels are proposed to fuse face and iris modalities in separate chapters.

1.5 Related Works

Face recognition has been extensively studied by many researchers in the last two decades. In the early nineties, Turk and Pentland [25] considered the use of PCA for face recognition in their work; in fact they applied PCA to compute a set of subspace basis vectors that are called eigenfaces. Generally face recognition based on the eigenfaces have been widely used by researchers in [26-34]. As an example in [31] a new approach for face recognition is proposed that is insensitive to large variations in lighting and facial expressions, they used a projection method based on Fisher's Linear Discriminant to generate well separated classes in a low-dimensional subspace using PCA. An efficient face recognition method based on local binary patterns (LBP) texture features is proposed in [35] in which the authors divided the face image into several regions to extract the LBP features and then the extracted features are concatenated in the next step into a vector to be considered as a face descriptor.

A critical survey of researchers across pose on face images has been performed by Zhang and Gao [36]. They classified the existing techniques across pose into three categories according to their methodologies, i.e. general algorithms, 2D techniques and 3D approaches. The advantages and limitations of each category are discussed and summarized in their study to provide several promising directions for future research of face recognition across pose.

A new scheme based on local feature extraction is proposed in Toygar and Altınçay [37], to preserve spatial information and overcome variations in appearance for face recognition. The local features are extracted in their work, from a randomly selected set of sub-images with random locations, numbers and sizes to define a composite feature vector for an individual ensemble member. Finally, majority voting is applied to combine the ensemble members to compute a joint decision. The authors also implemented PCA-based recognition systems (PCA, spPCA, mPCA) to compare the performance of the proposed method with the state-of-the-art systems.

An efficient unsupervised dimensionality reduction approach namely variance difference embedding (VDE) was proposed by Chen and Zhang [38] to extract facial features. Their method is obtained by maximizing the difference between global and local variances to provide a good projection for classification purposes. By solving an eigenvalue problem, the projection matrix is able to avoid "small samples problem" compared to techniques such as Local Preserving Projection (LPP) and Unsupervised Discriminant Projection (UDP).

Chiachia et al. [39] applied Census Transformation (CT) on face images to extract the basic facial features to achieve a fast face image structural description. They presented a method to match face samples directly based on a scanning window that is able to extract local histogram of Census features.

In [40], Anbarjafari proposed a PDF-based (probability distribution functions) face recognition system using LBP (local binary patterns). The system uses PDFs of pixels in different mutually independent color channels which are robust to frontal homogenous illumination and planer rotation. Discrete wavelet transform and singular value decomposition have been used to enhance the illumination of faces. The face images are then segmented using local successive mean quantization transform and Kullback_Leibler distance is used to measure the recognition accuracy.

On the other hand, iris recognition has been studied in different perspectives in the last decades. Daugman in [41, 42], performed a vast study on iris recognition algorithms as a reliable biometrics, and described a method based on the failure of a statistical test of independence for rapid visual recognition [41]. Daugman [41] proposed an integro-differential operator in order to find both the iris inner and outer borders. The author applied multiscale quadrature wavelets for extracting texture phase structure information of the iris to generate the iris code by comparing the difference between a pair of iris representations using computation of their Hamming distance [11].

In [1], an iris recognition algorithm using wavelet-based texture features is proposed to implement an automatic iris recognition system. Their proposed algorithm includes both iris detection and feature extraction modes and is successful to solve the problem arisen with partial occlusion of the upper part of the eye.

Proença and Alexandre in [43], studied on non-cooperative iris recognition and consequently alleviate the problems related to capturing iris images at large distances, under less controlled lighting conditions and without active participation. They proposed a new iris classification approach to divide the segmented and normalized iris into six regions in order to have an independent feature extraction and then compare each of these regions. A fusion rule is used to classify an iris using a threshold set that combines the dissimilarity values resultant from the comparison between corresponding iris regions. They achieved significant decrease in the error rates compared to Daugman iris classification method.

In [44], the authors suggest a structure for the iris biometrics literature and summarize most of the research publications and categorize them into one of the four major modules in iris biometrics as image acquisition, iris segmentation, texture analysis and matching of texture representation. As an example, they study the most important work in early history of iris biometrics proposed by Daugman [41] that is applied by many researchers as a standard approach.

Recently, many researchers study on multimodality in order to overcome the limitations of unimodal biometrics. In [45], Vatsa et al. proposed an intelligent 2v-support vector machine-based match score fusion algorithm to improve the recognition performance of face and iris by integrating the quality of images. Liau and Isa in [10] proposed a face-iris multimodal biometric system based on matching score level fusion using support vector machine (SVM). In their study, it has been extended to improve the performance of face and iris recognition by selecting an optimal subset of features. The authors used Discrete Cosine Transformation (DCT) for facial feature extraction and log-Gabor filter for iris pattern extraction. The article emphasizes the selection of optimal features using Particle Swarm Optimization (PSO) algorithm and the use of SVM for classification. A SVM-based fusion rule is also proposed in [18] to combine two matching scores of face and iris.

Lumini and Nanni in [17], applied a strategy to obtain an appropriate pattern representation by extracting the information using an over-complete global feature combination and finally the selection of the most useful features has been done by sequential forward floating selection (SFFS). A multimodal identification scheme based on RBF (radial basis function) neural network fusion rules has been proposed by Wang et al. in [14]. The proposed method uses transformation-based score fusion and classifier-based score fusion. They concatenate normalized face and iris matching scores in order to classify a person from his/her face and iris images.

A more recent approach has been proposed by Eskandari and Toygar in [46] which uses local and global feature extractors on face-iris multimodal recognition. Local Binary Patterns method is used as facial feature extractor and subspace LDA as iris feature extractor. The authors used Tanh score normalization and Weighted

Sum Rule fusion techniques and achieved improved performance compared to the unimodal and several existing multimodal methods.

1.6 Research Contributions

The contribution of this PhD thesis can be categorized into several parts. Generally the aim of this work is to use iris patterns with optimized features of local and global based facial feature extraction methods using one feature selection method as PSO to remove redundant data for the fusion of face-iris multimodal system. The proposed schemes in this dissertation can be used practically in person identification and verification systems using facial images. The iris information from left and/or right eye can be extracted from the face image of the same individual and the fusion of face-iris multimodal system can be performed to improve the performance of the individual face and iris recognition systems. The main contribution of each proposed scheme is described at the end of the corresponding chapter based on the proposed method. A list of itemized contributions generally for this thesis can be considered as:

- Applying local and global feature extractors for the fusion of face and iris to combine their advantages in order to enhance the recognition performance.
- Solving the problem of high dimensionality, time and memory computation raised in feature level fusion by concatenating the face and iris matched scores.
- Solving the problem of high dimensionality in feature level fusion by applying a feature selection method to choose the optimal methods and features.
- Removing redundant data from face and fused left and right irises of one individual by selecting optimized weights and optimized features.

1.7 Outline of the Dissertation

The organization of the thesis is as follows. Chapter 2 presents the details of feature extractors and statistical methods applied on face and iris biometrics. Chapter 3 describes the employed databases to test the statistical methods and construct the multimodal biometric systems and therefore validate the proposed schemes. Face-iris multimodal system using local and global feature extractors (proposed scheme1) is detailed in Chapter 4 while Chapter 5 is devoted to face-iris multimodal system using concatenation of face-iris matching scores (proposed scheme2). Chapter 6 explains optimal feature extractors for face-iris multimodal system (proposed scheme3). The last scheme which is face-iris fusion scheme based on feature and weights selection (proposed scheme4) is described in Chapter 7. Finally, Chapter 8 draws some conclusions about the multimodal systems proposed in this thesis.

Chapter 2

FEATURE EXTRACTORS AND STATISTICAL METHODS

2.1 General Information: Face-Iris Feature Extractors

In this study, some standard local and global approaches have been applied on the face and iris images to extract the features in face-iris multimodal biometric system. These local and global methods are implemented in MATLAB for the extraction of facial and iris features. PCA [25] and subspace LDA [47] are global feature extraction methods used for facial feature extraction, while spPCA [48], mPCA [29] and LBP are local approaches for extracting facial features. LBP [35] is the method applied for local texture description, in which several local descriptions of a face image are generated and then combined into a global description.

PCA algorithm is implemented as in [25] based on the selection of maximum number of nonzero eigenvectors. In both subpattern-based PCA [48] and modular PCA [29], the facial images are initially partitioned into N^2 subimages. Eigenvectors corresponding to 97% of eigenvalues with $N=81$, where N is the number of partitions, are used for spPCA and mPCA. Each facial image is resized before partitioning in order to have equal size for each subimage. An example of partitioning is shown in Figure 2 with 81 partitions. In subspace LDA, initially PCA is applied on facial images for dimensionality reduction and the principal components extracted by PCA are used as inputs to LDA. The number of eigenvectors selected in the first and the second stages of subspace LDA method are selected experimentally as the maximum number of nonzero eigenvectors. For Local

Binary Patterns (LBP), the number of partitions used is $N=81$ as in spPCA and mPCA which is shown in Figure 2 and *(8,2)* circular neighborhood is used.

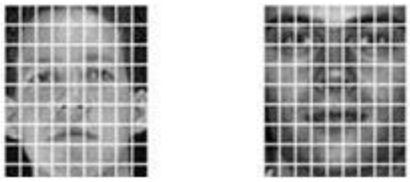

Figure 2: Facial Image Partitions

On the other hand, in order to extract iris features we also applied Libor Masek's iris recognition system on iris images in some experiments and schemes. This iris recognition system is a publicly available library implemented by Masek & Kovesi in MATLAB [16]. The typical processing steps of the iris recognition system are segmentation, normalization, feature encoding, and feature matching. The automatic segmentation system is based on the Hough transform, to localize the circular iris and pupil region, occluding eyelids and eyelashes, and reflections. The extracted iris region is then normalized into a fixed rectangular block (20×240) as demonstrated in Figure 3. In feature encoding step, 1D Log-Gabor filters are employed to extract the phase information of iris to encode the unique pattern of the iris into a bit-wise biometric template. Finally, the Hamming distance measurement is employed for classification of iris templates [16]. The details of each algorithm implemented for face and iris biometrics are described in different sections of this chapter.

Figure 3: Rectangular Block of Iris Pattern

2.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is known as a linear transform method in pattern recognition field. The PCA is a very effective approach to extract features successfully in pattern recognition area such as face classification [25, 49]. It can be used as a simple projection tool to reduce a complex data set with a high dimension to a lower dimension.

The role of PCA is to operate directly on whole patterns known as features to extract global features to be used for subsequent classification using a set of previously found global projectors from a given training pattern set [48]. Mainly PCA aims to preserve original pattern information maximally after extracting features, and consequently reducing dimensionality [48]. Generally, PCA involves consideration of the global information of images and is not assumed to work properly under different illumination conditions, pose, etc [28]. The typical steps of PCA algorithm are described in the following subsection [50].

2.2.1 PCA Algorithm

- Collecting I_i images (I_i= [I_1, I_2..., I_M]), where each image is stored in a vector of size L.
- Mean centering, the images should be mean centered by subtracting the mean image from each image vector using equation (2.1), where A is the mean image and can be obtained using equation (2.2).

$$Y_i = I_i - A, \tag{2.1}$$

$$A = \frac{1}{M}\sum_{i=1}^{M} I_i \tag{2.2}$$

- Calculating the covariance matrix according to equation (2.3).

$$C = \frac{1}{M}\sum_{i=1}^{M} Y_i \cdot Y_i^T \tag{2.3}$$

- Determining the eigenvalues of the covariance matrix using equation (2.4), where E is the set of eigenvectors related to the eigenvalues Λ.

$$CE = \Lambda E \tag{2.4}$$

- Sorting the eigenvalues and corresponding eigenvectors in descending order.
- Projecting each of the centered training images into the created eigenspace based on a new ordered orthogonal basis with the first eigenvector having the direction of the largest variance of the data using equation (2.5), where E_k's are the eigenvectors corresponding to the Λ significant eigenvectors which are chosen as those with the largest corresponding eigenvalues of C and K varies from 1 to Λ.

$$W_{ik} = E_K^T . Y_i \quad \forall i, k \tag{2.5}$$

- Recognizing images by projecting each test image I_{test} into the same eigenspace using equation (2.6).

$$W_{testk} = E_K^T .(I_{test} - A) \quad \forall k \tag{2.6}$$

2.3 Subspace Linear Discriminant Analysis (ssLDA)

Generally, subspace LDA is considered to be very similar to PCA differing principally in the area of class accountability. LDA mainly makes an effort to discriminate the input data by dimension reduction, while PCA aims to generalize the input data by dimension reduction. In order to project the input data into a lower dimensional space, LDA [47,51] tries to find the best projection in the way that the patterns are discriminated as much as possible. The main goal of LDA can be stated as maximizing the between-class scatter (S_b) and at the same time minimizing the within-class scatter (S_w) in the projective feature vector space.

In this work, we use subspace LDA [47] on face and iris images. In fact this method applies PCA to reduce the dimension by generalizing the data and LDA for the purpose of classification because of its discrimination power. In other words, subspace LDA can be viewed as combination of PCA and LDA algorithms; PCA to project the input data onto the eigenspace and LDA to classify the eigenspace projected data. The common steps of subspace-LDA algorithm are described in the following subsection.

2.3.1 Subspace LDA Algorithm

- Collecting x_i images.
- Applying *PCA* on the stored vectors to take PCA projection (P).
- Providing input for *LDA* using the projected data obtained from *PCA*.
- Finding within-class scatter matrix (S_w), for the i^{th} class, a scatter matrix (S_i) is needed to be calculated as the sum of the covariance matrices of the centered images in the class according to equation (2.7), where m_i is the mean of the images in the i^{th} class. Consequently sum of all scatter matrices (within-class) is calculated based on equation (2.8).

$$S_i = \sum_{x \in X_i} (x - m_i)(x - m_i)^T \tag{2.7}$$

$$S_w = \sum_{i=1}^{L} S_i \tag{2.8}$$

- Finding between-class scatter matrix (S_b) using equation (2.9), where n_i is the number of images in the class, m_i is the mean of images in the class and m is the mean of all images.

$$S_b = \sum_{i=1}^{C} n_i (m_i - m)(m_i - m)^T \tag{2.9}$$

- Computing the eigenvectors of the projection matrix using equation (2.10).

$$W = eig(S_w^{-1} S_b) \tag{2.10}$$

- Projecting the images by using the projection matrix as equation (2.11).

$$M = W \times P \tag{2.11}$$

- Comparing the projection matrix of test image with each training image's projection matrix.

2.4 Subpattern-based Principal Component Analysis (spPCA)

Subpattern-based PCA involves consideration of a set of partitioned subpatterns of the original pattern to obtain a set of projection sub-vectors for each partition in order to extract corresponding local sub-features and then concatenates them into a composite feature vector to achieve global features for subsequent classification [48]. A single classifier is then generated which operates on this composite feature vector. On the other hand, the global vector may contain redundant or useless local information which may affect the final classification performance [28]. In fact, the description of the subpattern-based approaches can be conducted as partitioning the images into equal-width non-overlapped subpatterns and then extracting the sub-features of each of these subpatterns [52]. In this method, PCA is used to be applied on each of the subpattern sets and subsequent classification is achieved from combination of extracted sub-features into a global feature vector of the original whole pattern. The details of different steps of the subpattern-based PCA algorithm is described in the following subsection.

2.4.1 SpPCA Algorithm

- Collecting x_i images.
- Partitioning an original whole image into K d-dimensional subpatterns in a non-overlapping way and reshaping into a d-by-K matrix X_i using equation (2.12).

$$X_{ij} = (x_{i((j-1)d+1)}, \ldots , x_{i(jd)})^{\mathrm{T}} \qquad j=1, 2, \ldots , K. \tag{2.12}$$

- Constructing PCA for the jth subpattern to obtain its projection vectors using equation (2.13).

$$SP_j = \{X_{ij}, i=1, 2, \ldots , N \}, \qquad j=1, 2, \ldots , K. \tag{2.13}$$

- Defining covariance matrix of each subpattern to find each set of projection sub-vectors using equation (2.14), where $\overline{X}_j$ is subpattern mean and calculated as in equation (2.15).

$$S_j = \frac{1}{N}\sum_{i=1}^{N}(X_{ij} - \overline{X}_j).(X_{ij} - \overline{X}_j)^T \tag{2.14}$$

$$\overline{X}_j = \frac{1}{N}\sum_{i=1}^{N} X_{ij} \qquad j = 1, 2, \ldots, K. \tag{2.15}$$

- Finding the eigenvectors and corresponding eigenvalues of covariance matrix of each subpattern based on equation (2.16), where Φ_j is the set of eigenvectors related to the eigenvalues Λ_j of each subpatterns.

$$S_j\, \Phi_j = \Lambda_j\, \Phi_j \tag{2.16}$$

- Sorting each subpattern eigenvector in descending order.
- Collecting all individual projection sub-vectors from partitioned subpattern sets and then synthesizing them into a global feature.
- Performing classification.

2.5 Modular Principal Component Analysis (mPCA)

Modular PCA algorithm is an extension of the conventional PCA. In modular Principal Component Analysis (mPCA), an image is first partitioned into several smaller regions called sub-images. Then a single conventional PCA is applied to each of these sub-images, and therefore, the variations in the image, such as illumination and pose variations, will only affect some regions in mPCA rather than the whole image in PCA [28]. In other words, modular Principal Component Analysis (mPCA) overcomes the difficulties of regular PCA and subpattern-based Principal Component Analysis (spPCA). Generally, conventional PCA considers the global information of each image and represents them with a set of weights. Under these conditions the weight vectors will vary considerably from the weight vectors of the images with normal pose and illumination, hence it is difficult to identify them correctly. On the other hand, mPCA method applies PCA on smaller regions and the resultant distance scores are averaged. Consequently, local information of the image can show the weights better and for variation in the pose or illumination, only some of the regions will vary and the rest of the regions will remain the same as the regions of a normal image [29]. The details of mPCA algorithm are explained in the following subsection.

2.5.1 MPCA Algorithm

- Collecting I_i images ($I_i = [I_1, I_2 \ldots, I_M]$).
- Dividing each image in the training set into N smaller images (subimages).
- Calculating average image of all the training sub-images using equation (2.17), where i varies from 1 to M and j varies from 1 to N.

$$A = \frac{1}{M.N} \sum_{i=1}^{M} \sum_{j=1}^{N} I_{ij} \tag{2.17}$$

- Normalizing each training sub-image using equation (2.18).

$$Y_{ij} = I_{ij} - A \quad \forall i, j \tag{2.18}$$

- Computing the covariance matrix from the normalized sub-images according to equation (2.19).

$$C = \frac{1}{M.N} \sum_{i=1}^{M} \sum_{j=1}^{N} Y_{ij} . Y_{ij}^{T} \tag{2.19}$$

- Finding the eigenvectors ($E_1, E_2, \ldots, E_{M'}$) of covariance matrix that are associated with the M' largest eigenvalues.

- Computing the projection of training sub-images is performed by using equation (2.20), where K varies from 1 to M', n varies from 1 to r, r being the number of images per individual and p varies from 1 to p, p being the number of individuals in the training set.

$$W_{pnjk} = E_K^T . (I_{pnj} - A) \quad \forall p, n, j, K \tag{2.20}$$

- Finding the projection for the test sub-images into the same eigenspace using equation (2.21).

$$W_{test\,jk} = E_K^T . (I_{test\,j} - A) \quad \forall j, k \tag{2.21}$$

- Comparing the projected test sub-image with every projected training sub-image.

2.6 Local Binary Patterns (LBP)

LBP is one of the strongest local feature extractor that is able to provide a simple and effective way to represent patterns. LBP is introduced as a powerful local descriptor for microstructures of images. Designation of LBP operator originally was for texture description. Using the operator, a label is assigned to every pixel of an image by thresholding the 3x3-neighborhood of each pixel with the center pixel value and considering the result as a binary number. Then the histogram of the labels can be used as a texture descriptor [35]. We can state that the resulting LBP with a pixel at (x_c,y_c) in the decimal form is as follows:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \tag{2.22}$$

where n runs over the 8 neighbors of the central pixel, i_c and i_n are the gray-level values of the central pixel and the surrounding pixel, and $s(x)$ is 1 if $x \geq 0$ and 0 otherwise [53]. The original operator later is extended in order to be able to deal with textures at different scales [54]. Therefore, the extended LBP is able to use neighborhood of different sizes, to capture dominant features at different scales. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. The notation (P,R) denotes a neighborhood of P equally spaced sampling points on a circle of radius of R. On the other hand, another extension was proposed to use a small subset of the 2^P patterns called uniform patterns, produced by the operator LBP(P,R), to describe the texture of images. These patterns contain at most two bitwise transitions from 0 to 1 or vice versa when considered as a circular binary string. For example, 00000000, 001110000 and 11100001 are uniform patterns. In this extension of the operator, most of the texture information was contained. Labeling the patterns which have more than 2 transitions with a single label yields an LBP operator, denoted

LBP*(P,R,u2)*, which produces much less patterns without losing too much information [53]. Then a histogram of the labeled image was applied to take texture descriptor. The common stages for LBP algorithm are represented in the following subsection.

2.6.1 LBP Algorithm

- Collecting images.
- Dividing each image into N non-overlapping regions.
- Assigning label to each pixel in the corresponding region using equation (2.23), assigned label is 1 if the pixel value of neighbors (X_p) are bigger than the center pixel value (X_c) and 0 otherwise.

$$LBP_{(p,r)}(X_c) = \sum_{p}^{p-1} u(X_p - X_c)2^p \quad (2.23)$$

- Calculating the histogram of the labels to take texture descriptor.
- Concatenating the descriptions obtained from each region to obtain a global description.
- Comparing training and test images using the global descriptor.

2.7 Masek & Kovesi Iris Recognition System

Masek & Kovesi iris recognition system is a publicly available library in which the system is generally inputted with an eye image and an iris template is produced as an output of the system. The automatic segmentation system is based on the Hough transform to localize the circular iris and pupil region. In segmentation step, the system tries to isolate the actual iris region in a digital manner and it can be stated that the role of segmentation step is so important and may affect the recognition rate. Therefore the quality of eye images has a significant role in the success of segmentation step. The successfully extracted iris region in the next step is then normalized into a fixed rectangular block and to normalize iris regions, a method based on Daugman's rubber sheet model is used. The size of each fixed rectangle block achieved from normalization step is 20×240. In fact, the segmentation and normalization steps can be viewed easily as iris image preprocessing step.

The next step after segmentation and normalization is to obtain and extract the significant features of the iris and then by encoding the extracted features, accurate recognition of individuals can be provided. In feature encoding step, 1D Log-Gabor filters are employed to extract the phase information of iris to encode the unique pattern of the iris into a bit-wise biometric template based on four quantized levels. Indeed, the 2D normalized iris pattern is broken up into a number of 1D signals to be convolved with 1D Gabor Wavelets. The output of the encoding stage for each eye image is a bitwise template involving a number of information bits along with its corresponding noise mask that contains corrupted regions within the iris pattern.

Finally, the Hamming distance measurement is employed for classification of iris templates. In general, Hamming distance is a measure to compare the same number of bits between iris patterns therefore this method is effective to make a decision on iris patterns to observe whether the patterns are produced from the same individual or different one. In this system only appropriate bits are employed to calculate the Hamming distance between iris templates. It means that just the corresponding 0's bits in noise mask of iris patterns are used and then bits produced from true iris patterns are involved in Hamming distance calculation. The common steps of this iris recognition system are described in the following subsection.

2.7.1 Masek & Kovesi Algorithm

- Collecting eye images.
- Performing automatic segmentation based on the Hough transform to localize the circular iris and pupil region.
- Normalizing the segmented iris into a fixed (20×240) rectangular block.
- Applying feature encoding using 1D Log-Gabor filters to extract the phase information of iris in order to encode the unique pattern of the iris into a bit-wise biometric template.
- Classifying the iris templates using Hamming distance measurement according to equation (2.24), where X_j and Y_j are the two bit-wise templates to be used for comparison, Xn_j and Yn_j are the corresponding noise masks for X_j and Y_j , and finally N is the number of bits from each template.

$$HD = \frac{1}{N - \sum_{K=1}^{N} Xn_K (OR) Yn_K} \sum_{j=1}^{N} X_j (XOR) Y_j (AND) Xn'_j (AND) Yn'_j \quad (2.24)$$

Chapter 3

DESCRIPTION OF DATABASES

3.1 Face Databases

In order to validate our unimodal and multimodal systems, we performed several experiments on different subsets of face, iris and multimodal biometric databases. Face databases employed in this work are *FERET* [55], *ORL* [56] and *BANCA* [57]. Combination of *ORL-BANCA* databases is also used to test the validity of our unimodal and multimodal systems in different conditions in terms of illumination and pose in face images. Subsequent subsections have a brief overview on each face database separately.

3.1.1 FERET Database

The Face Recognition Technology (*FERET*) database is a standard dataset prepared from 1993 through 1997 in 15 sessions for facial recognition system evaluation by the Defense Advanced Research Projects Agency (DARPA) and the National Institute of Standards and Technology (NIST). Face images in the *FERET* database have been captured under semi-controlled conditions. The *FERET* dataset contains a total number of 14126 face images from 1564 sets of images with involving 1199 individuals and 365 duplicate sets of images [55]. Duplicate sets cover the second image sets of the same individuals captured in different days; it was a gap over two years for taking the images of the same individual in duplicate sets. The dimension of each image is considered as 256×384. Table 1 denotes the naming convention based on different categories of *FERET* database including pose angle, description and number of images and individuals.

Table 1: Naming Convention of FERET Database [55].

Two letter code	***Pose Angle (degrees)***	***Description***	***# in Database***	***# of Subjects***
Fa	0 = frontal	Regular facial expression	1762	1010
Fb	0	Alternative facial expression	1518	1009
ba	0	Frontal "b" series	200	200
bj	0	Alternative expression to ba	200	200
bk	0	Different illumination to ba	200	200
bb	+60	Subject faces to his left which is the photographer's right	200	200
bc	+40		200	200
bd	+25		200	200
be	+15		200	200
bf	-15	Subject faces to his right which is the photographer's left	200	200
bg	-25		200	200
Bh	-40		200	200
bi	-60		200	200
ql	-22.5	Quarter left and right	763	508
qr	+22.5		763	508
hl	-67.5	Half left and right	1246	904
hr	+67.5		1298	939
pl	-90	Profile left and right	1318	974
pr	+90		1342	980
Ra	+45	Random images. See note below. Positive angles indicate subject faces to photographer's right	322	264
Rb	+10		322	264
Rc	-10		613	429
Rd	-45		292	238
Re	-80		292	238

In this work, we used randomly 170 frontal face images with 4 samples to test our algorithms. Some sample images of *FERET* database are presented in Figure 4.

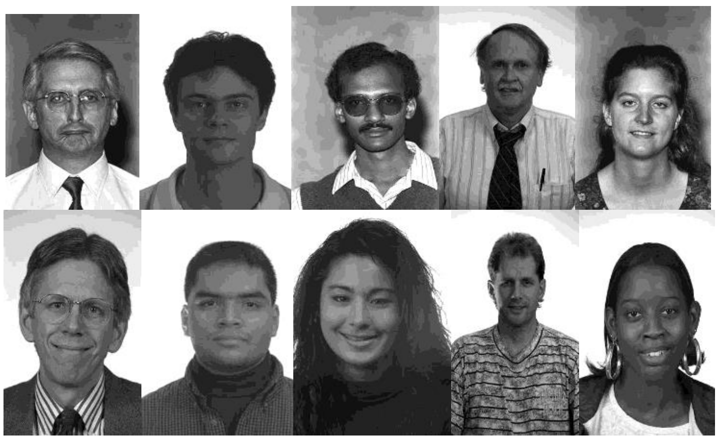

Figure 4: Sample Images of FERET Dataset

3.1.2 BANCA Database

BANCA database is a European project and its aim is to develop a secure system and improve identification, authentication and access control schemes in four different languages (English, French, Italian and Spanish) [57]. In fact, *BANCA* is a multimodal database with two modalities namely face and voice. In this study, we only used face images to test our unimodal and multimodal systems. The face images in this database were taken under 3 different realistic and challenging operating scenarios. The *BANCA* database contains 52 subjects, half men and half women. In this database, 12 recording sessions are employed for each subject under different conditions and cameras. The data in sessions 1-4 is captured under *Controlled* conditions and sessions 5-8 and 9-12 concentrate on *Degraded* and *Adverse* scenarios respectively. Generally, in the face image database, 5 frontal face images are extracted from each recorded video. In order to test the validity of our unimodal and multimodal systems, the face images from session 1 taken under *Controlled* conditions are used. Forty subjects of *BANCA* database with 10 samples are selected randomly to test the algorithms. Figure 5 represents a few samples of *BANCA* database (session 1) face images.

Figure 5: Sample Images of BANCA Dataset

3.1.3 AT & T (ORL) Database

AT & T face database known as *ORL* is a standard face database that contains face images of 40 distinct subjects. Each subject has ten different frontal images and they are captured at different times and with a dark homogeneous background. The size of each face image in *ORL* database is 112×92 pixels. Different variations in facial expression such as open/closed eyes, smiling/non-smiling and scale variations exist in this database images. In this study, all 40 subjects of this database are considered to test the unimodal and multimodal systems. Some sample face images of *ORL* database are depicted in Figure 6.

Figure 6: Sample Images of ORL Dataset

3.2 Iris Databases

The iris images implemented in this study to validate the unimodal and multimodal systems and to form the experimental datasets are selected from *CASIA* [58] and *UBIRIS* [59] iris databases. Our purpose for selecting *CASIA* and *UBIRIS* iris databases is to have different and enough number of noisy and non-noisy iris images. Combination of *UBIRIS* and *CASIA* iris images is also used to construct a robust database with noisy and non-noisy images and with enough number of individuals and samples to test the performance of the algorithms and fusion schemes. Subsequent subsections explore briefly each iris database separately.

3.2.1 CASIA Database

CASIA database is a well known and widely used iris database; this database is developed by the Institute of Automation from the Chinese Academy of Sciences. In the first version of *CASIA* iris image database (version 1.0) 756 iris images from 108 eyes are available for researchers. The images in *CASIA* database were captured within a highly constrained capturing environment. They present very close and homogeneous characteristics and their noise factors are exclusively related to iris obstructions by eyelids and eyelashes.

In this study, *CASIA-IrisV3* is used with including three subsets which are labeled as *CASIA-IrisV3-Interval, CASIA-IrisV3-Lamp, CASIA-IrisV3-Twins. CASIA-IrisV3* contains a total of 22,051 iris images from more than 700 subjects. All iris images are 8 bit gray-level JPEG files. Different subsets of *CASIA-IrisV3-Interval* are used in this work to test the algorithms; almost all subjects are Chinese [58]. The size of each iris image of *CASIA-IrisV3-Interval* is 320×280. Figure 7 illustrates some samples of *CASIA-IrisV3-Interval.*

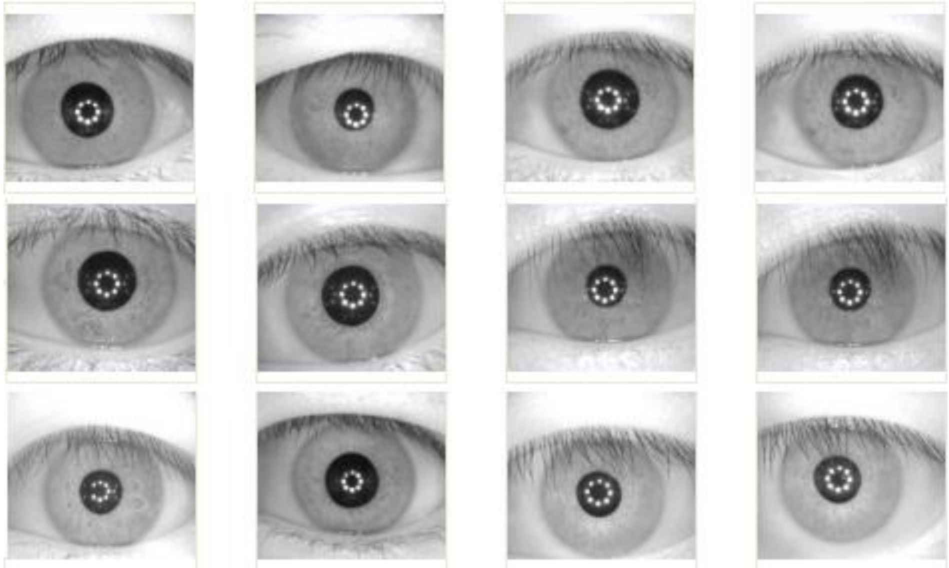

Figure 7: Sample Images of CASIA Dataset

3.2.2 UBIRIS Database

UBIRIS is a publicly and freely available iris image database. It is a ”noisy iris image database” and is comprised of 1877 images collected from 241 subjects within the University of Beira Interior in two distinct sessions [11]. These two sessions include different level of noise and both are used in this study. Generally, *UBIRIS* database images were captured to provide images with different types of noise, without or with minimal collaboration from the subjects, to become an effective resource for the evaluation and development of robust iris identification methodologies. For the first image capturing session, the minimization of noise factors, especially those relative to reflections, luminosity and contrast was tried. In the second session, the capturing location, in order to introduce natural luminosity factor, was changed [60]. The original size of *UBIRIS* iris images is 200×150. Different subsets of *UBIRIS* database from both sessions are used in this work. Figure 8 illustrates some samples of *UBIRIS* iris images.

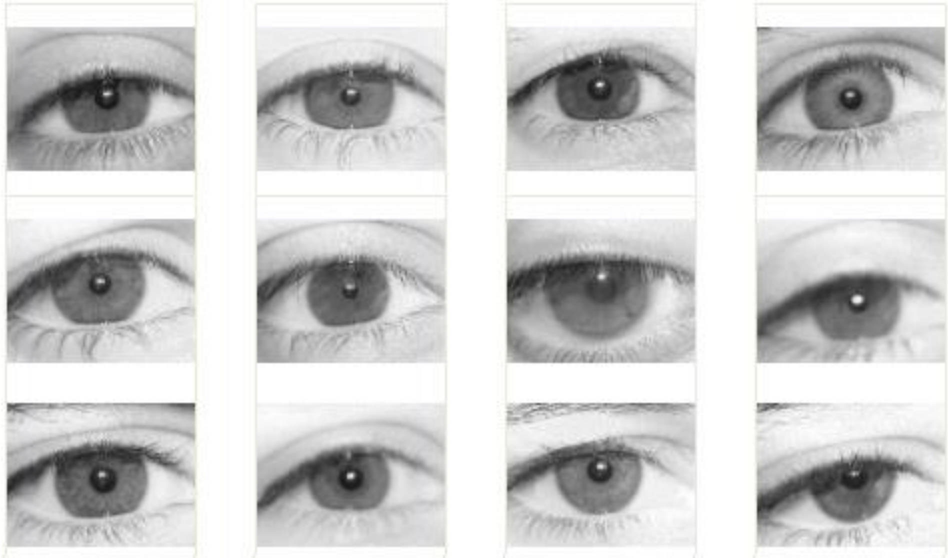
Figure 8: Sample Images of UBIRIS Dataset

3.3 Multimodal Databases

Generally finding publicly available face-iris multimodal databases that include the face and iris of the same person is not an easy task. On the other hand, the focus of this study is on multimodal biometric systems involving face and iris biometrics, therefore we performed our last set of experiments using a multimodal database called *CASIA Iris Distance* [61] to evaluate the unimodal and the proposed schemes implemented in this study on the face and iris of the same individual. The details of *CASIA Iris Distance* database can be found in the following subsection.

3.3.1 CASIA-Iris-Distance Database

CASIA-Iris-Distance is a recently publicly available multimodal biometric database. *CASIA-Iris-Distance* images were captured by a high resolution camera, so both dual-eye iris and face patterns are included in the image region with detailed facial features for multimodal biometric information fusion [61]. The full database includes 142 subjects and a total number of 2567 images. Face images were acquired at-a-distance of ~3 meters from camera [61]. In this thesis, we consider 90 subjects 10 samples randomly selected from each subject or individual to construct our multimodal face and iris biometric system. The chosen subjects cover the proper information needed for building the multimodal system including the whole face images and clear dual-eye iris patterns. Figure 9 represents a sample of one individual face and iris taken from [61].

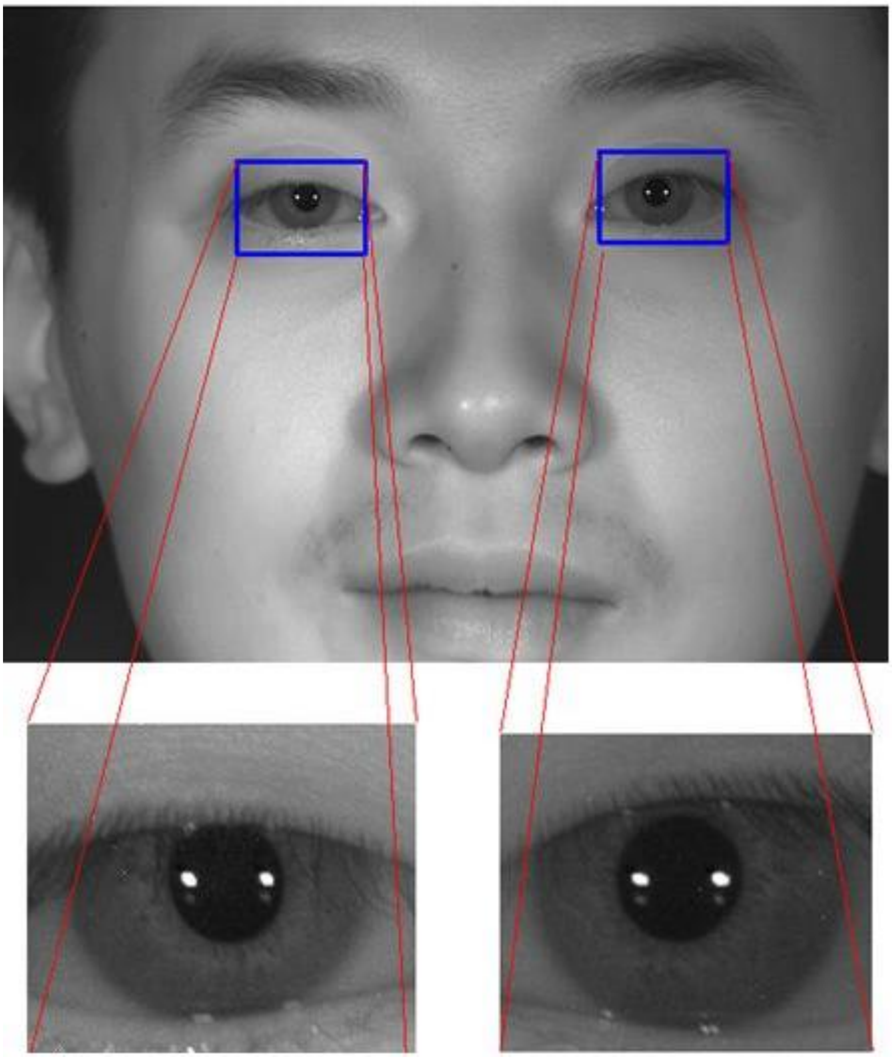

Figure 9: Face and Iris of One Individual from CASIA-Iris-Distance Dataset [61].

Chapter 4

FACE-IRIS MULTIMODAL SYSTEM USING LOCAL AND GLOBAL FEATURE EXTRACTORS (PROPOSED SCHEME 1)

4.1 Description of Proposed Scheme 1

In the first proposed scheme, face and iris biometrics are used to obtain a robust recognition system by using several standard feature extractors, score normalization and fusion techniques. In the literature, fusion of face and iris biometrics was studied using specific feature extractors such as Discrete wavelet transform (DWT), Discrete Cosine Transform (DCT) and Gabor filters [10, 17, 18]. These studies concentrated on the fusion stage that is using an original SVM classifier or an improved version of that classifier [10, 18, 45]. On the other hand, local and global feature extractors are efficient in different modalities because of the nature of the considered biometrics. For example, local feature extractor based approaches mainly aim to achieve robustness to variations in facial images by assuming that only some parts of the facial images may be affected [37]. However, for iris biometrics, the images are taken by special high quality cameras and the whole iris pattern will be shown without variations. Although there may be some illumination changes and partial occlusions on irises, the general appearance of the iris pattern will not be changed for different samples of iris images.

In our study, we concentrated on how to improve the recognition accuracy for the fusion of face and iris biometrics using different local and global feature extractors. Face recognition can be performed using local feature extractors in order to get high recognition accuracy [37]. However, iris recognition is done with a very high accuracy using global feature extractors [44] whenever there is no occlusion on the iris images. In that case, we were motivated to use both local and global feature extractors for the fusion of face and iris biometrics in order to investigate the feature extraction methods that are the most appropriate for face and iris feature extraction separately. In order to obtain a better multimodal system, the methods used for extracting local feature vectors of individual systems must be robust to distortion of these modalities. Face and iris biometrics have their own problems such as changes in illumination, pose and partial occlusions. These problems can be solved for face and iris separately before the fusion stage.

Although the same feature extraction methods, either local or global, can be used to extract the features of face and iris biometrics, which is improving the recognition accuracy compared to the individual systems, we propose to investigate different set of feature extractors for face and iris biometrics to achieve the best recognition accuracy for the fusion. In that case, each modality will be considered separately to extract its features and to overcome the individual problems that are decreasing the individual system performance. In general, the proposed method consists of six stages as shown in Figure 10 and each stage is described below.

Image preprocessing stage: Image preprocessing is performed on face and iris images using different techniques for each biometrics. Face images undergo a preprocessing procedure including Histogram Equalization (HE) and Mean-Variance Normalization (MVN). On the other hand, iris images are detected and encoded to a rectangular form and then Histogram Equalization and Mean-Variance Normalization are used on this rectangular form.

Feature extraction stage: The proposed method is extracting the face features using a local extraction method and iris features using a global extraction method.

Normalization stage: The matching scores for each biometrics image dataset are obtained which will undergo a series of normalization procedure. Tanh normalization is applied on the matching scores before the fusion.

Fusion stage: In the fourth stage of the proposed system, fusion of normalized face and iris data is done using Weighted Sum Rule.

Classification stage: In the fifth stage, Nearest Neighbor Classifier is used to classify the individuals after the fusion of their normalized face and iris data.

Decision stage: Finally, the joint decision is obtained in this last stage. In fact, the recognition accuracy can be obtained for all the possibilities/methods used in stages 2 to 5. The results demonstrated in the experimental part in the next sections show that the proposed system with LBP facial feature extractor and subspace LDA iris feature extractor has an improved recognition accuracy compared to the individual systems and the systems employing the other feature extractors such as PCA, spPCA and mPCA.

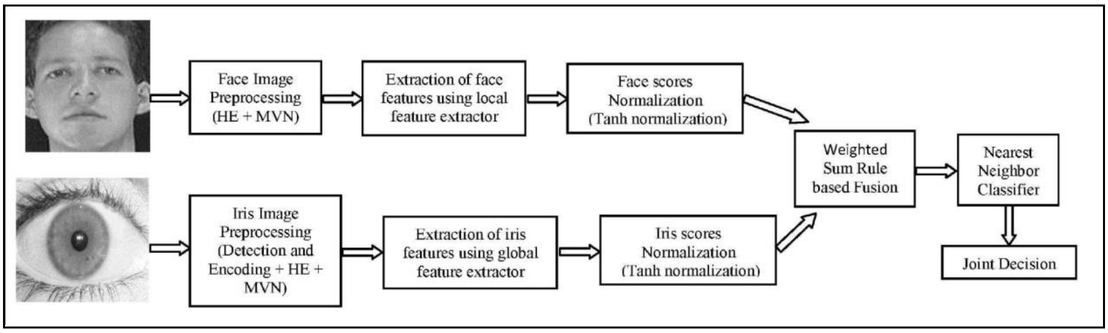

Figure 10: Block Diagram for Combining the Decisions of Face and Iris Classifiers

4.2 Unimodal Systems and Fusion Techniques of Scheme 1

Local and global approaches applied on the face and iris images to extract the features are PCA and subspace LDA as global feature extraction methods, and spPCA, mPCA and LBP as local approaches. Generally, image preprocessing, training, testing and matching are common processing steps used on face and iris images. Histogram equalization (HE) and mean-and-variance normalization (MVN) [15] are applied on the images in order to reduce illumination effects on the images. Iris images preprocessing step is performed using Libor Masek MATLAB open-source code [16] to detect the irises and convert them in a fixed rectangle block. The facial and iris features are then extracted in the training stage. In testing stage, the aim is to obtain the feature vector for the test image using the same procedure applied in the training stage. Finally in the last step, Manhattan distance measurement is used between training and test feature vectors to compute the matching scores. Manhattan distance measurement is represented in equation (4.1), where X and Y are the feature vectors of length n.

$$d(X,Y)=\sum_{i=0}^{n}\left|X_i-Y_i\right| \tag{4.1}$$

One of the most significant stages for proposed scheme 1 is developing the multimodal score vector of normalized face and iris verifiers to authenticate the reality of a person. Development of the multimodal system has been done using fusion techniques at the matching score level. In general, information fusion of several multimodal biometric systems can be performed at four different levels: sensor level, feature level, matching score level and decision level [10]. Matching score fusion level is more popular among all fusion levels because of the ease in accessing and combining the scores. In this fusion method, different matchers may produce different scores such as distances or similarity measures with different probability distributions or accuracies [20]. Matching score level fusion can be considered as classification of the face and iris scores into one of two classes, Accept/Reject, or combination of the face and iris scores in order to provide an individual scalar score [18].

In this proposed method, we applied combination of the face and iris scores based on the Product, Sum and Weighted Sum Rules to fuse our normalized scores. Weighted Sum Rule is a method that can be used to compute combined matching scores of the individual matchers. Jain and Ross in [62] have proposed to compute the weighted sum of scores from the different modalities using user-specific weights. Usually, weights are computed using equal error rate (EER), distribution of scores, quality of the individual biometrics or empirical schemes [19]. In this work, empirical weighting scheme is used to calculate the weights due to its efficiency compared to others [23]. In order to find the proper weights we changed them from 0 to 1 in the way that weights summation is 1 and, finally the best performance determined the weights. Weighted Sum Rule (ws) formula of the face (s_f) and iris (s_i) score matchers is demonstrated in equation (4.2), where w_1 and w_2 are weights and $w_1 + w_2 = 1$.

$$ws = w_1 \times s_f + w_2 \times s_i \tag{4.2}$$

Sum Rule is one of the simplest fusion strategies to apply on the matching distances of individual classifiers in which equal weights for each modality are used during the fusion process [14]. Usually, Sum Rule is more efficient compared to Product Rule to meet the requirements especially under circumstances with high level of noise. The sum (s) of the scores is represented in equation (4.3), where s_f corresponds to face matchers and s_i corresponds to iris matchers.

$$s = s_f + s_i \tag{4.3}$$

The base of Product Rule is on the presumption of statistical independence of vectors (X_1, X_2... X_N) demonstrations. Generally, variant biometric traits of an individual are reciprocally independent and this property makes the Product Rule to be used easily in a multimodal biometric system [63]. The product of the scores is represented in equation (4.4), where p_f represents face matchers and p_i represents iris matchers.

$$p = p_f \times p_i \tag{4.4}$$

Fusion of face and iris scores performed using Sum Rule, Product Rule and Weighted Sum Rule is demonstrated in the following section on different datasets.

4.3 Experiments and Results of Scheme 1

The performance of unimodal and multimodal systems is experimented on two sets of multimodal biometric databases. In most of the recent fusion studies [10, 17, 18, 45] on face and iris biometrics, experiments are carried out on independent face and iris databases. It was difficult to find a publicly available face-iris multimodal database in the past years that includes the face and iris of the same person. Since face and iris biometrics are independent from each other, in this proposed scheme 1, an arbitrary but fixed iris class is assigned to a face class using different face and iris databases as in [14, 64]. In this study, the experiments are performed on two datasets. The first dataset named "Dataset1" consists of ORL face database, CASIA and UBIRIS iris databases. In ORL face dataset, 10 different frontal face images for 40 different subjects are available. In our multimodal system, all 40 subjects are considered; we assigned randomly 5 images per subject for training and the rest for testing. From CASIA iris images, randomly eight iris images were selected for 40 subjects, 3 for training and the remaining 5 for testing. For UBIRIS noisy iris database, the same strategy applied in CASIA was used to select the images (40 subjects: 3 for training and 5 for testing). The experiments are carried out with two subsets of Dataset1, namely ORL+CASIA and ORL+UBIRIS. The second dataset named "Dataset2" includes a larger number of subjects compared to Dataset1. It consists of the images selected from FERET face database and CASIA and UBIRIS iris databases. From FERET database, 4 different frontal face images for 170 different subjects are selected. Accordingly, we selected 170 subjects from CASIA and 170 subjects from UBIRIS iris databases with 4 samples for each subject. Two of the samples are selected randomly to be used for training and the remaining two samples for testing.

The first set of experiments is carried out to measure the performance of face and iris unimodal systems. PCA and subspace LDA are global methods that are applied on the whole images of face and iris datasets. SpPCA, mPCA and LBP are local feature extractors which are applied by partitioning the images into subregions. These set of experiments is performed to select the most appropriate feature extraction method, either local or global, for face and iris recognition separately.

The first set of experiments is carried out on Dataset1 as shown in Table 2. The performances of all the algorithms implemented using face and iris images on ORL, CASIA and UBIRIS datasets of Dataset1 are illustrated. The accuracy achieved by PCA algorithm is based on the selection of maximum number of nonzero eigenvectors; for subpattern-based PCA and modular PCA, eigenvectors corresponding to 97% of eigenvalues were used and the best performance was obtained with $N=81$ where N is the number of partitions. In subspace LDA, eigenvectors for the first and second stages of the algorithm were selected experimentally as the maximum number of nonzero eigenvectors. For Local Binary Patterns method, the number of partitions used is $N=81$ as in spPCA and mPCA and *(8, 2)* circular neighborhood is used in both face and iris datasets.

Table 2: Recognition Performance of Different Feature Extraction Methods on Dataset1 of Face and Iris Images

	Face Recognition	Iris Recognition	
	ORL	CASIA	UBIRIS
PCA	82.00	87.50	83.00
ssLDA	90.50	**96.00**	**87.00**
spPCA	83.50	90.00	84.00
mPCA	82.50	94.00	85.50
LBP	**91.50**	93.50	75.00

As shown in Table 2, the best accuracy for face recognition on ORL database is obtained using the local feature extractor LBP. For iris recognition, the best accuracies on both CASIA and UBIRIS datasets are achieved using ssLDA global feature extractor. The same set of experiments is performed on Dataset2 using FERET, CASIA and UBIRIS datasets. The performance of all local and global feature extraction algorithms are shown in Table 3. The results are compatible with the ones obtained from Table 2 and it is shown that the best accuracy for face recognition is obtained with LBP feature extraction method. Additionally, for iris recognition, the global feature extraction method ssLDA achieves the best accuracies.

Table 3: Recognition Performance of Different Feature Extraction Methods on Dataset2 of Face and Iris Images

	Face Recognition	Iris Recognition	
	FERET	CASIA	UBIRIS
PCA	78.24	81.48	79.71
ssLDA	86.77	**93.83**	**84.42**
spPCA	81.48	82.06	80.30
mPCA	82.65	88.53	81.48
LBP	**89.00**	80.30	76.18

In general, the results of the experiments on unimodal systems indicate that the global feature extraction method ssLDA performs better than the other methods for iris recognition while the local feature extraction method LBP achieves the best accuracy for face recognition.

On the other hand, fusion of multimodal face and iris system scores lead to a higher recognition accuracy compared to the unimodal biometric systems. Improved recognition accuracies achieved using multimodal systems compared with unimodal systems on two subsets of Dataset1 (ORL+CASIA and ORL+UBIRIS) are illustrated in Tables 4 and 5, respectively. In these experiments, features of face and iris biometrics are extracted using one of the five algorithms (PCA, ssLDA, spPCA, mPCA, LBP). The same feature extractor is applied on both face and iris images. The matching scores from both face and iris image datasets are normalized using tanh and minmax normalization methods. The fusion of face and iris matching scores are achieved using Sum Rule. The results for the fusion of face and iris multimodal systems indicate that multimodal system leads to a better performance compared to unimodal systems and the multimodal system using tanh score normalization achieves better recognition accuracies compared to the system using minmax normalization. Therefore, in the rest of the experiments, tanh score normalization will be used before the fusion of two modalities.

Table 4: Unimodal Systems and Multimodal Systems with Different Score Normalization Methods for the Fusion of Face and Iris Recognition System on ORL+CASIA Subset of Dataset1

	Unimodal Systems		Multimodal System with Sum Rule Fusion	
			ORL+CASIA	
	ORL	CASIA	Tanh Normalization	Minmax Normalization
PCA	82.00	87.50	**97.50**	97.00
ssLDA	90.50	96.00	**99.00**	98.50
spPCA	83.50	90.00	**97.50**	97.00
mPCA	82.50	94.00	**99.00**	97.50
LBP	91.50	93.50	**99.00**	98.50

Table 5: Unimodal Systems and Multimodal Systems with Different Score Normalization Methods for the Fusion of Face and Iris Recognition System on ORL+UBIRIS Subset of Dataset1

	Unimodal Systems		Multimodal System with Sum Rule Fusion	
			ORL+UBIRIS	
	ORL	UBIRIS	Tanh Normalization	Minmax Normalization
PCA	82.00	83.00	**93.00**	92.50
ssLDA	90.50	87.00	**95.00**	95.50
spPCA	83.50	84.00	**93.50**	93.50
mPCA	82.50	85.50	**94.00**	93.50
LBP	91.50	75.00	**95.50**	95.00

Fusion of face and iris modalities is also performed using different fusion techniques. It is an important issue to select the most appropriate fusion technique for multimodal systems. The next set of experiments is carried out for the selection of the fusion technique. Sum Rule, Product Rule and Weighted Sum Rule are used for the fusion of face and iris scores and the results are demonstrated in Table 6. As shown in the table, Sum Rule and Product Rule fusion techniques achieve the same recognition accuracy on both subsets of Dataset1. On the other hand, Weighted Sum Rule technique shows similar results as the other fusion techniques on ORL+CASIA subset, however it demonstrates better performance for most of the feature extraction methods on ORL+UBIRIS subset of Dataset1. Therefore, in the rest of the experiments, Weighted Sum Rule will be used as the fusion technique.

Table 6: Fusion Methods for Face and Iris Recognition System on ORL+CASIA and ORL+UBIRIS Subsets of Dataset1

	Score Normalization: Tanh					
	ORL+CASIA			ORL+UBIRIS		
	Sum Rule	Product Rule	Weighted Sum Rule	Sum Rule	Product Rule	Weighted Sum Rule
PCA	97.50	97.50	**97.50**	93.00	93.00	93.00
ssLDA	99.00	99.00	98.50	95.00	95.00	**97.00**
spPCA	97.50	97.50	**97.50**	93.50	93.50	**94.50**
mPCA	99.00	99.00	98.50	94.00	94.00	94.00
LBP	99.00	99.00	**99.00**	95.50	95.50	**97.00**

All possible methods for extracting face and iris features are used in the next set of experiments using all subsets of Dataset1 and Dataset2. The results for ORL+CASIA dataset and ORL+UBIRIS subsets of Dataset1 are presented on Tables 7 and 8 using Weighted Sum Rule fusion method and tanh score normalization method with 5 global and local feature extraction methods mentioned before. Similar experiments are performed for the fusion of face-iris biometrics on FERET+CASIA and FERET+UBIRIS subsets of Dataset2. The results are demonstrated on Tables 9 and 10. The results demonstrate that the proposed method using local and global feature extraction methods for face and iris respectively, achieves the best accuracies.

For ORL+CASIA subset of Dataset1, ssLDA feature extraction method achieves the best recognition accuracy as 99.50%, and for ORL+UBIRIS subset of Dataset1, both PCA and ssLDA methods achieve the best recognition accuracy (99.00%) when they are applied on iris images with LBP face extractors on facial images. These experiments are repeated on a larger dataset, namely Dataset2, in order to demonstrate the reliability of the results obtained using the two subsets of Dataset1 images. The recognition accuracies achieved using all feature extraction methods, tanh normalization and Weighted Sum Rule fusion technique are presented in Tables 9 and 10. The best recognition accuracies for both FERET+CASIA and FERET+UBIRIS subsets of Dataset2 are obtained with the fusion of LBP facial feature extractor and ssLDA iris feature extractors as 98.53% and 97.35% respectively.

Table 7: Weighted Sum-Rule Fusion on ORL+CASIA Subset of Dataset1 Using Combination of Different Methods

Fusion Sets	Iris-PCA	Iris-ssLDA	Iris-spPCA	Iris-mPCA	Iris-LBP
Face-PCA	97.50	99.00	98.50	98.00	98.00
Face-ssLDA	98.00	99.00	98.00	99.00	97.00
Face-spPCA	97.50	99.00	97.50	98.00	98.00
Face-mPCA	95.50	99.00	96.00	98.50	96.00
Face-LBP	97.50	**99.50**	99.00	99.00	99.00

Table 8: Weighted Sum-Rule Fusion on ORL+UBIRIS Subset of Dataset1 Using Combination of Different Methods

Fusion Sets	Iris-PCA	Iris-ssLDA	Iris-spPCA	Iris-mPCA	Iris-LBP
Face-PCA	93.00	94.50	94.00	93.50	95.00
Face-ssLDA	95.50	97.00	95.00	94.50	96.00
Face-spPCA	95.00	94.50	94.50	94.50	94.50
Face-mPCA	93.50	93.50	92.50	94.00	92.50
Face-LBP	**99.00**	**99.00**	98.50	97.00	97.00

Table 9: Weighted Sum-Rule Fusion on FERET+CASIA Subset of Dataset2 Using Combination of Different Methods

Fusion Sets	Iris-PCA	Iris-ssLDA	Iris-spPCA	Iris-mPCA	Iris-LBP
Face-PCA	92.35	96.76	94.41	95.59	95.00
Face-ssLDA	95.88	97.65	97.65	97.06	96.47
Face-spPCA	94.41	96.47	95.88	96.76	95.88
Face-mPCA	95.00	97.94	95.88	97.94	97.06
Face-LBP	96.76	**98.53**	97.65	97.94	97.65

Table 10: Weighted Sum-Rule Fusion on FERET+UBIRIS Subset of Dataset2 Using Combination of Different Methods

Fusion Sets	Iris-PCA	Iris-ssLDA	Iris-spPCA	Iris-mPCA	Iris-LBP
Face-PCA	89.12	93.53	90.29	91.76	91.76
Face-ssLDA	91.76	96.76	92.06	94.12	94.71
Face-spPCA	91.47	95.00	91.18	93.53	92.94
Face-mPCA	92.94	95.00	91.76	93.24	94.12
Face-LBP	94.41	**97.35**	94.12	95.88	96.18

Fusion of face-iris biometrics gives the best results whenever LBP is applied for face feature extraction on both Dataset1 and Dataset2 with global feature extractors on iris images. Therefore, global approaches achieve the best recognition accuracy on iris datasets while local approaches extract facial features in the best way for the improvement on recognition accuracy on face-iris multimodal biometrics systems. Since iris image is converted to a rectangular form, it is better to consider this new iris form as a whole for feature extraction. This is the main reason behind the results obtained from the experimental study. On the other hand, face images may be corrupted partially, therefore, using local feature extractors will help to remove the corrupted sub-images. In that case, the results obtained from the best quality sub-images will improve the recognition accuracy.

In general, for face recognition, the local feature extractors, specifically LBP, achieve the best accuracies. Iris recognition is performed on the transformed rectangular form obtained from the iris and global methods such as ssLDA and PCA achieve the best recognition accuracies. Actually, ssLDA is better than PCA and it is a powerful feature extractor, however for noisy images with illumination changes, PCA can be an alternative for extracting features to get the best recognition accuracy for the fusion of face-iris biometrics. In our iris datasets CASIA and UBIRIS, all images are transformed into rectangular form to perform feature extraction on the iris. However, UBIRIS images are noisy images and we increased the brightness of these images to obtain a better quality image for the transformation of rectangular form. This is the main reason that PCA extracts the iris features of noisy UBIRIS images in a better way compared to local feature extraction methods in Table 8 using ORL+UBIRIS subset of Dataset1. In general, it can be stated that the local feature extractor LBP for facial images and the global feature extractor ssLDA for iris images can be used for feature extraction in a robust face-iris multimodal recognition system.

The proposed face-iris multimodal system presented in this chapter is compared with unimodal systems using ROC (Receiver Operator Characteristic) analysis. False Acceptance Rate (FAR) and False Rejection Rate (FRR) are used as a function of decision threshold which controls the tradeoff between these two error rates. The probability of FAR versus the probability of FRR is plotted for different values of decision threshold. The Equal Error Rate (EER) of each system given on top of the curves in Figures 11 and 12 is obtained from the point on ROC curve where the value of FAR is equal to the value of FRR. Figure 11 shows the ROC curve of unimodal methods and the proposed multimodal method on ORL and CASIA subsets of Dataset1.

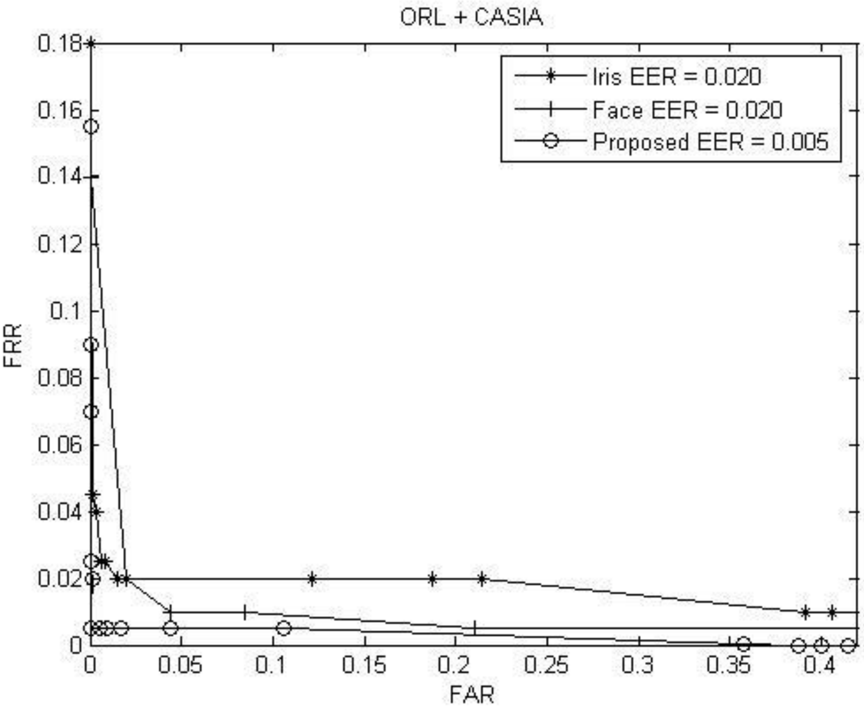

Figure 11: ROC Curves of Unimodal Methods and the Proposed Method on ORL and CASIA Subsets of Dataset 1.

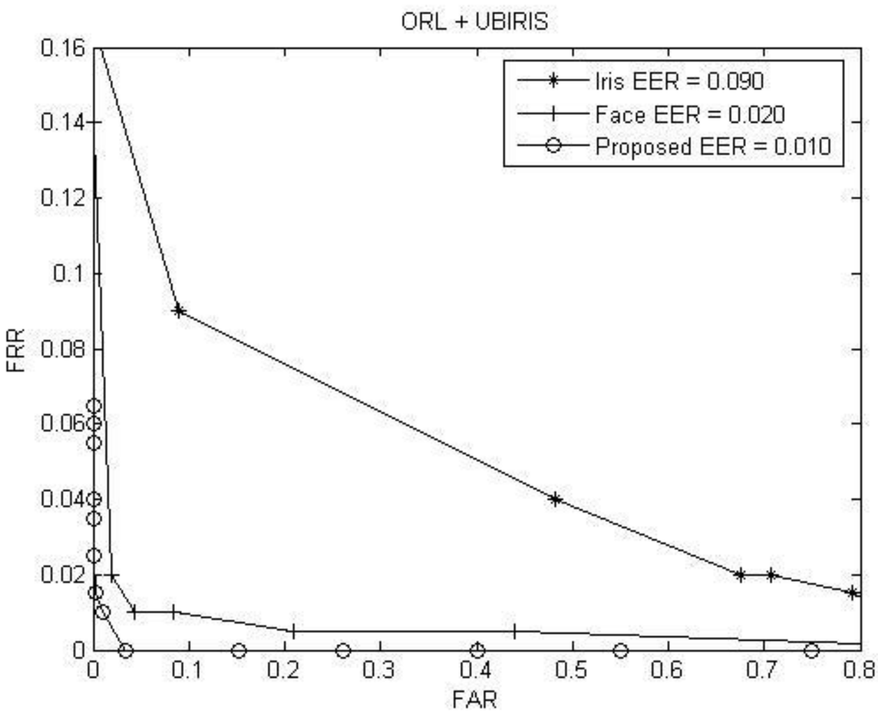

Figure 12: ROC curves of Unimodal Methods and the Proposed Method on ORL and UBIRIS Subsets of Dataset1.

The unimodal (face and iris) methods achieve the performance of 2% EER. The proposed multimodal face and iris method achieves a performance of 0.5% EER. The improvement of the proposed method over the unimodal methods is clearly shown on ROC curve in Figure 11. The improvement of the proposed multimodal system over the unimodal systems on ORL and UBIRIS subsets of Dataset1 is demonstrated in Figure 12. The ROC curve demonstrates the reliability of face recognition system (with 2% EER) over iris recognition system (with 9% EER). The proposed system achieves a performance of 1% EER which shows the improvement of the proposed multimodal system over the unimodal systems.

The proposed multimodal system is also compared with unimodal systems using ROC analysis on FERET+CASIA and FERET+UBIRIS subsets of Dataset2. The ROC curves are presented in Figures 13 and 14. The unimodal face and iris systems achieve a performance of 10% EER and 6% EER, respectively for FERET+CASIA subset as shown in Figure 13. The proposed multimodal system achieves a performance of 2.5% EER which is significantly better than unimodal systems. Meanwhile, the results of ROC analysis on FERET+UBIRIS subset of Dataset2 as shown in Figure 14 are compatible with the results presented in Figure 13. Face and iris unimodal system demonstrate a performance of 10% EER and 15.5% EER, respectively. The proposed system achieves a performance of 3% EER which is a significant improvement over the unimodal systems.

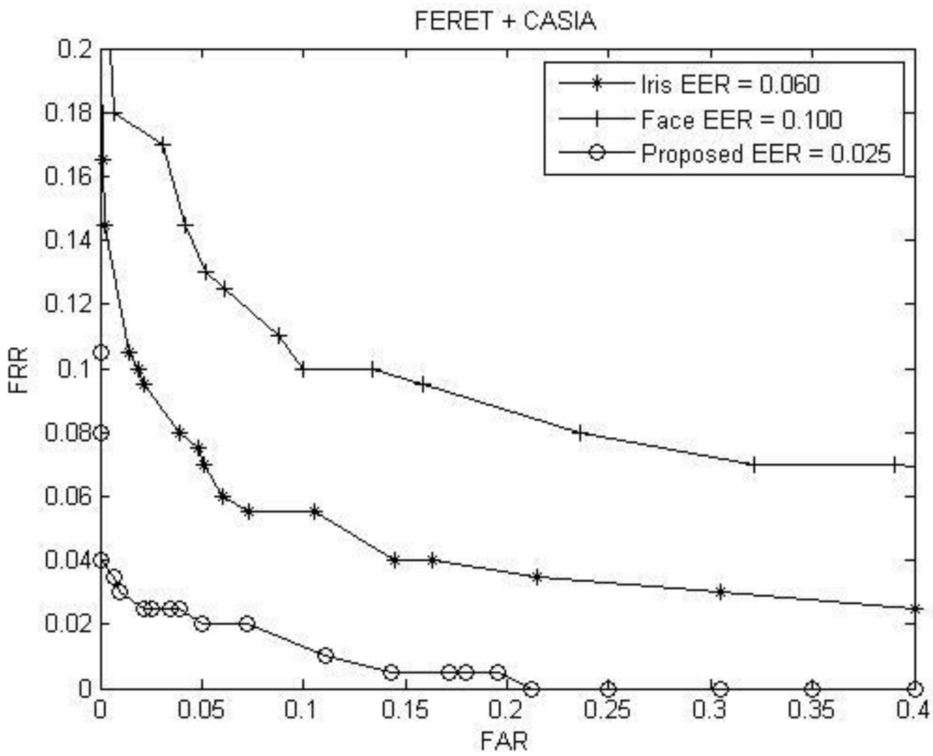

Figure 13: ROC Curves of Unimodal Methods and the Proposed Method on FERET and CASIA Subset of Dataset2.

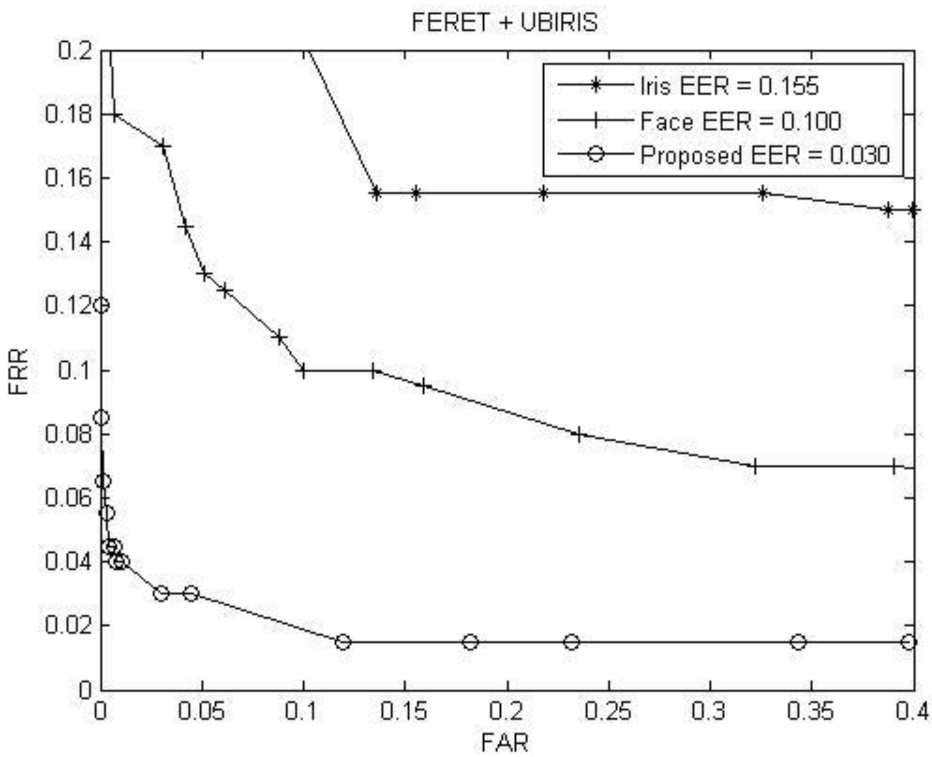

Figure 14: ROC Curves of Unimodal Methods and the Proposed Method on FERET and UBIRIS Subset of Dataset2.

On the other hand, the proposed method is compared with the existing methods in the literature. The results reported in recent articles are used and the results for our unimodal and proposed multimodal methods are obtained using the same experimental setup with ORL and CASIA subsets of Dataset1. Total error rate (TER) of the proposed methods is calculated to compare the results with the results of the existing systems. Total error rate is the sum of FAR and FRR, which is equal to twice the value of EER. Table 11 demonstrates minimum TER of our unimodal face and iris recognition methods and the existing unimodal methods on ORL and CASIA subsets of Dataset1. The existing methods used in [10] for face and iris recognition achieve a minimum TER of 0.142 and 0.113, respectively. Total error rate (TER) of unimodal iris and face systems using all global and local feature extraction methods are also presented in Table 11. Unimodal face and iris recognition methods using LBP and subspace LDA feature extractors outperform the existing methods with a minimum TER of 0.040.

Table 11: Minimum Total Error Rates of Unimodal Methods on ORL and CASIA Datasets

	Method	Minimum total error rate (TER)	Performance (at 0.01% FAR)
Face Recognition	Liau &Isa's method[10]	0.142	N/A
	PCA-based method	0.120	70.50
	ssLDA-based method	0.080	82.00
	spPCA-based method	0.130	71.50
	mPCA-based method	0.120	71.00
	LBP-based method	**0.040**	83.50
Iris Recognition	Liau &Isa's method[10]	0.113	N/A
	PCA-based method	0.110	74.00
	LBP-based method	0.070	84.50
	spPCA-based method	0.110	75.50
	mPCA-based method	0.070	87.00
	ssLDA-based method	**0.040**	90.00
	Proposed method (LBP+ssLDA)	**0.010**	97.00

The last row of the table presents the TER of the proposed multimodal method with 0.010. TER of the proposed method is better than TER of all unimodal systems with local and global feature extractors including Liau & Isa's face and iris recognition methods given in [10]. The proposed method reduces the error by at least 6% compared to the unimodal methods. On the other hand, the last column of Table 11 demonstrates the results of unimodal systems and proposed multimodal system in terms of verification accuracy at 0.01% false acceptance rate (FAR). The best performance is achieved using LBP feature extractor which provides verification accuracy of 83.5%. Iris recognition performance achieved by ssLDA method outperforms the other unimodal methods and provides verification accuracy of 90.0%. The performance improvement of the proposed multimodal system at 0.01% FAR is presented at the end of the table. The proposed method yields a verification accuracy of 97.0% which performs at least 7% better than the unimodal methods.

The existing multimodal methods reported in [10] with minimum TER's are compared with our proposed face-iris multimodal system in Table 12. As shown in the table, minimum TER of the proposed method is 0.01 which shows that the proposed multimodal method is better than several existing fusion methods on the same set of face and iris images.

Table 12: Minimum Total Error Rates of Multimodal Fusion Methods on ORL and CASIA Datasets

Method	Minimum total error rate (TER)
Sum Rule[10]	0.0481
Weighted sum Rule[10]	0.0472
LDA[10]	0.0650
Liau &Isa's SVM method[10]	0.0440
Proposed	0.0100

4.4 Contribution and Conclusion of Scheme 1

High cooperation with the people is not required to take their face images. However, for high quality iris images cooperation with the people is needed. With high–quality iris images obtained in cooperative situation, iris biometrics achieves high recognition accuracies. Iris recognition provides high performance and it is a reliable biometrics [41, 42].

Local Binary Patterns (LBP)-based face recognition has become a highly popular approach due to its discriminative power and computational simplicity. On the other hand, using iris information extracted from a face image is advantageous in order to improve face recognition performance. Consequently, fusion of face and iris biometrics is used to improve face recognition performance. In this respect, noisy iris images can be included into multimodal systems to perform the experiments as in practical applications.

The contribution of our work is to use Local Binary Patterns-based facial feature extraction with global subspace LDA-based iris feature extraction for the fusion of face-iris multimodal system with tanh score normalization and Weighted Sum Rule fusion method. We used other local and global feature extraction methods to compare the performance of the proposed scheme with unimodal and multimodal face-iris systems. The proposed scheme can be used practically in person identification systems using facial images. The iris information can be extracted from the face image and the fusion of face-iris multimodal system can be performed to improve the performance of the individual face recognition system.

Chapter 5

FACE-IRIS MULTIMODAL SYSTEM USING CONCATENATION OF FACE-IRIS MATCHING SCORES (PROPOSED SCHEME 2)

5.1 Description of Proposed Scheme 2

The proposed scheme 2 concentrates on different fusion techniques at matching score level, feature level and decision level on two widely studied modalities namely face and iris. We explore in this proposed scheme the recognition performance of face-iris unimodal and multimodal biometric system using several local and global feature extraction methods and fusion techniques. We propose a new scheme at score level fusion and compare this new scheme with the state-of-the-art schemes using different fusion levels in order to represent the robustness and effectiveness of the proposed method.

For each of the face and iris modalities, 5 different standard local and global feature extractors are applied, namely spPCA, mPCA and LBP methods as local feature extractors and global feature extractors used for this study are PCA and subspace LDA. The second proposed scheme fuses face-iris multimodal biometric system at matching score level fusion. In fact, availability of sufficient information content and the ease in accessing and combining matching scores encouraged us to propose a new scheme using matching score fusion techniques. In this proposed scheme, instead of concatenating the original feature sets from face and iris, the matching scores obtained from face and iris features are concatenated. Specifically, the proposed method uses transformation-based and classifier-based score fusion techniques after extracting face and iris features using several local and global feature extraction methods. The normalized scores are then concatenated to classify a person from his/her face and iris images.

The related works done previously show dimensionality and redundancy problems in feature level fusion, thus leading to performance degradation [23]. Decision level fusion is too rigid due to limitation in availability of information amount [22]. On the other hand, matching scores prepare sufficient information content and easiness for integration. Indeed consideration of matching scores in concatenation solves dimensionality and redundancy problems raised by feature level fusion and limitation in availability of information amount problem raised by decision level fusion, thus consequently leads to performance improvement of the multimodal biometric system.

In general, the proposed scheme consists of six stages as shown in Figure 15. Image preprocessing is performed on face and iris images using different techniques for each biometrics. Face and iris images undergo a preprocessing procedure including detection, Histogram Equalization (HE) and Mean-Variance Normalization (MVN). Iris images are then detected and encoded to a rectangular form before applying Histogram Equalization and Mean-Variance Normalization. The proposed scheme is then extracting the face and iris features using method i where i =1,...,5. Each value of i corresponds to a different feature extraction method (1=PCA, 2=subspace LDA, 3=spPCA, 4=mPCA, 5=LBP). The matching scores for each biometrics image datasets are obtained which will undergo a series of normalization procedure. Tanh normalization is applied on the matching scores before the fusion. In the fourth stage of the proposed system, fusion of normalized face or iris scores is done using Sum Rule. In fact, the proposed scheme combines the results achieved from scores of 5 different feature extraction methods using Sum Rule for face and iris separately. In the fifth stage, fused score vectors of face are concatenated with fused iris score vectors of the previous step using Sum Rule. In the sixth stage, Nearest Neighbor Classifier is used to classify the individuals after the fusion of their normalized face and iris data as represented in Figure 15.

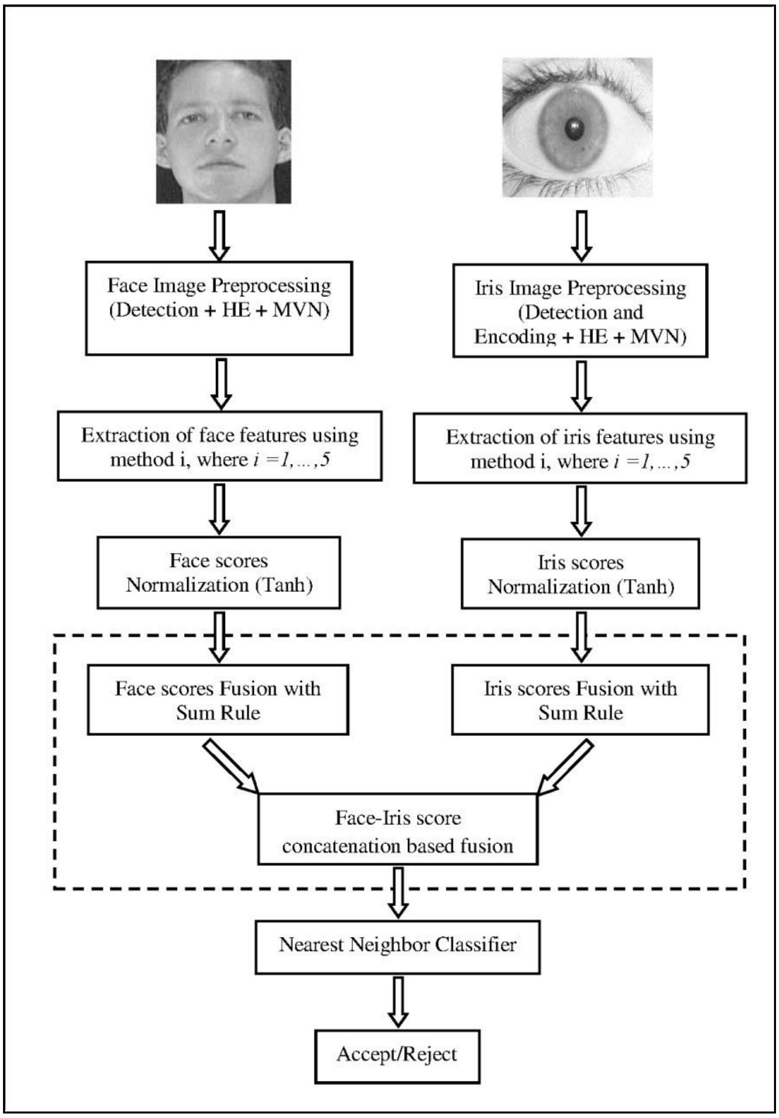

Figure 15: Block Diagram of the Proposed Scheme for Face-Iris Fusion Using Score Concatenation (*Method i[1,...,5]={PCA, ssLDA, spPCA, mPCA, LBP}*)

The results and experiments in the next sections demonstrate that the proposed system has an improved recognition accuracy compared to the individual systems and the systems employing feature level fusion, decision level fusion and the well-known matching score fusion techniques such as Sum Rule or Product Rule.

5.2 Unimodal Systems and Fusion Techniques of Scheme 2

Face and iris unimodal biometric systems are implemented using 5 different local and global feature extractors. PCA and subspace LDA are global feature extraction methods used, while subpattern-based PCA, modular PCA and LBP are local approaches for extracting the features which are used as feature extractors. On the other hand, the computation of matching scores in the unimodal systems is done using Manhattan distance measurement. Image preprocessing, training, testing and matching are common processing steps used on face and iris databases. Histogram equalization (HE) and mean-and-variance normalization (MVN) are applied on the face and iris images in order to reduce illumination effects on the images. The facial and iris features are then extracted in the training stage. In testing stage, the aim is to obtain the feature vector for the test image using the same procedure applied in the training stage. Finally in the last step, Manhattan distance measurement is used between training and test feature vectors to compute the matching score. In this scheme, for iris image preprocessing step, Libor Masek Matlab open-source code is used to detect the irises. This detected iris region is normalized to a fixed dimension rectangular strip.

Development of the multimodal system is done using fusion techniques at the matching score level, feature level and decision level. Matching score level fusion can be considered as classification of the face and iris scores into one of two classes, Accept/Reject or combination of the face and iris scores in order to provide an individual scalar score. We apply combination of the face and iris scores based on the Sum Rule to fuse normalized scores. In addition, focus of this proposed scheme to normalize the matching scores is on Tanh method. Sum Rule which is used as a fusion strategy to apply on the matching distances of individual classifiers in which equal weights for each modality are used during the fusion process. Fusion of the data at feature level fusion is performed using the features of face and iris extracted from each feature extractor separately (PCA, subspace LDA, spPCA, mPCA, LBP) and concatenated. The method fuses face and iris features from each feature extractor into a long vector. In order to classify the fusion features, Manhattan distance is used. In decision level fusion, Majority Voting is employed to combine the results from our 5 different classifiers (PCA, subspace LDA, spPCA, mPCA, LBP) and yield final fused decision. Majority Voting is a commonly used classifier-based voting scheme. In this scheme, all classifiers provide an identical confidence in classifying a set of objects via voting. This scheme will output the label that receives the majority of the votes. Prediction of each classifier is counted as one vote for the predicted class. At the end of the voting process, the class that received the highest number of votes wins [65].

5.3 Experiments and Results of Scheme 2

The performance of the proposed scheme is tested by constructing a mixed multimodal biometric database. ORL and BANCA face databases and CASIA and UBIRIS iris databases are used in order to have different conditions in terms of illumination and pose in face images; noisy and non-noisy iris images, and enough number of people and samples to measure the performance. In our multimodal system, for combined face dataset, 80 subjects with 8 different frontal face images are considered. We assigned randomly 3 images per subject for training and the rest for testing. From CASIA-UBIRIS iris data set, randomly eight iris images have been selected for 80 subjects, 3 for training and the remaining 5 for testing. It is needed to state that Torch3 vision [66], a powerful machine vision library, has been applied on BANCA database in order to detect the face images. This library is based on Torch3 computer machine learning library (Marcel & Rodriguez 2007) which is written in C++.

The local and global methods for feature extraction are used on both face and iris datasets. PCA and subspace LDA methods are applied on the whole images of face and iris datasets. SpPCA, mPCA and LBP are local feature extractors which are applied by partitioning the images into subregions. Table 13 illustrates the performance of all the algorithms implemented using face and iris images from all databases. The accuracy achieved using PCA algorithm is based on the selection of maximum number of nonzero eigenvectors. On the other hand, subpattern-based PCA and modular PCA use eigenvectors corresponding to 97% of eigenvalues and the best performance was obtained with $N=81$ where N is the number of partitions. In subspace LDA method, eigenvectors were selected experimentally to obtain the best recognition accuracy. The number of partitions used for Local Binary Patterns method is $N=81$ and $(8, 2)$ circular neighborhood is used in both face and iris databases.

Table 13: Recognition Performance Using Local and Global Methods on Face and Iris Images

Feature Extraction Method	**Face Recognition ORL-BANCA (%)**	**Iris Recognition CASIA-UBIRIS (%)**
PCA	70.00	86.75
ssLDA	78.50	**91.25**
spPCA	76.25	84.25
mPCA	73.50	89.75
LBP	**79.75**	83.50

The best accuracy for face recognition on ORL-BANCA database is obtained using the local feature extractor LBP with 79.75% as shown in Table 13. For iris recognition, the best accuracy on CASIA-UBIRIS dataset is achieved as 91.25% using subspace LDA global feature extractor. Table 14 demonstrates the performance of the implementation of different fusion methods and the new proposed scheme. The results show fusion of face and iris in all fusion levels considered in this scheme that leads to a higher recognition accuracy compared to the unimodal biometric systems.

Table 14: Recognition Performance of Different Fusion Methods

Fusion Method	**Recognition Performance**
Feature Level Fusion (Concatenating the Features)	93.500
Decision Level Fusion (Majority Voting)	97.125
Score level fusion (Sum Rule)	97.750
Proposed Scheme	**98.250**

The second proposed face-iris multimodal system presented in the previous sections is compared with unimodal systems using ROC analysis. The probability of FAR versus the probability of FRR is plotted for different values of decision thresholds. The Equal Error Rate (EER) of each system demonstrated on top of the curve which is the point on ROC curve where the value of FAR is equal to the value of FRR. In the case of noncontinuous score distributions, finding EER is difficult and can be calculated using equation (5.1).

$$EER = \begin{cases} \dfrac{FAR(t_1) + FRR(t_1)}{2} & if\ FAR(t_1) - FRR(t_1) \le FRR(t_2) - FAR(t_2) \\ \dfrac{FAR(t_2) + FRR(t_2)}{2} & Otherwise \end{cases} \tag{5.1}$$

where $t_1 = \max_{t \in S}\{t \mid FRR(t) \le FAR(t)\}$, $t_2 = \min_{t \in S}\{t \mid FRR(t) \ge FAR(t)\}$ and S is the set of thresholds used for computing the score distributions [74].

The ROC curves of the methods that achieved the best performance of unimodal methods and the proposed multimodal method on the combined face and iris datasets are demonstrated in Figure 16. The Equal Error Rate of each system is demonstrated on top of the curve for unimodal and multimodal systems. The unimodal face and iris methods achieve the performance of 6.75% and 5.75% EER, respectively. The ROC curves demonstrate that face recognition system is less reliable than iris recognition system. The proposed scheme for multimodal face and iris recognition achieves 1.02% EER. The improvement of the proposed method over the unimodal methods is clearly shown on ROC Curve in Figure 16. The improvement of the proposed scheme over the score level fusion, decision level fusion and feature level fusion is demonstrated in Figure 17. As shown in Figure 17, EER of the proposed method is 1.02% which shows the superiority of the proposed multimodal scheme over several existing fusion methods on the same set of face and iris images.

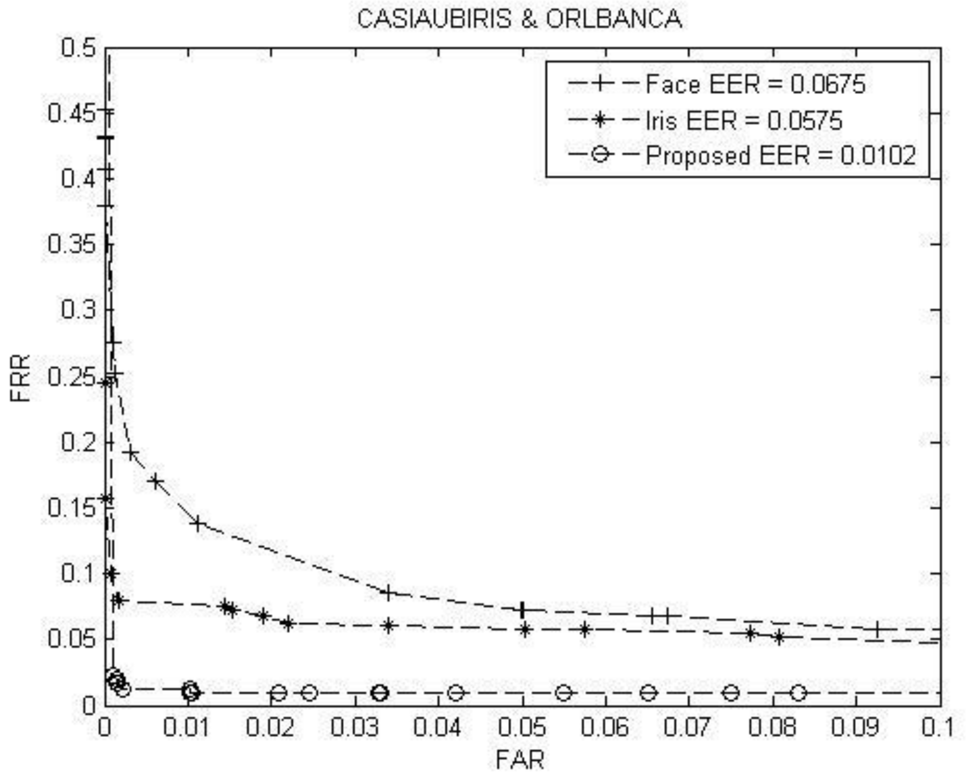

Figure 16: ROC Curves of Unimodal Methods and the Proposed Scheme.

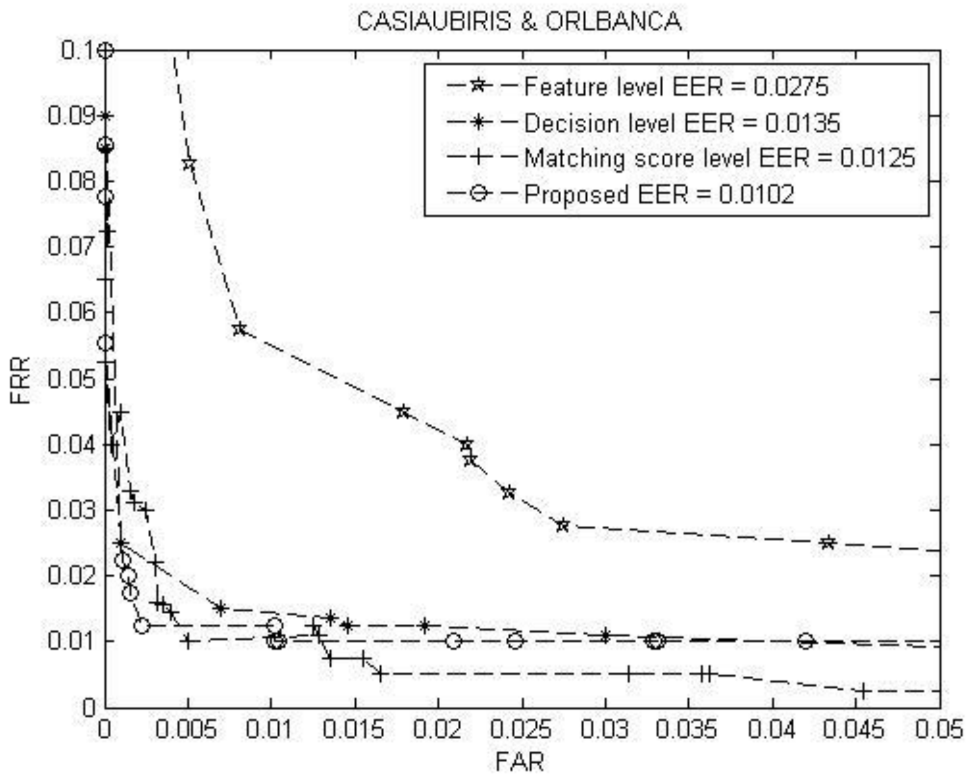

Figure 17: ROC Curves of the Proposed Method and the State of the art Fusion Methods

5.4 Contribution and Conclusion of Scheme 2

A new scheme for the fusion of face and iris biometrics is proposed using transformation-based score fusion and classifier-based score fusion in this proposed scheme. The proposed method is compared with the state-of-the-art fusion techniques of feature level, score level and decision level fusion. In the matching score level fusion, Sum Rule is applied and the fusion of the scores from local and global extractors is conducted by Tanh normalization of face and iris scores. In feature level fusion, features of face and iris are extracted by each feature extractor separately and concatenated into a long vector. In decision level fusion, Majority Voting has been used to combine the results from different classifiers and obtain final fused decision. In the proposed scheme, instead of performing original feature sets concatenation of face and iris, we involve face and iris matching scores in concatenation step. The proposed method achieves improved recognition accuracy compared to unimodal methods and the state-of-the-art systems such as feature level fusion, decision level fusion and commonly used matching score level fusion techniques such as Sum Rule or Product Rule.

The contribution of our work is to use the concatenated scores of all 5 local and global feature extraction methods for the fusion of face-iris multimodal system with tanh score normalization and Weighted Sum Rule fusion method. We used other techniques to compare the performance of the proposed scheme with unimodal and multimodal face-iris systems. The proposed scheme can be used practically in person identification systems using facial images. The iris information can be extracted from the face image and the fusion of face-iris multimodal system can be performed to improve the performance of the individual face recognition system.

Chapter 6

OPTIMAL FEATURE EXTRACTORS FOR FACE-IRIS MULTIMODAL SYSTEM (PROPOSED SCHEME 3)

6.1 Description of Proposed Scheme 3

In the third proposed scheme, we propose a multimodal system using LBP feature extractor method for facial feature extraction and feature vector fusion (iris-FVF) for iris feature extraction using a feature selection method, namely Particle Swarm Optimization (PSO) [67], to improve the performance of iris recognition by removing the redundant and irrelevant information. The fusion of these two modalities is then performed using Weighted Sum Rule on tanh normalized face and iris scores. Taking into account the fact that local features based methods achieve better accuracies compared to global methods [37], we used spPCA, mPCA and LBP methods as local feature extractors. Beside these local methods, global feature extractors such as PCA and subspace LDA are also used to compare the performance of global feature extractors on face and iris images separately. Local feature based methods achieve better accuracies and they are robust to variations in face recognition since some parts of the images can be affected by variations such as illumination, facial expression and partial occlusions [29, 35, 37, 48].

Among all local feature extraction methods, our studies show that LBP feature extraction method achieves better performance compared to other methods on face images. LBP is originally designed for efficient texture classification and provides a simple and effective way to represent faces [68]. On the other hand, the same feature extraction methods are applied on iris images in this scheme and the best recognition performance is obtained by subspace LDA global feature extraction method. Several fusion techniques at score level and feature level are applied on our proposed multimodal biometric system.

The proposed method involves the consideration of a face-iris multimodal biometric system using score-level fusion and feature level fusion. In fact, availability of sufficient information content and the ease in accessing and combining matching scores encouraged us to propose a new scheme using matching score fusion techniques along with feature level fusion. As mentioned earlier, 5 different standard feature extractors are applied separately on face and iris images. In order to fuse face and iris, we performed feature concatenation on original face and iris feature sets which lead to dimensionality and redundancy problems and performance degradation but can be alleviated using feature selection methods as shown in Figure 18. Feature selection methods lead to select an optimized subset of features from original feature sets by removing the redundant and irrelevant data that can be done based on a certain objective function [10]. For this proposed scheme, particle swarm optimization (PSO) technique is used as a feature selection method to improve the recognition performance. The most important reasons to select PSO technique as a feature selection method can be stated as the considerable success of applying PSO in numerous applications of feature selection [11]. In addition, feature selection generally needs search in very large dimension spaces and PSO has a good ability to improve performance in searching large spaces for various applications. PSO is computationally low-cost in terms of both speed and memory requirements, in fact only primitive mathematical operations is applied in PSO calculation process rather than complex evolutionary operators such as crossover and mutation used in genetic algorithms. Another important advantage of PSO compared to other methods such as genetic algorithm is its memory.

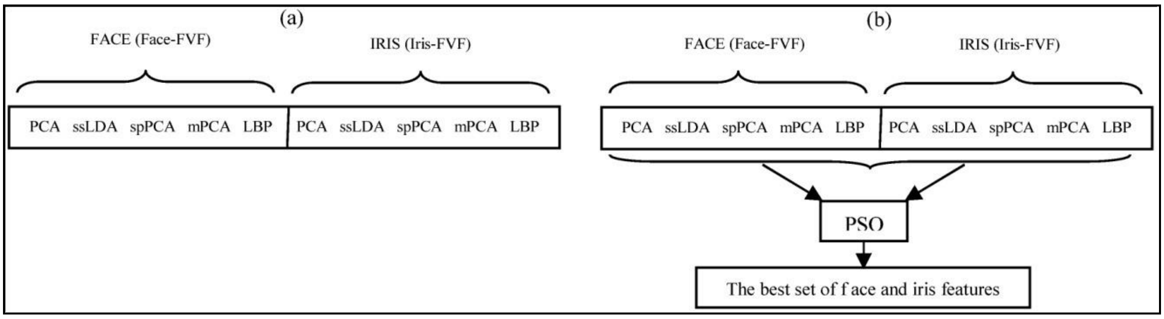

Figure 18: Concatenation of Feature Selection Methods without and with PSO

On the other hand, the need to increase the recognition accuracy motivated us to find a new design to fuse data. Our scheme considers the combination of feature level fusion scores of one modality with scores of another modality. Face and iris features of five aforementioned local and global methods are concatenated separately to obtain the features of face feature vector fusion (Face-FVF) and iris feature vector fusion (Iris-FVF). Then, the corresponding scores of the concatenated features of each modality can be used to combine face and iris as shown in Figure 18 (a). In this step, we performed experiments in order to find the best set of feature extraction methods for the fusion of face-iris multimodal biometrics using PSO as demonstrated in Figure 18 (b). We applied Weighted Sum Rule on the normalized face and iris scores that guided us to a better performance compared to unimodal systems. We then performed the fusion using Face-FVF scores and all possible combinations of unimodal scores. This means that Face-FVF scores combined with all possibilities of iris unimodal scores are fused by Weighted Sum Rule. On the other hand, the experiments were repeated with Iris-FVF and all possibilities of face unimodal scores. The best and the most comparable performance is achieved using Iris-FVF scores and LBP face scores which shows the power of LBP on facial feature extraction and face recognition.

The main idea of the proposed scheme is to fuse scores of LBP facial features with Iris-FVF scores, as demonstrated in Figure 19 (a). For Iris-FVF, before producing the scores, PSO is applied to select the best set of iris features as shown in Figure 19 (b). This proposed scheme leads to a better recognition performance. In order to fuse the scores of the proposed scheme, actually several techniques can be used such as Sum Rule, Product Rule and etc. which generally achieve similar performance. Therefore, we considered Weighted Sum Rule in our study since the weights are able to reflect the relative difference in unimodal systems performance. The block diagram of the proposed method is presented in Figure 20. The details of PSO feature selection method is given in the next subsection.

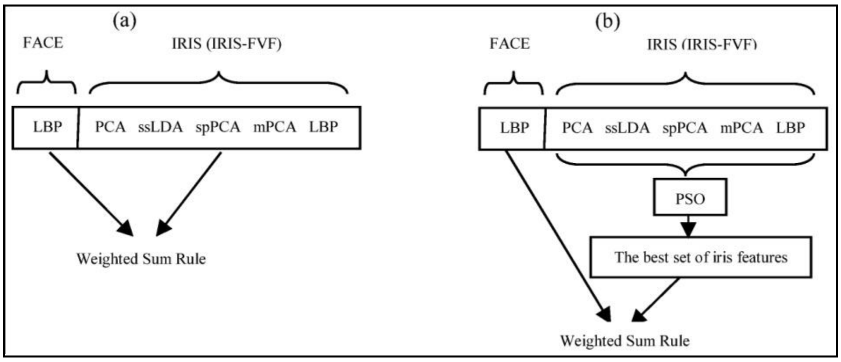

Figure 19: Fusion of LBP Facial Feature Scores and Iris-FVF Scores without and with PSO

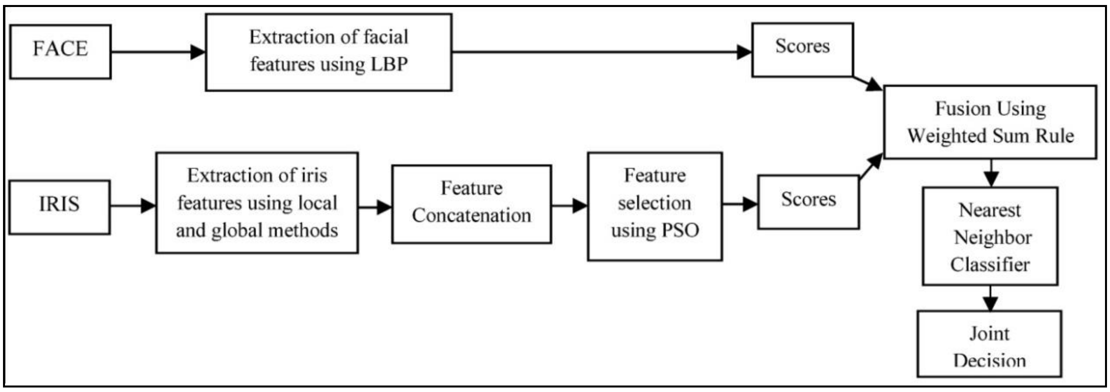

Figure 20: Block Diagram of the Proposed Method

6.1.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) technique was first described by Kennedy and Eberhart in 1995 [67]. PSO aims to find an optimized solution in a search space and it is initialized with a population of random solutions called particles to be evaluated using a fitness function. Each particle is treated as a point in an n-dimensional feature space. The *i*th particle is represented as $x_i = (x_{i1}, x_{i2}, \ldots, x_{in})$. The ability of PSO to memorize the best previous positions at each iteration causes to update each particle by two best values *pbest* and *gbest*. *Pbest* is the position giving the best fitness value of any particle which can be recorded and represented as $p_i = (p_{i1}, p_{i2}, \ldots, p_{in})$, where P is the size of the population. The index of the best particle among all the particles in the population is called *gbest* and represented as p_g. The velocity for *i*th particle is represented as $v_i = (v_{i1}, v_{i2}, \ldots, v_{in})$. A particle's new velocity is calculated according to its previous velocity and the distances of its current position from its own best position and from the group's best experience. The particles are updated according to the equations (6.1), (6.2) and (6.3) [10, 19, 67]:

$$v_i = wv_i + c1 \times rand_1()(p_i - x_i) + c2 \times rand_2()(p_g - x_i), \tag{6.1}$$

$$x_i = x_i + v_i \tag{6.2}$$

$$x_i = \begin{cases} 1 & if \ \dfrac{1}{1+e^{-v_i}} > rand_3() \\ 0 & Otherwise \end{cases} \tag{6.3}$$

where w is the inertia weight, $c1$ and $c2$ are acceleration constants and $rand_1()$, $rand_2()$, $rand_3()$ are separate random numbers.

Generally, selecting a proper inertia weight provides a balance between global and local explorations and consequently results in finding sufficient optimal solution faster. The acceleration constants *c1* and *c2* are used to pull the particle towards *pbest* and *gbest*. Indeed, employing an appropriate fitness function to optimize the problem in feature selection techniques such as PSO is an important issue. In this study, the inertia weight is set to 1, and the acceleration constants c_1 and c_2 are both set as 2. A particle's new velocity is calculated according to its previous velocity and the distances of its current position from its own best position and from the group's best experience. Evaluation of the experience is done using the fitness function. In this proposed scheme, the fitness function is the recognition rate and the selection of features is based on a bit string of length *M*, where *M* is the number of feature extraction methods applied on face and iris unimodal systems. In other words, every bit here represents one feature extraction method; value '1' means that all features of corresponding feature extraction method are selected and '0' means that they are not selected. In our work, we assigned the size of the population as 10 and iteration size as 20. The PSO algorithm is applied in the same way as in [10].

6.2 Unimodal Systems and Fusion Techniques of Scheme 3

Face and iris unimodal biometric systems employ the same strategy and structure in order to recognize human beings from their face or iris images. Image preprocessing, training, testing and matching are common processing steps used on face and iris databases. Histogram equalization (HE) and mean-and-variance normalization (MVN) are applied on the face and iris images in order to reduce illumination effects on the images. The facial and iris features are then extracted in the training stage. In testing stage, the aim is to obtain the feature vector for the test image using the same procedure applied in the training stage. Finally in the last step, Manhattan distance measurement is used between training and test feature vectors to compute the matching score.

In this study, five different local and global feature extraction methods are applied on facial images. PCA algorithm is implemented as in [25] based on the selection of maximum number of nonzero eigenvectors. In both subpattern-based PCA and modular PCA, the images are initially partitioned into N^2 subimages. Eigenvectors corresponding to 97% of eigenvalues with $N=81$, where N is the number of partitions, are used for spPCA and mPCA. Each facial image is resized before partitioning in order to have equal size for each subimage. In subspace LDA, initially PCA is applied on facial images for dimensionality reduction and the principal components extracted by PCA are used as inputs to LDA. The numbers of eigenvectors selected in the first and the second stages of subspace LDA method are selected as the maximum number of nonzero eigenvectors. For Local Binary Patterns (LBP), the number of partitions used is $N=81$ as in spPCA and mPCA and *(8,2)* circular neighborhood is used. Among all feature extraction methods applied for facial images, LBP is the strongest and popular one due to its discriminative power and computational simplicity to represent patterns. LBP is introduced as a powerful local descriptor for microstructures of images and it was originally designed for texture description. In this scheme, face images are divided into 81 non-overlapping subregions and then the texture descriptors are extracted by applying the histogram. The extracted descriptors are then concatenated to form a global description of the face. Iris features are extracted with the same methods used for facial feature extraction (e.g. PCA, ssLDA, spPCA, mPCA, LBP). Similar to the face recognition stage explained, the iris matching scores is calculated using Manhattan distance measure. In preprocessing step, all iris images are detected and normalized to a fixed dimension rectangle. Development of the multimodal system based on feature and score level fusion techniques to authenticate the reality of a person is one of the most significant stages in our work. Matching score level fusion can be considered as classification of the face and iris scores into one of two classes, Accept/Reject, or combination of the face and iris scores in order to provide an individual scalar score [18]. Feature level fusion considers concatenation of original feature sets of different modalities that may lead to high dimension vectors.

In feature level fusion stage of this study, we concatenated all features of all feature extraction methods to combine the data. In matching score level fusion stage, we applied Weighted Sum Rule to fuse the normalized scores. In this work, empirical weighting scheme is used to calculate the weights due to its efficiency compared to others [23]. Focus of this scheme for normalization is on tanh normalization technique to normalize the matched scores from face and iris.

6.3 Experiments and Results of Scheme 3

The performance of unimodal systems, multimodal systems and the proposed scheme are validated by constructing a mixed multimodal biometric database. It is needed to state that, finding a publicly available face-iris multimodal database that includes the face and iris of the same person was difficult in the past years. Since face and iris biometrics are independent from each other, an arbitrary but fixed iris class is assigned to a face class using different face and iris databases as in [14, 64].

ORL and BANCA face databases and CASIA and UBIRIS iris databases are used in order to have different conditions in terms of illumination and pose in face images; noisy and non-noisy iris images; and also to have enough number of people and samples to measure the performance of the unimodal and multimodal systems. In our multimodal system, for combined face dataset, 80 subjects with 8 different frontal face images are considered. We assigned randomly 3 images per subject for training and the rest for testing. From CASIA-UBIRIS iris dataset, randomly 8 iris images have been selected for 80 subjects, 3 for training and the remaining 5 for testing. Additionally, Torch3 vision [66], a powerful machine vision library, is applied on BANCA database in order to detect the face images.

In the first set of experiments, face and iris unimodal systems are used to measure the performance of individual systems. All global and local feature extraction methods and Face-Feature Vector Fusion (Face-FVF) and Iris-Feature Vector Fusion (Iris-FVF) approaches are used to carry out the experiments. PCA and ssLDA are global methods that are applied on the whole images of face and iris datasets. SpPCA, mPCA and LBP are local feature extractors which are applied by partitioning the images into subregions.

In Face-FVF and Iris-FVF approaches, all feature sets of all feature extraction methods are concatenated and then Manhattan Distance measurement is used to compare the images. The experiments are shown in Table 15 where the best accuracy for face recognition is achieved using the local feature extractor LBP. In case of iris recognition, the best accuracy is obtained using ssLDA global feature extractor. These experiments demonstrate that the concatenation of all facial and iris features does not achieve the best accuracy for unimodal systems. Although LBP for face and ssLDA for iris recognition achieve the best recognition performance on unimodal systems, feature concatenation of some of the face and iris feature extractors will improve the recognition accuracy of multimodal systems.

Table 15: Recognition Performance on Unimodal Systems

Unimodal System	PCA	ssLDA	spPCA	mPCA	LBP	FVF
Face	70	78.50	76.25	73.50	79.75	75.00
Iris	86.75	91.25	84.25	89.75	83.50	89.00

Fusion of multimodal face and iris systems lead to a higher recognition accuracy compared to the unimodal biometric systems. The best recognition accuracies obtained for unimodal face and iris systems are used to compare the accuracy of multimodal face-iris system. Figure 21 demonstrates the ROC Analysis on unimodal face (using LBP feature extractor) and iris (using ssLDA feature extractor) systems with the multimodal system using Face-FVF and Iris-FVF with Weighted Sum Rule fusion method. The multimodal system is also compared with unimodal systems using ROC analysis. The Equal Error Rate (EER) of each system given on top of the curves in Figure 21 is obtained from the point on ROC curve where the value of FAR is equal to the value of FRR. Face and iris unimodal systems demonstrate a performance of 6.75% and 5.55% EER, respectively. The multimodal system achieves a performance of 3% EER which is a significant improvement over the unimodal systems.

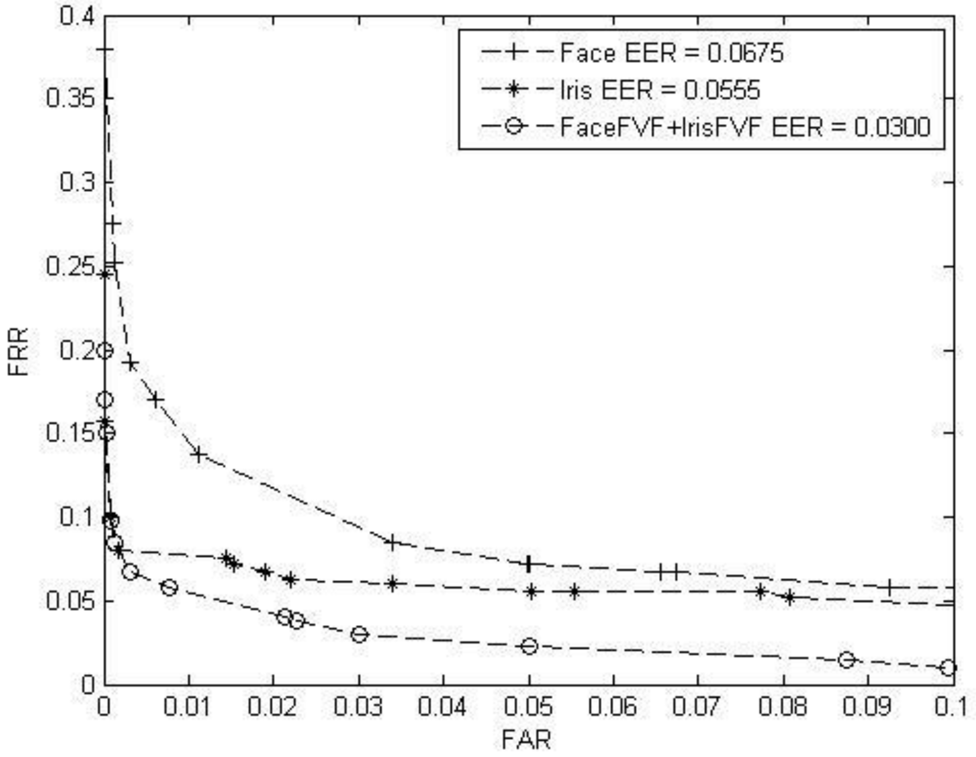

Figure 21: ROC Curves of Unimodal and Multimodal Systems

As shown in Table 16, applying Weighted Sum Rule on face and iris scores obtained from Face-FVF and Iris-FVF achieves 93.75% recognition performance. On the other hand, we also concatenated face and iris features of all feature extraction methods (Face-FVF and Iris-FVF) with and without applying PSO. Feature level fusion without PSO achieves 93.5% recognition performance as shown in Table 16, however feature concatenation with PSO obtains 94.25% performance which is an improvement over the other considered multimodal systems.

Table 16: Recognition Performance of Multimodal Systems Using Score Level Fusion and Feature Level Fusion

Face-FVF + Iris-FVF with Weighted Sum Rule	Feature Concatenation without PSO	Feature Concatenation with PSO
93.75	93.50	94.25

On the other hand, Figure 22 demonstrates the ROC Analysis of the above mentioned multimodal systems using score level fusion (Face-FVF + Iris-FVF) and feature level fusion with and without PSO. Score level fusion method achieves a performance of 3% EER, while feature level fusion methods with and without PSO achieve 2.75% and 3.5% EER, respectively. PSO method helps to achieve an improvement over the other methods as demonstrated in Figure 22. Feature concatenation with PSO achieves the best result using several solutions with the feature extraction methods for face and iris biometrics. For example, one solution is to use LBP for face and iris; another is to use PCA and ssLDA for face and ssLDA and spPCA for iris biometrics. There are also other solutions with the same performance of 94.25%. On the other hand, according to experimental results, we are motivated to use a feature extraction method for one biometrics, either face or iris, and the concatenation of all or some methods for the other biometrics. These set of experiments are demonstrated in Tables 17 and 18. In Table 17, fusion of face or iris unimodal scores with the scores resulting from Face-FVF or Iris-FVF using Weighted Sum Rule is illustrated. As shown in this table, the best result for Face-FVF scores and unimodal iris scores is obtained using ssLDA which includes a slight improvement compared to the feature concatenation approach with PSO. The same set of experiments is carried out on Iris-FVF scores and unimodal face scores. These set of experiments achieved the best results compared to others and the best result is obtained using LBP face scores when the fusion is done with Iris-FVF scores.

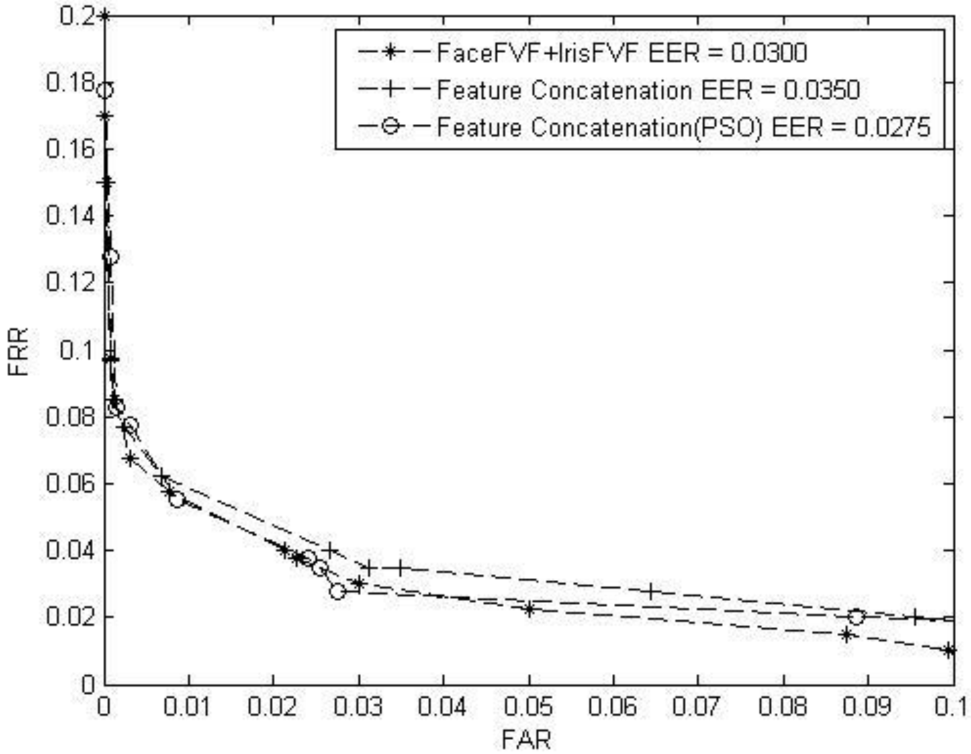

Figure 22: ROC Curves of Multimodal Systems Using Score Level Fusion and Feature Level Fusion

Table 17: Recognition Performance of Multimodal Systems Using Score Level Fusion

Fusion Sets	**Face-FVF**	**Iris-FVF**
Iris/Face-PCA	93.00	92.75
Iris/Face-ssLDA	**95.75**	95.25
Iris/Face-spPCA	91.75	94.25
Iris/Face-mPCA	94.50	95.50
Iris/Face-LBP	95.00	**96.25**

Table 18: Recognition Performance of the Multimodal Method without PSO and the Proposed Method with PSO

Face LBP + Iris FVF-Fusion without PSO	**Proposed Method** (**Face LBP + Iris FVF Fusion** with PSO)
96.25	**97.50**

In fact, the power of LBP algorithm on face images can be seen in this experiment that yields a recognition performance of 96.25% with Weighted Sum Rule fusion and outperforms the previous fusion methods without applying PSO algorithm. On the other hand, instead of using Iris-FVF, we used ssLDA feature extractor for iris and LBP for facial feature extraction with Weighted Sum Rule fusion method as in [46] to combine face and iris biometrics. The result is 96.75% which is better than the performance obtained from the previous experiment using Iris-FVF for iris and LBP for face feature extraction. Finally, the proposed method is applied with PSO on Iris-FVF and then we applied matching score level fusion with LBP face scores using Weighted Sum Rule fusion method. The proposed approach achieves 97.5% recognition accuracy which makes it the best approach among all other considered methods. The results of the multimodal approaches with and without PSO are demonstrated in Table 18. It is clearly demonstrated that fusing Iris-FVF scores with face LBP scores using Weighted Sum Rule and PSO improves the recognition performance that outperforms all unimodal and multimodal methods presented in this study. Using PSO method for Iris-FVF, the best solution is obtained with LBP and ssLDA methods.

The ROC Analysis of the multimodal method without PSO (Face LBP + Iris FVF) and the proposed method with PSO is demonstrated in Figure 23. The aforementioned multimodal method achieves a performance of 2.25% EER while the proposed method achieves 1.5% EER. The improvement of the proposed method over the other multimodal methods is clearly shown in Figure 23. Finally, Figure 24 shows the ROC curve of unimodal methods and the proposed multimodal method. The ROC curve demonstrates the EER of unimodal face recognition using LBP (with 6.75% EER), Iris-FVF (with 5.55% EER) and the proposed scheme (with 1.50% EER). The proposed scheme achieves a performance of 1.50% EER which shows the performance improvement of the system over the unimodal and the other multimodal systems considered in this study.

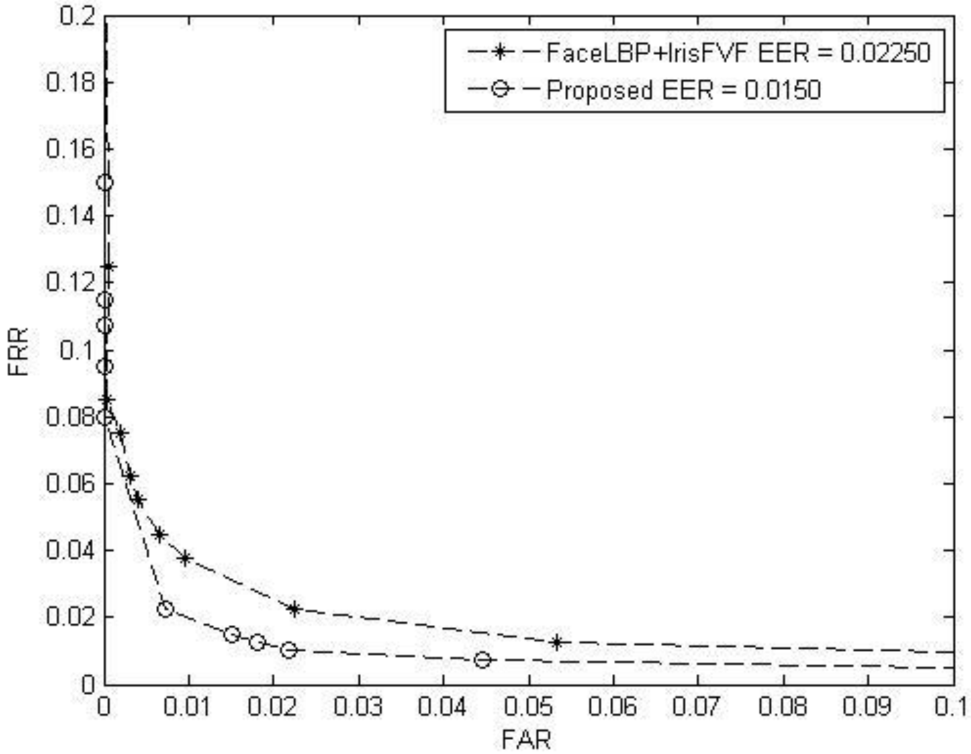

Figure 23: ROC Curves of Multimodal Methods and the Proposed Method.

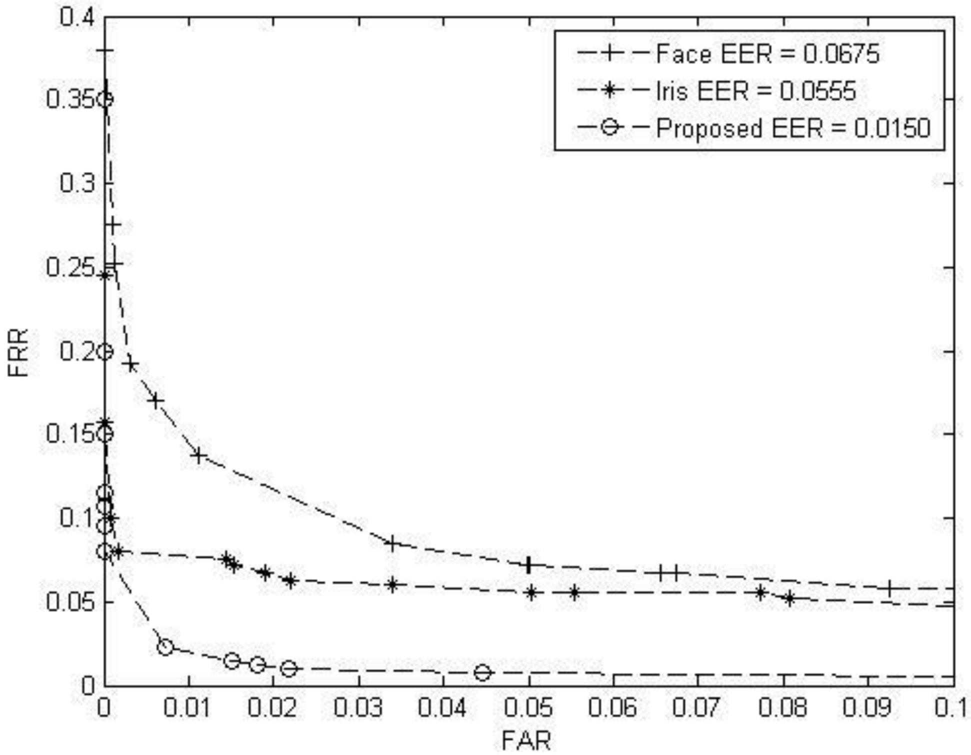

Figure 24: ROC Curves of Unimodal Methods and the Proposed Method

6.4 Contribution and Conclusion of Scheme 3

Fusion of face and iris biometrics is presented using several local and global feature extraction methods with score level and feature level fusion techniques in proposed scheme 3. The proposed method considered concatenation of different feature sets of local feature extractors, namely spPCA, mPCA and LBP; and global feature extractors such as PCA and subspace LDA for iris unimodal biometric systems. Specifically, iris feature vector fusion (Iris-FVF) and Weighted Sum Rule fusion has been employed on matching scores produced from Iris-FVF and LBP facial features to fuse face and iris. In order to improve the recognition performance of multimodal biometric systems, PSO method is also applied on Iris-FVF to select the best set of iris features. As a result, LBP and subspace LDA methods were selected by PSO for iris feature extraction. The experiments demonstrate that the proposed method using LBP facial features and LBP and ssLDA iris features with Weighted Sum Rule fusion method achieves improved recognition accuracy compared to the considered unimodal and multimodal methods.

The contribution of the third proposed scheme is to use Local Binary Patterns-based facial feature extraction with Iris-FVF using PSO to remove redundant data for the fusion of face-iris multimodal system with tanh score normalization and Weighted Sum Rule fusion method. The proposed scheme can be used practically in person identification systems using facial images. The iris information can be extracted from the face image and the fusion of face-iris multimodal system can be performed to improve the performance of the individual face recognition system.

Chapter 7

FACE-IRIS FUSION SCHEME BASED ON FEATURE AND WEIGHT SELECTION (PROPOSED SCHEME 4)

7.1 Description of Proposed Scheme 4

The structure of the proposed scheme is based on a face-iris multimodal biometric system using score-level fusion and feature level fusion. In fact, availability of sufficient information content and the ease in accessing and combining matching scores encouraged us to propose a new scheme using matching score fusion techniques along with feature level fusion. In this study, 5 different standard feature extractors are applied separately on face images and to extract iris features, Libor Masek's iris recognition system is applied on the left and right irises of the corresponding face image. Prior to construction of our multimodal biometric system, we combined face and iris features and scores separately using different techniques. The iris patterns of both left and right eye are used in this scheme to improve the performance of the multimodal biometric system in identification and verification modes. Both of the irises undergo with the basic steps of the method implemented by Libor Masek [16].

Typically, five stages can be considered for an iris recognition system namely preprocessing, segmentation, normalization, encoding and matching [69]. In preprocessing step, an input eye image of an individual is given to extract the eye, for our case, both left and right eye. Automatic cropping based on manual distance calculated from localized pupil is performed to take the left and right iris. Focus of segmentation step is on the Hough transform to localize the circular iris and pupil region, occluding eyelids and eyelashes, and reflections. The extracted iris region is then normalized into a fixed rectangular block. In feature encoding step, 1D Log-Gabor filters are employed to extract the phase information of iris to encode the unique pattern of the iris into a bit-wise biometric template. Finally, the Hamming distance measurement is employed for classification of iris templates.

On the other hand, in order to enhance the accuracy of face and iris unimodal and multimodal systems, face images are detected and aligned based on the center position of both left and right eyes. Indeed, by using the center positions, angle of head roll and iris rotation can be measured to align the face images and rotate back the iris patterns. In this work, in order to improve the recognition performance of face images, *AAM* toolbox (Active Appearance Modeling) [72] is used to detect face images based on the center position of left and right irises. The toolbox aims to model and annotate human face images and obtain a precise location of facial features such as mouth, nose, eyes, and eyebrow. The precise center position of both irises is achieved by the toolbox and therefore we are able to measure the angle of head roll that may happen during acquisition of a face image as depicted in Figure 25. In fact, using the center positions and the measured angle, both eyes can be aligned in the face image.

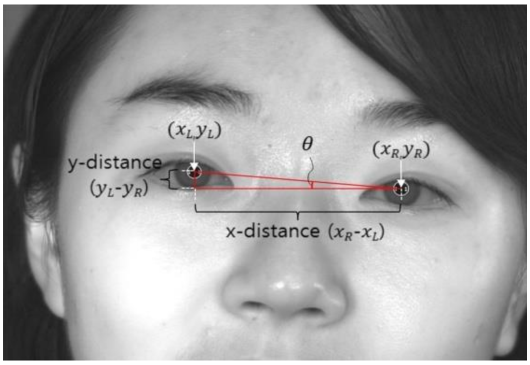

Figure25: Head Roll Angle Calculation [73].

The performance of iris recognition system is needed to be improved by using rotation of the iris patterns. In other words, during acquisition of a face image, the iris patterns may rotate frequently because of the user head roll to left or right shoulder that may lead to degrade iris recognition performance [73]. The rotation of face images and consequently iris images causes circular shifting of the iris features and therefore if the rotation angles of the irises are different, the extracted feature codes can be misaligned which affects the recognition accuracy [73]. In this respect, plenty of researches are conducted to solve this problem based on shifting the iris feature codes to perform matching. In [73], the authors proposed a new method by measuring the angle of head roll to shift the iris feature codes. In this study, we apply a similar algorithm with some modifications to improve the iris recognition accuracy. The next subsection contains the details of head roll angle measurement to detect and align face images and shift the iris feature codes.

In fact during face image capturing, the head roll to left or right shoulder may change the location of both eyes. In order to align the eyes to a horizontal line, rotation of the face image can be applied. It is possible to rotate the face image with measuring the head roll angle using the x and y distances of left and right iris center coordinates. The center coordinates of left and right pupils achieved by *AAM* toolbox were used to calculate the x and y distances. The rotation angle can be achieved as:

$$\theta = \sin^{-1}\left\{\frac{y_L - y_R}{x_L - x_R}\right\} \tag{7.1}$$

where, x_L and are y_L center coordinates of left pupil and x_R and y_R are corresponding center coordinates of right pupil.

The rotation can be done based on the calculated angle to the left or right, if $y_L > y_R$ then θ is a positive roll angle and the face image is rotated in the counterclockwise direction. On the other hand, if $y_L < y_R$ then θ is a negative roll angle and the face image is rotated in the clockwise direction. After aligning the eyes to a horizontal line, cropping the face image is done based on the length and width of the face image and location of eyes in the face.

In order to solve the problem of misalignment of the iris patterns due to rotation, bit-shifting of iris feature codes is done in this study based on the calculated head roll angle in the previous step. In fact, after generating iris codes using Libor Masek's iris recognition system, some small changes have been done in iris code matching of the system. In this part, instead of solving the misalignment problem with constant bit-shifting, the shifting and consequently matching is done based on the calculated angle. The number of bit-shifting to the right or left in Libor Masek's iris recognition system is 8, but we changed this number based on the calculated angle for each person.

One test iris feature code is matched against all the trained (enrolled) iris pattern templates based on the following algorithm.

1Calculate the angle difference between test and trained irises.

$$\theta_{dif} = \theta_{Train} - \theta_{Test} \tag{7.2}$$

2 Calculate the error that may happen during angle calculation, in this work the error (θ_{err}) is set as 0.1322 degree (deg) and the value is achieved experimentally [73].

3 Determine the number of shifts based on θ_{dif} and θ_{err} .

$$S = \begin{cases} -8 & if \left|\theta_{dif}\right| < \theta_{err} \\ \left\lfloor \dfrac{\theta_{dif} - \theta_{err}}{\theta_{\sec}} \right\rfloor & Otherwise \end{cases} \tag{7.3}$$

$$E = \begin{cases} +8 & if \left|\theta_{dif}\right| < \theta_{err} \\ \left\lfloor \dfrac{\theta_{dif} + \theta_{err}}{\theta_{\sec}} \right\rfloor & Otherwise \end{cases} \tag{7.4}$$

where, S and E are starting and ending range for bit-shifting and $\theta_{\sec}$ is the degree between each sector of normalized iris image (20 × 240), in our case it is 1.5 deg (360 deg/240).

4 Perform iris code matching based on the calculated bit-shifting for left and right iris templates.

5 Compute Hamming Distance values of left and right irises of an individual based on the left and right iris templates respectively.

6 Obtain the improved recognition performance using left and right Hamming Distance (HD_L and HD_R) by applying Weighted-Sum Rule score level fusion.

$$HD = w_1 \times HD_L + w_2 \times HD_R \tag{7.5}$$

where, w_1 and w_2 are user specific weights.

The fusion of face and iris can be done with only one of the irises (left or right) or combination of both irises. This leads to improve the multimodal biometric system performance especially whenever the fusion is done using face and information obtained from combined scores of both irises. Since combining the information of both left and right irises can improve the authentication accuracy even with the images with low quality [70], in the proposed scheme, we consider the combination of two irises as demonstrated in Figure 26. The score fusion of left and right irises is done using Sum Rule.

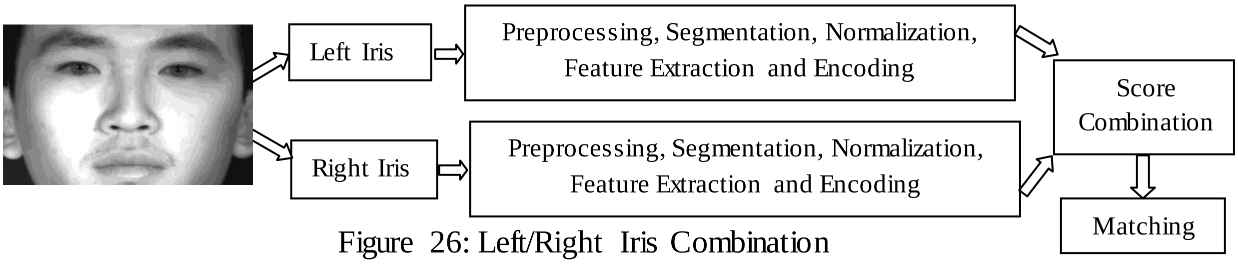

Figure 26: Left/Right Iris Combination

On the other hand, we performed feature concatenation on original face feature sets that may result dimensionality and redundancy problems and performance degradation. These kinds of problems can be alleviated using feature selection methods such as PSO by selecting an optimized subset of features from original feature sets and removing the redundant and irrelevant data based on a certain objective function. Therefore, we apply "PSO in two different levels" to select proper and optimized feature extractors and features. In addition, in order to combine face and iris, in each PSO level, several fusion techniques are employed with left iris, right iris and combination of left and right irises as shown in Figure 27.

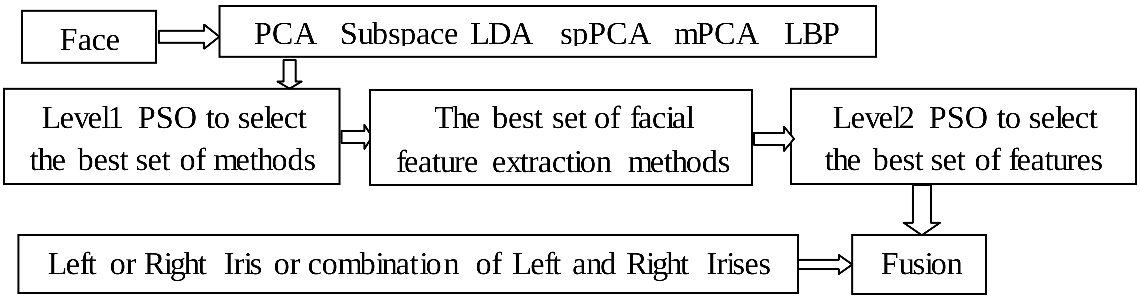

Figure 27: Face and Iris Fusion Using Level1 PSO and Level2 PSO

Fusion of face and iris explained in the above schemes in Figure 27 may help to enhance the performance of the overall multimodal biometric system although the need to improve the performance of the system motivated us to find a new design to fuse face and iris information. The proposed scheme considers the combination of facial feature level fusion scores in both levels along with all the facial scores achieved using the five aforementioned feature extractors of an individual to be fused with the combined scores of left and right iris of the same individual. It is needed to state that the combination of all facial scores obtained using the five local and global feature extractors (PCA, subspace-LDA, spPCA, mPCA, LBP) is done using Sum Rule. On the other hand, Weighted Sum Rule fusion is applied on the normalized face and iris scores that guided us to a better performance compared to unimodal and other existing multimodal systems in this study according to the performed experiments.

The proposed scheme considers the implementation of optimized weights using PSO with the fact that the proper weights are able to reflect the relative difference in unimodal systems performance compared to other fusion techniques [19]. The main idea of the proposed scheme is to fuse scores of all implemented algorithms and techniques on face and iris modalities to take the advantages of each technique on a specific modality for increasing the ability of the multimodal system. The block diagram of the proposed method is presented in Figure 28.

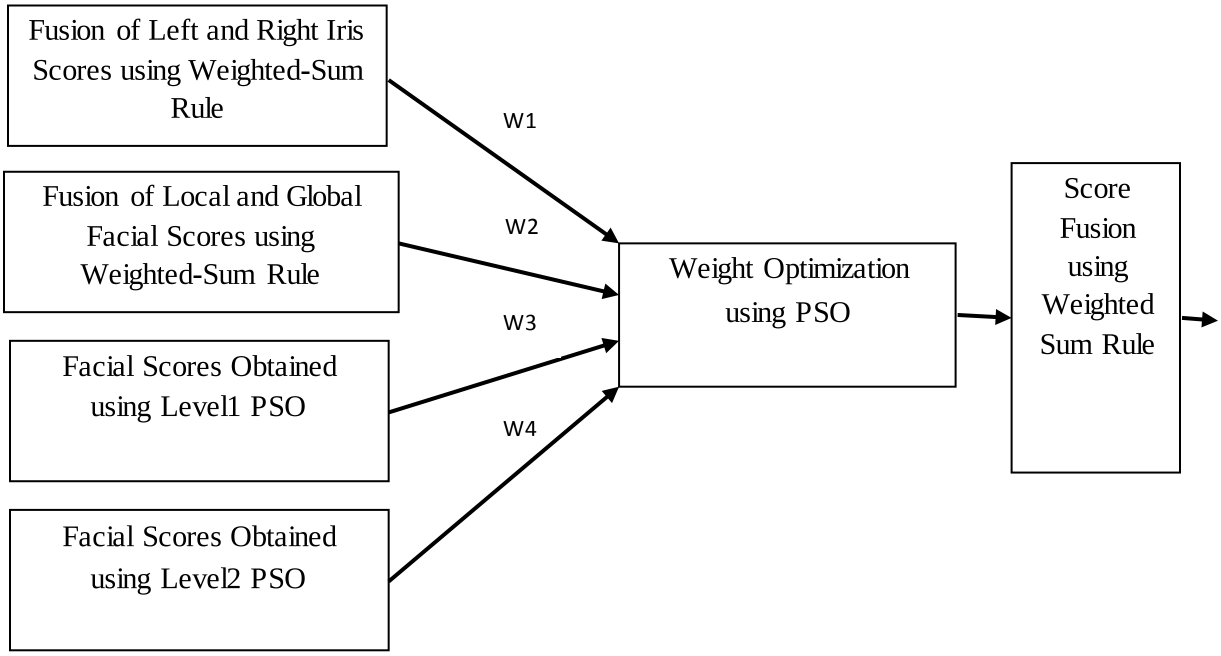

Figure 28: Block Diagram of Proposed Scheme

As shown in the block diagram of the proposed method in Figure 28, four different weights are needed to fuse the face and iris scores using Weighted Sum Rule. In other schemes of this study, applying Weighted Sum Rule is done using user-specific weights selection introduced in [62] by Jain and Ross. The proposed scheme uses PSO to find the optimal weights for four different sets of scores. In fact, development of face-iris multimodal biometric system is one of the most significant steps in this proposed scheme.

7.2 Unimodal Systems and Fusion Techniques of Scheme 4

Face and iris biometrics are considered in this scheme to construct the structure of the unimodal and consequently multimodal system. The face system used in the study employs 5 local and global feature extraction methods namely subpattern-based PCA (spPCA), modular PCA (mPCA), Local Binary Patterns (LBP), Principal Component Analysis (PCA) and subspace Linear Discriminant Analysis (subspace LDA) to examine the performance. The facial images in subpattern-based PCA and modular PCA are initially partitioned into N^2 subimages. Eigenvectors corresponding to 97% of eigenvalues with $N=81$, where N is the number of partitions, are considered for both spPCA and mPCA. Each facial image before partitioning is resized in order to have equal size for each subimage. PCA algorithm is implemented as described in [25] based on the selection of maximum number of nonzero eigenvectors. In subspace LDA, in order to have dimensionality reduction, PCA is applied on facial images initially and then extracted principal components by PCA are used as inputs to LDA. The numbers of eigenvectors selected in the first and second stages of subspace LDA method are selected as the maximum number of nonzero eigenvectors. For Local Binary Patterns (LBP), the number of partitions used is $N=81$ as in spPCA and mPCA and *(8,2)* circular neighborhood is used.

The common processing steps for unimodal face system are image preprocessing, training, testing and matching. The illumination effects of face images are reduced by applying histogram equalization (HE) and mean-and-variance normalization (MVN) on facial images in preprocessing step. The facial features are then extracted in the training and testing stages to be examined by different techniques in matching score level fusion, feature level and/or combination of both fusion levels. Finally in the last step, in order to compute the matching score between train and test feature vectors Manhattan distance measurement is applied.

In order to extract iris features, Libor Masek's iris recognition system [16] is applied. The typical processing steps for this iris recognition system are segmentation, normalization, feature encoding, and feature matching. The automatic segmentation system is based on the Hough transform, to localize the circular iris and pupil region, occluding eyelids and eyelashes, and reflections. The extracted iris region is then normalized into a fixed rectangular block. In feature encoding step, 1D Log-Gabor filters are employed to extract the phase information of iris to encode the unique pattern of the iris into a bit-wise biometric template. Finally, the Hamming distance measurement is employed for classification of iris templates [16].

Generally, fusing different modalities denotes an advantage to enhance the strength of the system especially in case when one biometric trait of a person becomes defective. In the proposed scheme, as stated before, feature level fusion and matching score level fusion is considered to authenticate the reality of a person.

In feature level fusion, concatenation of the original feature sets of face and iris modalities is considered and therefore this level of fusion contains richer information about the raw biometric data. In this proposed method, involving 5 different local and global feature extractor methods to extract the original facial feature sets may lead high dimension vectors resulting to decrease the system performance. Therefore designing a scheme to retain the appropriate information from the fused features of the five algorithms namely Face Feature Vector Fusion (Face-FVF) with the ability of solving the dimensionality problem is needed to be considered. In order to overcome the dimensionality problem, we applied PSO [67] technique in 2 different levels as depicted in Figure 29 to select the optimized subsets of methods and features based on a certain objective function by removing the redundant and irrelevant data [10, 67].

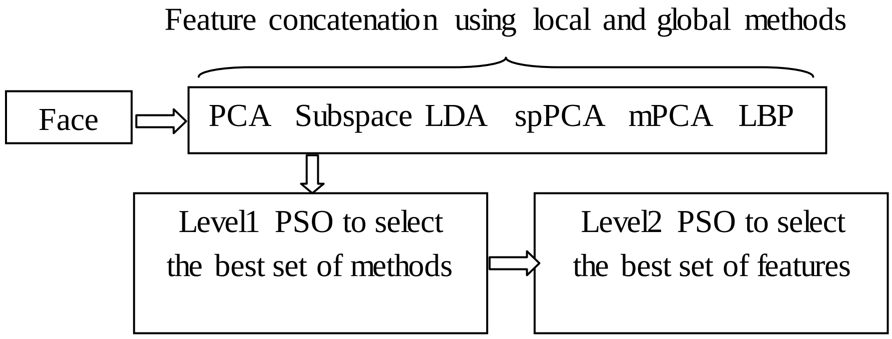

Figure 29: Face Feature Fusion Including PSO in 2 Different Levels

PSO that was introduced by Kennedy and Eberhart in 1995 [67] aims to find an optimized solution in a search space. It is initialized with a population of random solutions called particles to be evaluated using a fitness function. It should be stated that the explanation of PSO method is available in sub section 6.1.1.

Due to measuring verification and identification performance of biometric systems in this scheme, the consideration of two different fitness functions in implementing PSO is needed. The fitness function corresponding to identification aims to maximize the recognition rate by computing the distance of a test sample against all the training samples to find the match scores and selecting the lowest distance value to check if the distance belongs to the same person or not. On the other hand, the verification fitness function considers the distance between training and testing samples to obtain match scores and then computes FAR and its corresponding GAR to maximize by setting a threshold.

In this study, we set the inertia weight to 1, and the acceleration constants *c1* and *c2* both to 2 as in the original PSO [67]. Selection of features is based on a bit string of length *M*, where *M* is the number of feature extraction methods applied on face unimodal system in level1 and number of features in level2 that are taken from the selected feature extraction methods of level1. In other words, every bit here represents one feature extraction method or one feature in the sense that; value '1' means all features of corresponding feature extraction method are selected and '0' means that they are not selected for level1 PSO. In level2 PSO, value '1' means the feature of corresponding feature extraction method taken from level1 are selected and '0' means that they are not selected. In our work for level1 PSO, we assigned the size of the population and iteration as 6. In level2 PSO, population and iteration size are set to 20 and 30 respectively.

Matching score fusion level provides a rule to combine the different scores. In this fusion method, different matchers may produce different scores such as distances or similarity measures with different probability distributions or accuracies [20]. Matching score level fusion can be considered as the classification of the scores into one of two classes, Accept/Reject, or combination of the scores to provide an individual scalar score [18]. Match score level fusion involves several simple or complicated algorithms to combine the scores such as Sum Rule, Weighted Sum Rule, Product Rule, classification using SVM and estimation of scores density. Similar and equivalent performance from the aforementioned combination methods are reported in the recent studies [20, 23, 46,71]. Involving match score level fusion for this work is arranged to combine the left and right irises of a certain person, facial scores achieved by individual feature extractors, facial scores obtained in the feature level fusion step using PSO in two different levels and finally it is used to combine fused face and iris scores. In order to normalize the face and iris matching scores produced from Manhattan distance and Hamming distance, tanh normalization technique [21] is applied on the produced matching scores from face and iris images to transfer them into a common domain and range.

In this proposed scheme, we employ Sum Rule and Weighted Sum Rule techniques to combine the face and iris scores. Finding efficient weights to perform the experiments in both verification and identification modes is an important issue that can be effective for performance enhancement. Generally, Weighted Sum Rule is a method that can be used to compute combined matching scores of the individual matchers. In this work, we consider the idea of using continuous PSO to select the optimized weights to have a better evaluation on the multimodal system. Generally, assigning the proper weights to the scores obtained using individual biometric systems may produce sufficient output to guarantee the improved performance in both verification and identification modes. Each particle, *i*, representing the weighting vector $w_i = (w_{i1}, w_{i2}, \ldots, w_{in})$, is randomly initialized between 0 and 1 and then normalized with the constraint $\sum_{i=1}^{k} w_i = 1$, where k is the number of weights. The particle positions are updated using velocity and position functions according to continuous PSO technique. Fitness function is computed as a combination of EER's of involved scores in the proposed scheme with the weights represented by the particle as in equation (7.6) to be considered as an optimization problem for minimization, where $w_1, w_2, \ldots, w_n$ are the optimized weights for different modalities and $EER_1, EER_2, \ldots, EER_n$ are the Equal Error Rates obtained using the corresponding scores in the proposed scheme.

$$F\left(\sum_{i=1}^{k} w_i EER_i\right) \tag{7.6}$$

Three reference databases are used to test the proposed optimal weight selection part in order to choose the optimized weights and then the optimum weights are applied on our multimodal system. The size of the swarm in this study is set as 20 with maximum iteration of 100, inertia weight is 1, and the acceleration constants *c1* and *c2* are both set to 2.

7.3 Experiments and Results of Scheme 4

In order to evaluate the performance of our multimodal system, *CASIA-Iris-Distance,* a recent publicly available database, is used. In this study we consider 90 subjects to construct our multimodal face and iris biometric system. The chosen subjects cover the proper information needed for building the multimodal system including the whole face images and clear dual-eye iris patterns. Randomly 10 samples for each subject or individual are selected, 5 samples for training and the rest 5 for testing. In addition, in order to decide on the four optimized weights applied in the proposed scheme using PSO technique, three small subsets of FERET+UBIRIS database with 50 individuals and 4 samples from each database, ORL+UBIRIS database with 40 individuals and 3 samples from each database and BANCA+UBIRIS database with 50 individuals and 4 samples from each database are used. These subsets are only employed for weight selection. The averaged optimized selected weights are as w_1=0.10, w_2=0.31, w_3=0.24 and w_4=0.35.

In this study, the experiments are represented using ROC curves and GAR at FAR 0.01% as verification performance and also recognition rate as identification performance. We first describe the details of experiments done in identification mode on unimodal and multimodal systems and then go into the details of verification mode with explaining the ROC analysis using GAR values and EER's of the constructed techniques.

Face and iris unimodal systems are used to measure the performance of individual systems. All global and local feature extraction methods, Face-Feature Vector Fusion (Face-FVF) with and without PSO, scores combination of all local and global methods using Weighted Sum Rule on facial images and Libor Masek's iris recognition system together with approaches to combine left and right irises using

Sum Rule and Weighted Sum Rule on iris images are used to carry out the experiments. PCA and subspace LDA are global methods that are applied on the whole images of face images. SpPCA, mPCA and LBP are local feature extractors which are applied by partitioning the images into subregions.

In Face-FVF all feature sets of all feature extraction methods are concatenated and then Manhattan Distance measurement is used to compare the images. The experiments are shown in Tables 19, 20 and 21, on original images without aligning face, eyes and without rotating iris patterns, as identification mode, where the best accuracy for face recognition is achieved using the local feature extractor LBP as 80.89% in Table 19 and using Face-FVF with level2 PSO in Table 20 as 84% and combination of left and right irises with Weighted Sum Rule as 44.89% in Table 21. These experiments demonstrate that the fusion of face features/scores or iris scores separately leads to achieve better accuracy for unimodal face and iris systems.

Table 19: Performance Comparison between Unimodal Face, Right and Left Iris (Identification)

Face	PCA	ssLDA	spPCA	mPCA	LBP
	66.00	73.11	71.33	52.89	**80.89**
Iris Code of Daugman (Libor Masek Code)	Left Iris			Right Iris	
	41.55			39.78	

Table 20: Different Fusion Sets on Face Unimodal (Identification)

Fusion Sets	Recognition Performance (%)
Weighted Sum-Rule	80.89
Without PSO (Only Face-FVF)	70.22
With PSO Level 1 (Only Method Selection)	82.44
With PSO Level 2 (Method Selection + Feature Selection)	**84.00**

Table 21: Iris Fusion sets on Left and Right Irises (Identification)

Left/Right Iris Fusion	Sum-Rule	Weighted Sum-Rule
	43.78	**44.89**

Feature concatenation of some of the face extractors selected by level1 PSO, which is subspace-LDA and LBP for this study, and corresponding features selected by level2 PSO will improve the recognition accuracy of unimodal and consequently multimodal systems. Fusion of multimodal face and iris systems lead to a higher recognition accuracy compared to the unimodal biometric systems. In this study, we are motivated to use a feature extraction method from face biometric and the left/right or combination of two irises using Weighted Sum Rule of iris scores.

These set of experiments are demonstrated in Tables 22, 23 and 24 on original images without aligning face, eyes and without rotating iris patterns. In Tables 22 and 23, fusion of face unimodal scores with the scores resulting from Masek's iris code using Weighted Sum Rule is illustrated for left and right irises separately. As shown in these tables, the best result is obtained using LBP for unimodal face scores and left/right iris scores as 81.78% and 80.44%. In Table 24, fusion of face unimodal scores with the scores resulting from Masek's iris code using Weighted Sum Rule is illustrated for combined irises. In this table, the best result is obtained using LBP for face unimodal scores and combined left/right iris scores.

It is clearly shown that the combined left and right iris scores are able to improve the performance accuracy compared to the fusion with only one iris. The best result achieved is 86.44% as seen in Table 24. In order to increase the recognition performance of our multimodal system, we continue to perform experiment for the fusion, however this time, not only with scores obtained using unimodal face or iris but fused face scores/features are used to be combined with only one iris (left or right) and finally combination of left and right iris scores.

Table 22: Weighted Sum-Rule Fusion on Face and Left Iris Using Combination of Different Scores (Identification)

Fusion Sets	Left Iris Scores
Face-PCA	69.55
Face-ssLDA	77.78
Face-spPCA	72.89
Face-mPCA	63.11
Face-LBP	**81.78**

Table 23: Weighted Sum-Rule Fusion on Face and Right Iris Using Combination of Different Scores (Identification)

Fusion Sets	Right Iris Scores
Face-PCA	70.89
Face-ssLDA	78.00
Face-spPCA	74.22
Face-mPCA	66.00
Face-LBP	**80.44**

Table 24: Weighted Sum-Rule Fusion on Face and combined Iris Using Combination of Different Scores (Identification)

Fusion Sets	Left/Right Iris Combined Scores
Face-PCA	74.89
Face-ssLDA	82.44
Face-spPCA	79.11
Face-mPCA	68.22
Face-LBP	**86.44**

The best accuracies for both left and right irises as demonstrated in Table 25, are as 86.22% and 84.44% respectively. It can be easily seen that applying PSO to select the proper face feature extraction methods and then selecting the optimized subsets of features of these proper methods together with scores from left or right iris is able to improve the recognition accuracy.

Table 25: Different Fusion Sets on Face and Left or Right Iris Using Weighted Sum-Rule (Identification)

Fusion Sets	Left Iris	Right Iris
All Face Methods with Weighted Sum-Rule	82.00	81.33
Without PSO (Only Face-FVF)	72.44	74.44
With PSO Level 1 (Only Method Selection)	85.11	83.33
With PSO Level 2 (Method Selection + Feature Selection)	**86.22**	**84.44**

We performed similar experiments with face scores/features and combined left and right irises to observe the effect of fusion on fused face and fused iris and attain their advantage. That is, combining the strength of each modality separately and then by using the available strength and intensity improves the accuracy of the system. As shown in Table 26, with considering the fused face scores and fused iris scores, the performance is enhanced compared to the previous experiments. According to the experiments, the proposed method outperforms all other unimodal and multimodal techniques implemented in this study. As demonstrated in Table 26, the proposed scheme involves the fused face scores from all five local and global feature extractors along with the scores obtained from level1 PSO to select the optimal subsets of feature extractors and the scores achieved from level2 PSO to choose the optimized subsets of features of the methods selected by level1 PSO together with the fused left and right iris scores and it achieves the performance of 88.89%. This performance shows the significant improvements of 5.89% as compared to the case when only the best fused face features using level2 PSO is used and 44% improvement as compared to the case when only fused iris scores using Weighted Sum Rule is used.

Table 26: Different Fusion Sets on Combined Left and Right Irises Using Weighted Sum-Rule and Proposed Method (Identification)

Fusion Sets With Combined Left and Right Iris	Identification Rate (%)
All Face Methods with Weighted Sum-Rule	85.78
Without PSO (Only Face-FVF)	78.22
With PSO Level 1 (Only Method Selection)	87.55
With PSO Level 2 (Method Selection + Feature Selection)	88.00
Proposed Scheme	**88.89**

The same set of experiments as identification mode are done on cropped and aligned face images and iris images based on the calculated head roll angle in Tables 27 to 34. As it is shown in the tables, we achieve a comparable result based on the calculated angle. The best accuracy is obtained using LBP feature extractor for face recognition as 90.77% in Table 27 and using Face-FVF with level2 PSO in Table 28 as 92.77% and combined left and right irises using head roll angle rotation of feature codes as 77.65% in Table 29. In addition, the fusion of aligned and cropped face information and rotated left or right irises or combined left and right irises can improve recognition performance as shown in Tables 30, 31 and 32 as 93.77%, 93.33% and 96.00% respectively.

Table 27: Performance Comparison between Unimodal Face, Right and Left Iris on Aligned and Rotated face-iris Images (Identification(%))

Aligned Face (504X504)	PCA	ssLDA	spPCA	mPCA	LBP
	80.22	87.44	83.66	76.44	**90.77**
Iris Code of Daugman (Libor Masek Code)	Left Iris			Right Iris	
	68.22			68.88	

Table 28: Different Fusion Sets on Face Unimodal on Aligned and Rotated face-iris Images (Identification(%))

Fusion Sets	Recognition Performance (%)
Weighted Sum-Rule	90.77
Without PSO (Only Face-FVF)	82.22
With PSO (Only Method Selection)	90.22
With PSO (Method Selection + Feature Selection)	**92.77**

Table 29: Iris Fusion sets on Left and Right Irises on Aligned and Rotated face-iris Images (Identification(%))

Left/Right Iris Fusion	Sum-Rule	Weighted Sum-Rule
	73.11	**77.65**

Table 30: Weighted-Sum Rule Fusions on Face and Left Iris Using Combination of Different Scores on Aligned and Rotated face-iris Images (Identification(%))

Fusion Sets	Right Iris Scores
Face-PCA	89.11
Face-ssLDA	92.66
Face-spPCA	91.77
Face-mPCA	86.00
Face-LBP	**93.77**

Table 31: Weighted-Sum Rule Fusions on Face and Right Iris Using Combination of Different Scores on Aligned and Rotated face-iris Images (Identification(%))

Fusion Sets	Left Iris Scores
Face-PCA	89.33
Face-ssLDA	92.88
Face-spPCA	91.77
Face-mPCA	87.44
Face-LBP	**93.33**

Table 32: Weighted-Sum Rule Fusions on Face and Combined Iris Using Combination of Different Scores on Aligned and Rotated face-iris Images (Identification(%))

Fusion Sets	Left/Right Iris Combined Scores
Face-PCA	93.11
Face-ssLDA	94.00
Face-spPCA	95.22
Face-mPCA	90.77
Face-LBP	**96.00**

The detected and rotated fused face scores and rotated left/right or fused iris scores are useful to enhance the recognition performance as demonstrated in Table 33. The best result is achieved using Face-FVF with level2 PSO and left or right irises as 96.00% and 96.66%.

Table 33: Different Fusion Sets on Face and Left or Right Iris Using Weighted Sum-Rule on Aligned and Rotated face-iris Images (Identification(%))

Fusion Sets	Left Iris	Right Iris
All Face Methods with Weighted Sum-Rule	94.00	93.33
Without PSO (Only Face-FVF)	91.33	92.22
With PSO (Only Method Selection)	93.77	94.00
With PSO (Method Selection + Feature Selection)	**96.00**	**96.66**

The proposed scheme with involving the rotated and fused face scores of all five local and global feature extractors and the scores obtained from level1 PSO and also scores from level2 PSO together with rotated and fused left and right iris scores achieves the best accuracy among all the experiments as 98.00% as shown in Table 34.

Table 34: Different Fusion Sets on Face and Combined Left/Right Irises Using Weighted Sum-Rule and Proposed Method on Aligned and Rotated face-iris Images (Identification(%))

Fusion Sets	Combined Left and Right Iris
All Face Methods with Weighted Sum-Rule	96.44
Without PSO (Only Face-FVF)	94.00
With PSO Level 1 (Only Method Selection)	97.11
With PSO Level 2 (Method Selection + Feature Selection)	97.55
Proposed Scheme	**98.00**

The best accuracy achieved for each table in the identification mode is used to repeat the experiments in verification context using ROC curves and GAR at FAR 0.01%. As mentioned earlier, 450 training samples (90 x 5) and 450 testing samples (90 x 5) are considered in this study. Therefore 450 genuine scores and 40050 (90 x 89 x 5) imposter matching scores are used to validate the verification performance analysis. The proposed face-iris multimodal system presented in the previous sections is compared with unimodal and other existing multimodal systems using ROC analysis. False Acceptance Rate (FAR) and False Rejection Rate (FRR) are used as a function of decision threshold which controls the tradeoff between these two error rates. The probability of FAR versus the probability of FRR is plotted for different values of decision threshold. Tables 35 and 36 demonstrate the verification performance (GAR) of some schemes implemented in this study at FAR=0.01%. Figure 30 demonstrates the EER of the proposed scheme with cropping and rotation as 1.50% as shown in the figure. The best performance for the unimodal system is presented in Table 35 with GAR=80.11% at FAR 0.01% and GAR=87.33% at FAR 0.01% for face biometric whenever level2 PSO is applied without and with alignment process. On the other hand, the proposed scheme obtains the performance of GAR=84.96% at FAR 0.01% on non-aligned and non-rotated face and iris images that has 4.85% improvement compared to the best unimodal system performance as demonstrated in Table 36. The proposed method with alignment and rotation has also a good performance of GAR=94.44% at FAR 0.01%.

Table 35: Verification Performance of Face and Iris Unimodal Systems

	Method	GAR (at 0.01% FAR)
Face Recognition	LBP-based Method without Alignment	76.00
	LBP-based Method with Alignment	85.22
	PSO Level 2 (Method and Feature Selection) without Alignment	80.10
	PSO Level 2 (Method and Feature Selection) with Alignment	87.33
Iris Recognition	Combined Left and Right Iris Using Weighted Sum-Rule without Rotation	27.12
	Combined Left and Right Iris Using Weighted Sum-Rule with Rotation	71.55

Table 36: Verification Performance of Multimodal Systems and Proposed Scheme

	Method	GAR (at 0.01% FAR)
Multimodal Systems	Face-LBP and Left Iris without Alignment and Rotation	76.89
	Face-LBP and Left Iris with Alignment and Rotation	88.22
	Face-LBP and Right Iris without Alignment and Rotation	76.33
	Face-LBP and Right Iris with Alignment and Rotation	88.22
	Face-LBP and Combined Iris without Alignment and Rotation	82.22
	Face-LBP and Combined Iris with Alignment and Rotation	90.77
	PSO Level2 and Left Iris without Alignment and Rotation	82.44
	PSO Level2 and Left Iris with Alignment and Rotation	90.77
	PSO Level2 and Right Iris without Alignment and Rotation	80.89
	PSO Level2 and Right Iris with Alignment and Rotation	90.77
	PSO Level2 and Combined Iris without Alignment and Rotation	83.23
	PSO Level2 and Combined Iris with Alignment and Rotation	92.89
	Proposed Scheme without Alignment and Rotation	84.96
	Proposed Scheme with Alignment and Rotation	**94.44**

The ROC analysis of unimodal systems and the proposed scheme on non-aligned and non-rotated face and iris images is demonstrated in Figure 31. On the other hand, Figure 32 demonstrates the ROC analysis of the proposed scheme and unimodal systems on aligned and rotated face and iris images. The best performance is obtained by the proposed scheme as shown in the figures.

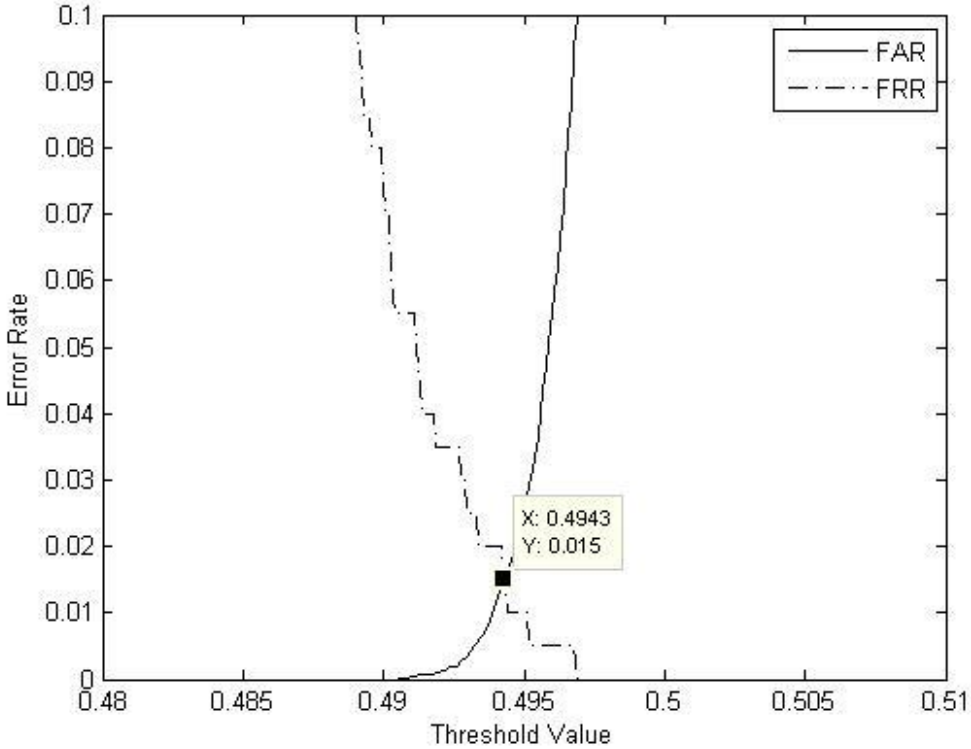

Figure 30: EER of the Proposed Scheme 4.

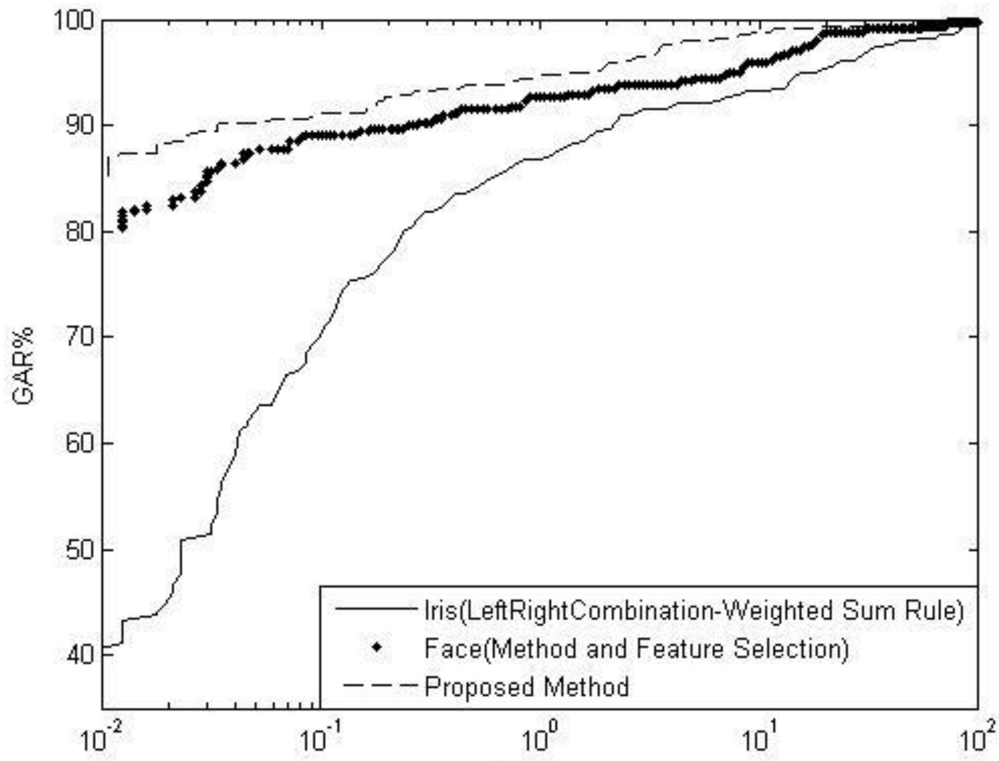

Figure 31: ROC Curves of Unimodal Systems and the Scheme 4 without Alignment-Rotation

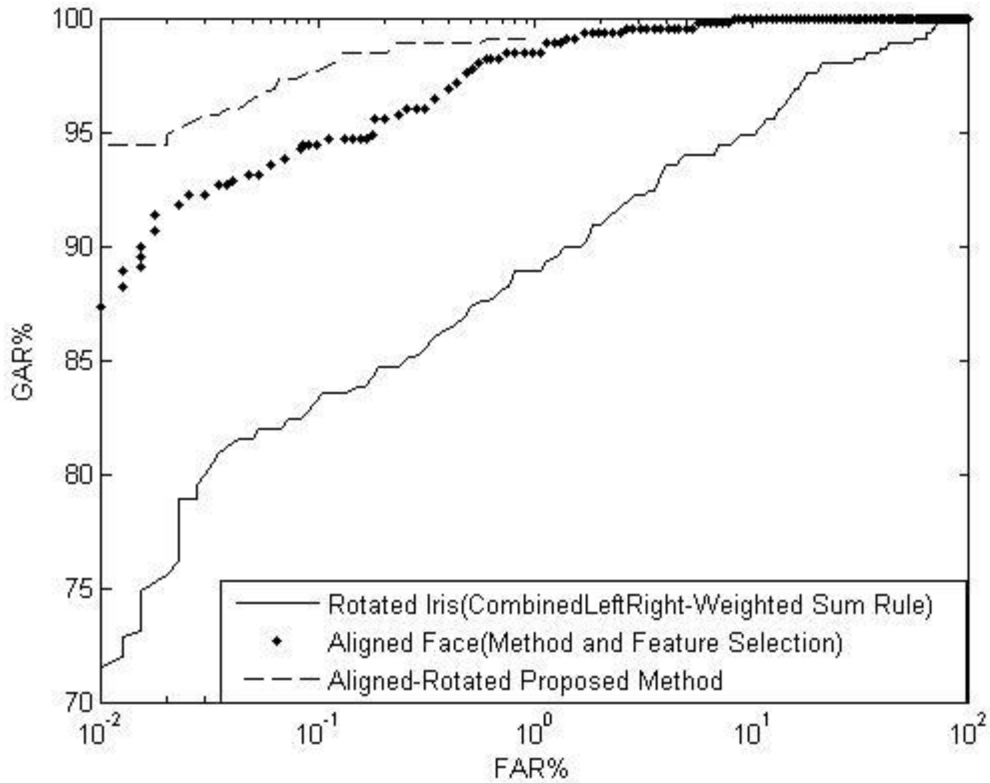

Figure 32: ROC Curves of Unimodal Systems and the Scheme 4 with Alignment-Rotation

7.4 Contribution and Conclusion of Scheme 4

The proposed scheme involves consideration of all face and both left and right iris scores along with PSO to select the optimized subset of features and weights prior to fusion. Tanh normalization was applied on the face and iris scores to transfer the scores into a common domain and range. The fusion of the two modalities, face and iris, is then tested with a well-known combination method namely Weighted Sum Rule. The proposed face-iris multimodal scheme was presented in verification performance and identification performance. The main idea of the proposed scheme is to fuse scores of all implemented algorithms and techniques on face and iris modalities to take the advantages of each technique on a specific modality for increasing the performance of the multimodal system. The iris recognition performance is improved by measuring the angle of head roll to shift the iris feature codes.

The contribution of proposed scheme 4 is to use left and right iris patterns with optimized features of local and global based facial feature extraction methods using PSO to remove redundant data for the fusion of face-iris multimodal system with tanh score normalization and Weighted Sum Rule fusion method where the weights are optimized using PSO. The proposed scheme can be used practically in person identification and verification systems using facial images. The iris information from left and right eye can be extracted from the face image of the same individual and the fusion of face-iris multimodal system can be performed to improve the performance of the individual face and iris recognition systems. In fact, recognition is performed on fusion of face and both of the eyes' iris patterns and therefore the verification becomes undisputable.

7.5 Comparison of All Proposed Methods

Generally, we performed fusion of face and iris biometrics in this study using four different proposed schemes in different fusion levels. The first and the second proposed schemes consider fusion of face and iris biometrics in score level fusion while the third and the fourth proposed schemes involve the consideration of score and feature level fusions together. In this section, our aim is to compare all the implemented proposed schemes together in order to find the best proposed method.

The evaluation of each proposed scheme is done based on CASIA Iris Distance database. The database contains the whole face and both left and right irises of the same individual and therefore it is proper to be used for testing all proposed methods. Totally, 90 individuals with 10 samples are used to test the proposed schemes, 5 samples are randomly selected to be used for training and the remaining 5 samples are used for testing. For the first three proposed schemes, left iris images are used to test the schemes and the fourth proposed scheme employs both left and right irises. Table 37 demonstrates the recognition performances achieved by each proposed method for the fusion of face and iris biometrics.

Table 37: Achieved Recognition Performance by Proposed Schemes

Proposed Schemes	Recognition Performance (%)
Proposed Scheme 1	96.66
Proposed Scheme 2	97.77
Proposed Scheme 3	97.11
Proposed Scheme 4	98.00

The best recognition performance is obtained using proposed scheme 4 as 98% that shows the robustness of this scheme compared to other implemented schemes in this thesis. Therefore based on the recognition performances demonstrated in the above table, we can conclude that whenever the fused scores of face is combined with fused iris scores using a feature selection method such as PSO to choose optimized weights and features, a robust and strong verification/identification system is obtained for the fusion of face and iris biometrics. In addition, the proposed scheme 2 has the recognition performance as 97.77% that indicates the effect of concatenated fused face and iris scores on recognizing the individuals. The recognition performance of the third proposed scheme as demonstrated in Table 37 is 97.11% and finally proposed scheme 1 achieved the recognition performance as 96.66%.

As a conclusion based on the achieved recognition performances, it can be concluded that all the obtained results are in the interval [96.66, 98.00] and are close to each other. In fact, it is possible to apply all the proposed schemes to obtain a robust and strong verification/identification system. However, our suggestion based on the recorded recognition performances in Table 37 is to use the last proposed scheme for the fusion of face and iris biometrics for person identity verification.

Chapter 8

CONCLUSION

Fusion of face and iris biometrics using several standard local and global feature extractors, normalization techniques and different fusion methods is presented in this thesis in different schemes. Local feature extractors, namely spPCA, mPCA and LBP, are investigated to extract facial and iris features. On the other hand, global methods such as PCA and subspace LDA are employed to extract face and iris patterns.

In the first proposed scheme, local feature extractors are used to extract facial features in order to remove the effect of partial occlusions. Iris patterns are extracted using global methods such as PCA and subspace LDA since global methods extract the transformed rectangular-shape iris patterns with high accuracy. The proposed scheme using LBP facial feature extractor and subspace LDA iris feature extractor with tanh score normalization and Weighted Sum Rule fusion method provides significantly better results compared to the unimodal systems and multimodal systems with the other feature extractor methods used on both modalities. The experiments are carried out on different subsets of ORL, FERET, CASIA and UBIRIS datasets to demonstrate the effectiveness of the proposed method.

In the second proposed scheme, fusion of face and iris biometrics using aforementioned local and global feature extractors in different fusion levels is presented. A new scheme for the fusion of face and iris biometrics is proposed using transformation-based score fusion and classifier-based score fusion. The proposed method is compared with the state-of-the-art fusion techniques of feature level, score level and decision level fusion. In the matching score level fusion, Sum Rule is applied and the fusion of the scores from local and global extractors is conducted by Tanh normalization of face and iris scores. In feature level fusion, features of face and iris are extracted by each feature extractor separately and concatenated into a long vector. In decision level fusion, Majority Voting is used to combine the results from different classifiers to obtain final fused decision. In fact, instead of performing original feature sets concatenation of face and iris, we involve face and iris matching scores in concatenation step. Prior to score concatenation, Sum Rule is used on the scores of each of five different feature extractors separately. The experiments are conducted on a combined database using ORL and BANCA face databases and CASIA and UBIRIS iris databases.

Concentration of the third proposed scheme is on the fusion of face and iris biometrics using several local and global feature extraction methods with score level and feature level fusion techniques. The proposed method considers concatenation of different feature sets of local feature extractors and global feature extractors for iris unimodal biometric systems. Specifically, Iris-FVF and Weighted Sum Rule fusion are employed on matching scores produced from Iris-FVF and LBP facial features to fuse face and iris. In order to improve the recognition performance of multimodal biometric systems, PSO method is also applied on Iris-FVF to select the best set of iris features. As a result, LBP and subspace LDA methods are selected by PSO for iris feature extraction. The experiments are conducted on a combined database using ORL and BANCA face databases and CASIA and UBIRIS iris databases. The experiments demonstrate that the proposed method using LBP facial features and LBP and subspace LDA iris features with Weighted Sum Rule fusion method achieves improved recognition accuracy compared to the considered unimodal and multimodal methods.

The last proposed scheme considers fusion of face and iris biometrics using several feature extraction methods with score level and feature level fusion techniques. The proposed method considers concatenation of different feature sets of local feature extractors and global feature extractors for face unimodal biometric systems using PSO in two levels. For iris recognition, a publicly available library implemented by Masek is applied to extract iris features. Generally, the proposed scheme involves consideration of all face and both left and right iris scores along with PSO to select the optimized subset of features and weights prior to fusion. Tanh normalization is applied on the face and iris scores to transfer the scores into a common domain and range. The fusion of the two modalities, face and iris, is then tested with a well known combination method namely Weighted Sum Rule. Different techniques at matching score level and feature level fusion on CASIA Iris Distance database are examined with PSO technique to optimize the weights and features. The proposed face-iris multimodal scheme is presented and compared with the existing unimodal and multimodal biometric systems using ROC curves and GAR at FAR 0.01% as verification performance and recognition rate as identification performance on original images without rotating face and iris patterns and also rotated and cropped face and iris images.

Finally, we compared all the implemented fusion schemes in this thesis to obtain the most robust and effective method on CASIA Iris Distance database. Based on the recognition performance achieved on this database, all the proposed schemes are close to each other and they can be used for fusion of face and iris biometrics, however, the best result is obtained by proposed scheme 4 as 98.00%.

List of Publications

1) Maryam Eskandari, Önsen Toygar and Hasan Demirel, Feature Extractor Selection in Face-Iris Multimodal Recognition, Signal Image and Video Processing, (2014 online), Springer-Verlag London, doi: 10.1007/s11760-014-0659-y.

2) Maryam Eskandari, Önsen Toygar and Hasan Demirel, A new approach for Face-Iris multimodal biometric recognition using score fusion, International Journal of Pattern Recognition and Artificial Intelligence, Vol. 27, No. 3, 2013, pp.1-15.

3) Maryam Eskandari and Önsen Toygar, Fusion of face and iris biometrics using local and global feature extraction methods, Signal Image and Video Processing, (2012 online), Springer-Verlag London, doi: 10.1007/s11760-012-0411-4.

4) Maryam Eskandari and Önsen Toygar, Score Level Fusion for Face-Iris Multimodal Biometric System, Lecture Notes notes on Electrical Engineering (LNEE), Information Sciences and Systems 2013 (ISCIS2013), Paris, Volume 264, 2013, pp 199-208.

5) Maryam Eskandari and Önsen Toygar, Person Identification Using Face and Iris Multimodal Biometric System, The 2012 International Conference on Image Processing, Computer Vision and Pattern Recognition (IPCV2012), Nevada, USA (July 16-19, 2012).

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