Distinguishing Identical Twins Using Facial Images and Various Feature Extractors

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ABSTRACT

Recognizing identical twins is considered as one of the most critical challenges in biometric systems due to the shortage of uniqueness and distinction between the identical twins. The lack of discriminative features could be compensated using different sources of information. In this thesis, two different hybrid approaches using three biometric traits namely frontal face, profile face and ear are proposed and implemented to distinguish identical twins. The proposed strategies are particularly based on feature-level fusion, score-level fusion and decision-level fusion. Both proposed approaches are evaluated using identical twins and non-twins individuals.

In the proposed method 1, frontal face is employed together with three feature extraction algorithms namely Principal Component Analysis, Histogram of Oriented Gradients and Local Binary Patterns. Fusion in this approach is conducted by all the aforementioned fusion techniques and different challenges are considered such as illumination, expression and ageing using ND-Twins-2009-2010 and FERET databases. The lowest Equal Error Rates of identical twins recognition that are achieved using the proposed method are 2.07% for natural expression, 0.0% for smiling expression and 2.2% for controlled illumination compared to 4.5%, 4.2% and 4.7% Equal Error Rates of the best state-of-the-art algorithm under the same conditions.

On the other hand, symmetry challenge of profile face and ear is tested in the proposed approach 2 by using Local Binary Patterns, Local Phase Quantization and Binarized Statistical Image Features feature extraction algorithms. The samples of both sides of profile face and ear are extracted from ND-Twins-2009-2010 and UBEAR databases. In this approach, the extent of symmetry of left and right sides of each trait is measured in order to be used for recognition purposes. Finally, symmetry experiments using multimodal biometric traits are implemented and compared with our proposed approach which uses feature-level and score-level fusion. The maximum accuracies achieved are 75% for identical twins using ND-Twins-2009-2010 database; moreover 88.04% and 79.89% for non-twins using ND-Twins-2009-2010 and UBEAR databases, respectively.

Keywords: identical twins, face recognition, ear recognition, score-level fusion, feature-level fusion, decision-level fusion, multimodal biometrics.

ÖZ

Biyometrik sistemlerde, tek yumurta ikizlerinin tanınması veya ayırt edilmesi, ikizlerin arasındaki benzerlikten dolayı en kritik zorluklardan biridir. Bu yüzden, tek yumurta ikizlerinin belirleyici özniteliklerinin çıkarılması için farklı bilgi kaynakları kullanılmaktadır. Bu tezde, tek yumurta ikizlerinin ayırt edilmesi için ön yüz, profil yüz ve kulak görüntülerini kullanan iki farklı melez yöntem önerilmiş ve uygulanmıştır. Önerilen yöntemlerde öznitelik seviyesi kaynaşım, skor seviyesi kaynaşım ve karar seviyesi kaynaşım stratejileri kullanılmıştır. Önerilen her iki yaklaşım da tek yumurta ikizleri ve ikiz olmayan kişilerin görüntüleri kullanılarak değerlendirilmiştir.

İlk önerilen yöntemde, ön yüz görüntülerinin öznitelikleri Ana Bileşenler Analizi, Gradientlere Yönelik Histogramlar ve Yerel İkili Örüntü yaklaşımları kullanılarak çıkarılmıştır. Bu yaklaşımda ayrıca bahsi geçen tüm kaynaşım teknikleri de uygulanmıştır. Aydınlatma, yüz ifadesi ve yaşlanma etkileri de farklı zorluklar olarak incelenip ND-Twins-2009-2010 ve FERET veritabanları üzerindeki deneylerde gözönüne alınmıştır. İlk önerilen yöntem tarafından elde edilen tek yumurta ikizlerinin tanınması deneylerindeki en düşük Eşit Hata Oranları, doğal yüz ifadesi için %2.07, gülümseyen yüz ifadesi için %0.0 ve kontrollü aydınlatma için %2.2 olarak saptanmıştır. Literatürdeki diğer yaklaşımların aynı koşullar altında elde ettikleri en iyi Eşit Hata Oranları ise sırasıyla %4.5, %4.2 ve %4.7 olarak bulunmuştur.

Diğer yandan, profil yüz ve kulak görüntülerindeki simetrik özellikler, ikinci önerilen yöntemde, Yerel İkili Örüntü, Yerel Faz Nicemleme ve İkili İstatistiksel Görüntü Öznitelikleri algoritmalarının yardımıyla test edilmiştir. Profil yüz ve kulak görüntülerinin her iki yandan çekilmiş görüntüleri ND-Twins-2009-2010 ve UBEAR veritabanları üzerinden elde edilmiştir. Bu yaklaşımda, bahsedilen herbir kişisel özelliğin sol ve sağ yanlarının (a)simetri derecesi ölçülmüş ve bu ölçümler ikiz ve ikiz olmayan kişilerin tanınması amacıyla kullanılmıştır. Son olarak, birden fazla biyometriğe dayalı simetri deneyleri yapılıp öznitelik seviyesi kaynaşım ve skor seviyesi kaynaşım tekniklerini barındıran önerilen yöntemle karşılaştırılmıştır. Deneyler sonucunda elde edilen maksimum doğruluk oranları, ND-Twins-2009-2010 veritabanı üzerinde tek yumurta ikizlerinin tanınması için %75 olup; ikiz olmayan kişiler için ND-Twins-2009-2010 ve UBEAR veritabanları üzerinde sırasıyla %88.04 ve %79.89 olarak hesaplanmıştır.

Anahtar kelimeler: tek yumurta ikizleri, yüz tanıma, kulak tanıma, skor seviyesi kaynaşım, öznitelik seviyesi kaynaşım, karar seviyesi kaynaşım, birden fazla biyometri.

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LIST OF ABBREVIATIONS

BSIF	Binarized Statistical Image Features
CNN	Convolution Neural Network
DDA	Dense Displacement Algorithm
DFT	Discrete Fourier Transforms
EER	Equal Error Rate
FAR	False Accept Rate
FRR	False Reject Rate
GAR	Genuine Accept Rate
GMM	Gaussian Mixture Models
HOG	Histogram of Oriented Gradients
ICA	Independent Component Analysis
LBP	Local Binary Patterns
LPQ	Local Phase Quantization
LR-PCA	Local Region Principle Component Analysis
PCA	Principal Component Analysis
PSF	Point Spread Function
ROC	Receiver Operating Characteristic
SDA	Simple Spare Displacement Algorithm
SFS	Shape From Shading
SIFT	Scale Invariant Feature Transform
SNLDA	Symmetrical Null Space Linear Discriminant Analysis
SPCA	Symmetrical Principal Component Analysis
UCN	Unconstrained Cohort Normalization

Chapter 1

INTRODUCTION

1.1 Biometric Systems

Biometrics has recently been widely-used for human recognition in many different countries to identify a person under controlled or uncontrolled environments. The traditional methods for person identification such as passwords and magnetic cards have many disadvantages compared with a biometric based method that depends on who the person is intrinsically, not what he knows or what he possesses extrinsically [1]. Biometric systems recognize the individuals based on their physical traits or behavioral characteristics, therefore, many factors must be considered when choosing any biometric trait [2, 3] to be used in a person recognition system.

Biometrics is the science of establishing the identity of an individual based on a vector of features derived from a behavioral characteristic or specific physical attribute that the person holds. The behavioral characteristic includes how the person interacts and moves, such as their speaking style, hand gestures, and signature, etc. The physiological category includes the physical human traits such as fingerprints, iris, face, veins, eyes, hand shape, palmprint and many more as presented in Figure 1.

1.1.1 Biometrics Phases

Constructing any biometric system should pass and implement the main phases presented in Figure 2 and explained as follows:

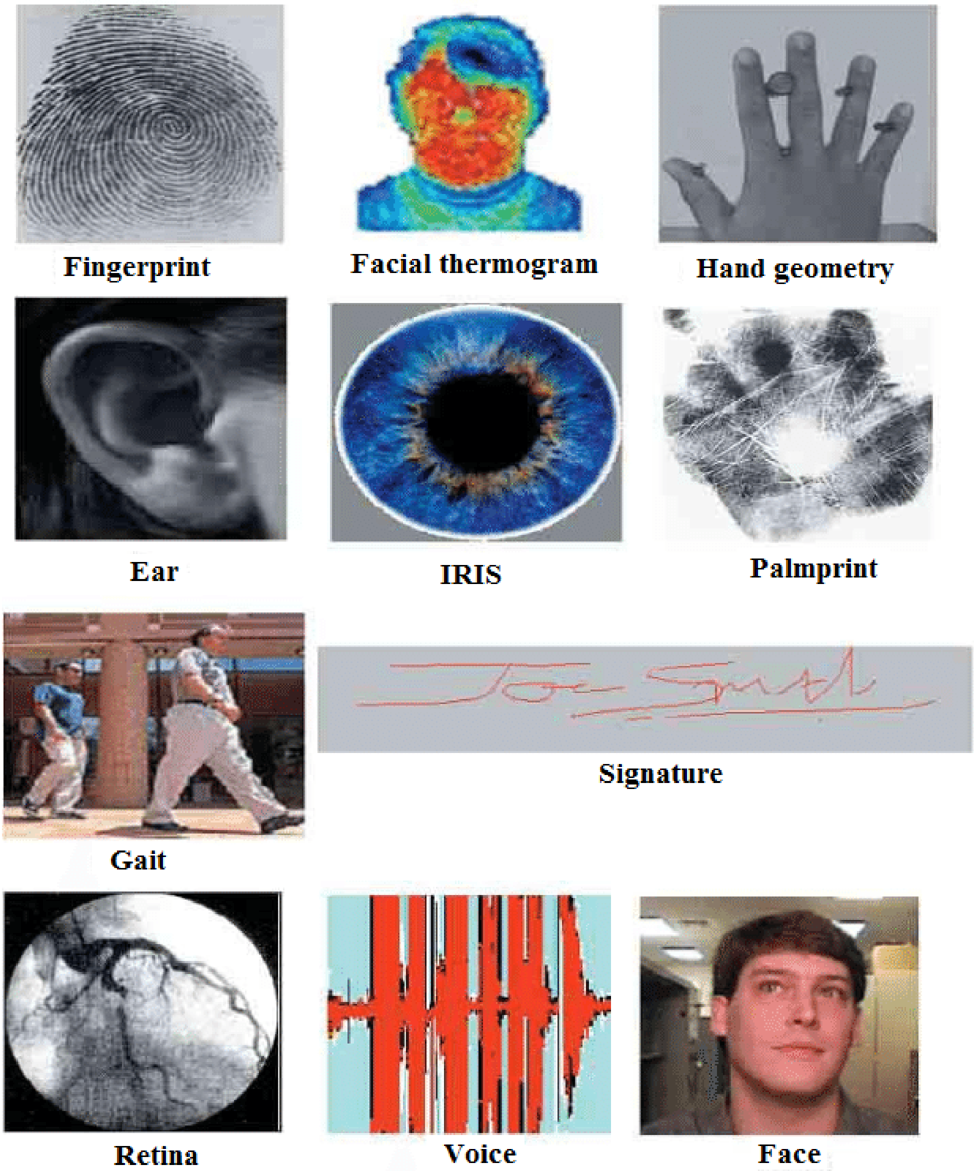

Figure 1: Some of Biometric Traits

1. Sensor: The first step is to get the raw data such as (voice or image) from the user in order to use it later for recognition process.
2. Pre-processing operations: some operations may be needed before processing of biometric data:
   - Quality assessment: Check if the quality of the raw data is suitable for other processing steps.
   - Segmentation: Remove the unnecessary part from the raw data, such as

noise and background.

- Quality enhancement: Applying some enhancement algorithms in order to increase the quality of the segmented data.

3. Feature extraction: Process of generating digital information from the raw data that is acquired by the sensor; the digital information may be called features which form a template. The template contains only discriminatory information which is used to recognize the individual.
4. Database: Templates should be stored in a database in order to retrieve them for matching; some other information may be stored in addition to the templates (name, address and passwords).
5. Matcher: The aim of the matcher process in biometrics is to estimate the differences between the stored templates with query features to find the match scores. Hence, a smaller difference indicates higher similarity between the template and the input sample.

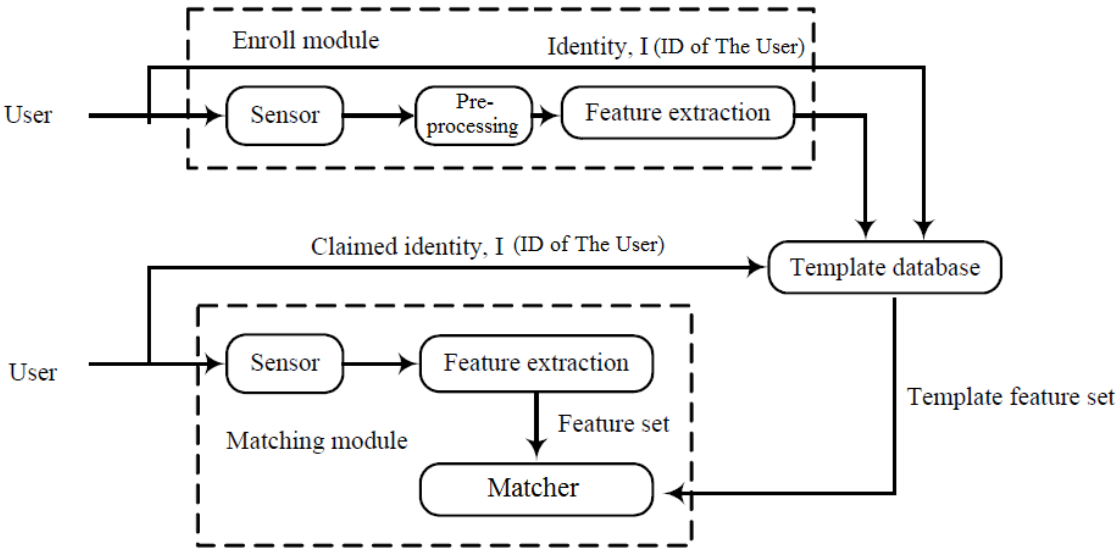

Figure 2: The Main Phases of a Biometric System [4]

1.1.2 Biometric Requirements

Some requirements must exist in any physiological or behavioral characteristic in order to be officially used in biometric systems as a biometric characteristic. Knowing that, absence of any of the following requirements will lead to a poor biometric system [1, 5, 6]:

- Universality: Any person who may join the system must have that characteristic.
- Distinctiveness: Different people should not have the same features of that trait characteristic.
- Permanence: Over a period of time, the characteristic should be stable or have as minimum change as possible.
- Collectability: The ability of the system to measure the characteristic quantitatively.
- Performance: Refers to the achievable recognition speed and accuracy, the resources required to achieve the desired recognition speed and accuracy, as well as the environmental and operational factors that affect the speed and accuracy.
- Acceptability: People should easily be able to use that biometric trait in their daily lives.
- Circumvention: Being able to enter the system by a person whose access is not permissible.

1.1.3 Modes of Biometrics

Both of verification and identification modes are implemented in this study, in the proposed method 1 and 2, respectively. Figure 3 shows the general block diagram of both modes. Based on how the system works and the strategy of searching in the database, the modes of biometrics are classified as verification and identification [7] which are described below:

1. Verification mode: Identity of the person is recognized by comparing the input image with the stored templates of the claimed ID. In such a system, a user should claim his/her identity to be recognized, usually via magnetic cards, user name, password, etc. The recognition system implements a one-to-one comparison to check if the claimed identity is genuine or an imposter. Positive recognition is mainly based on verification and the purpose is not to allow many users to use the same identity.
2. Identification mode: By searching all the saved templates of the users in the database, the recognition system recognizes an individual. Therefore, the system applies a one-to-many comparison to find an individuals identity (if the subject is available in the database or cannot be recognized) and there is no need for claimed identity to be submitted by the user. Negative recognition applications are considered as a critical component for identification systems, where the identification system reports the user's identity explicitly or implicitly. Preventing the same person to use multiple identities is the aim of negative recognition. Identification can also be used in positive recognition in order to achieve the inconvenience for the user where the user does not need to claim his identity.

1.2 Face Recognition

Face recognition is one of the most important abilities that we use in our daily lives. Face recognition has been an active research area over the last forty years and the first automated recognition system using face trait was implemented by Takeo Kanade in 1973 [8]. The increasing interest in the face recognition research is caused by the

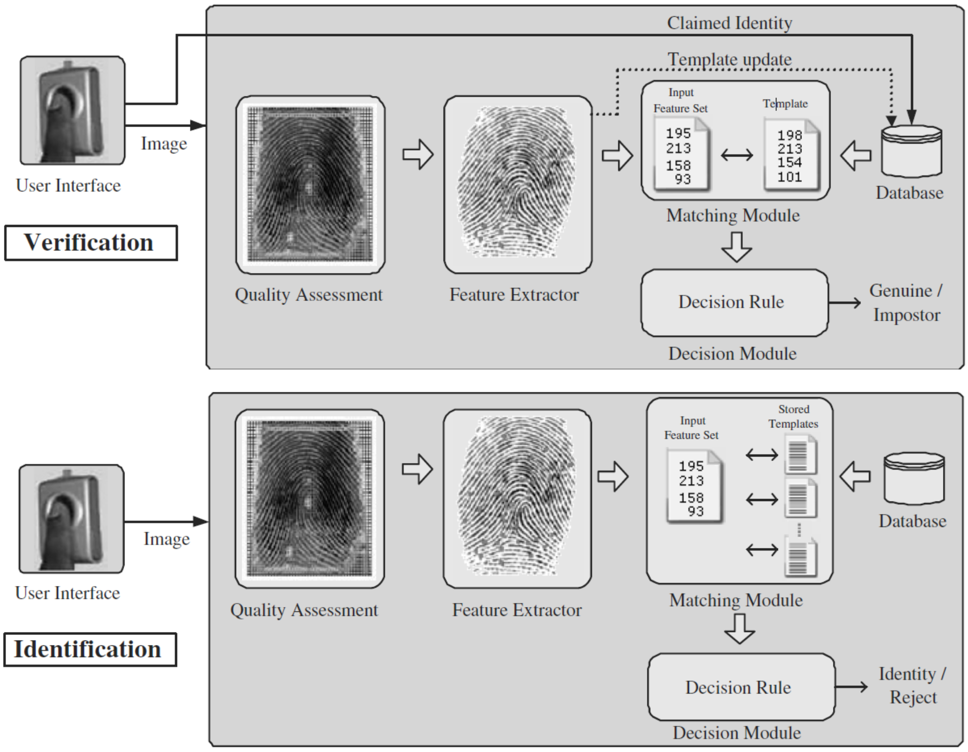

Figure 3: Verification and Identification in Biometric Systems [1]

satisfactory performance in many widely used applications such as the public security, commercial and multimedia data management applications that use face as biometric trait. Face recognition has several advantages compared to other biometrics such as ear and iris besides being natural and non-intrusive. Firstly, the most important advantage of face is that it can be captured at a distance and in covert manner. Secondly, in addition to the identity, the face can also show the expression and emotion of the individual such as sadness, wonder or scaring. Moreover it provides a biographic data such as gender and age. Thirdly, large databases of face images are already available where the users should provide their face image in order to acquire driver's license or ID card. Finally, the widely-used social media applications (e.g., Instagram) make the people more willing to popularize and share their personal images that already include face in the public domain. A face recognition system generally consists of four modules namely face detection, preprocessing, feature extraction, and matching as shown in Figure 4. An original face image and its preprocessed variant are also shown in Figure 5.

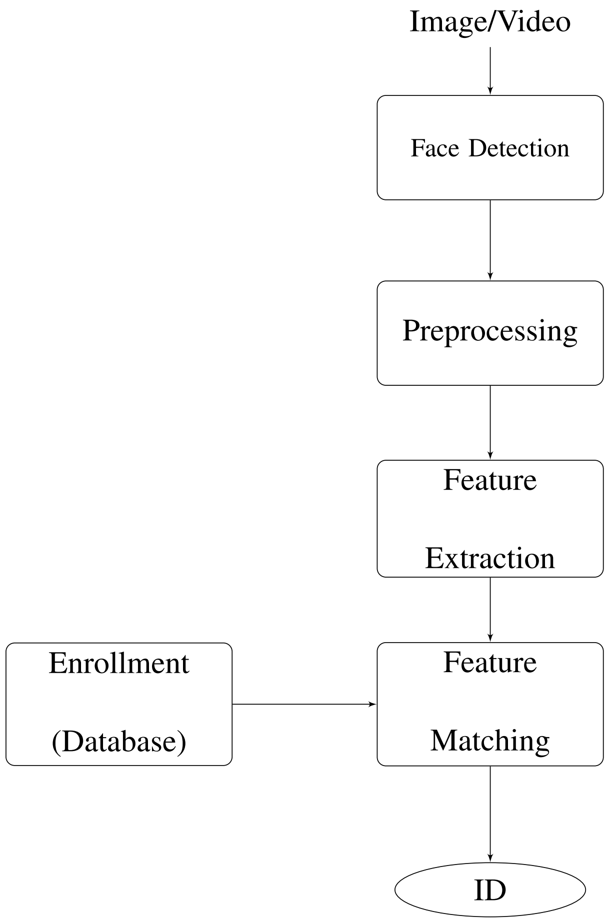

Figure 4: Block Diagram of a Face Recognition System

1.2.1 Face Recognition Challenges

There are many key factors and challenges which can strongly affect the face recognition performance as well as degrading the extraction of robust and discriminant features. Some of these challenges such as pose, illumination, ageing, facial expression variations and occlusions are briefly described below and these challenges are illustrated in Figure 6:

Figure 5: An Original and a Preprocessed Face Image

1. Pose: The images of a face or ear vary because of the camera pose (different viewpoints) as shown in Figure 6.a. In this condition, some facial parts such as the mouth or eyes may be fully or partially occluded. Pose variation has more influence on recognition process because of introducing self-occlusion and projective deformations. Consequently, it is possible that two different face samples, that correspond to the same individual, may contain different poses, may have intra-user variations or inter-user variations. There are many studies that deal with pose variation challenges as in [9–11].

2. Illumination: When the image is captured, it may be affected by many factors to some extent. The appearance of the face or ear is affected by factors such as illumination that includes source distribution, intensity and spectra, and also camera characteristics such as lenses and sensor response. Illumination variations can also have an effect on the appearance because of the reflectance properties of skin and the internal camera setting [12]. The variation of illumination chal-

lenge is one of the main technical problems in biometric systems especially for face and ear traits where the face can appear dramatically different as shown in Figure 6.b. In order to handle uncontrolled illumination conditions or pose, an image relighting technique based on pose-robust albedo estimation [22] can be implemented to generate multiple frontal face images that are related to the same individual under variable illumination.

3. Ageing: Ageing can be a natural cause of age progression and an artificial cause of using tools of makeup. Facial appearance changes more drastically at younger ages less than 18 years due to the change in subjects weight or stiffness of skin. All Ageing related variations such as wrinkles, speckles, skin tone and shape degrade face recognition performance. absence of a public domain database for studying the effect of Ageing [13] is the main reasons for the low number of researches that focus on face recognition in the context of age challenge. It is very difficult to collect a database for face images of human that includes samples for the same individual taken along his/her life at different ages. An example set of images for different ages of the same person is presented in Figure 6.c.

4. Facial expression: The appearance of faces is directly affected by a person's facial expression such as anger, surprise and disgust as shown in Figure 6.d. Additionally, facial hair such as beard and moustache can change facial appearance specifically near the mouth and chin regions. Moreover, facial expression causes large intra-class variations. In order to handle these facial expression problems, 3D-model-based approaches and local-feature-based approaches are

conducted [14].

5. Occlusion: Faces may be partially occluded by other objects such as scarf, hat, spectacles, beard, and mustache as shown in Figure 6.e. This makes the face detection process a difficult task and the recognition itself might be difficult because of some hidden parts of face making recognition of features harder. For these reasons, in surveillance and commercial applications, face recognition engines reject the images when some part of it is not detected. In the literature, local-feature based approaches were proposed in order to overcome these occlusion problems [15]. On the other hand, the iris may potentially be occluded due to the eyelashes, eyelids, shadows or specular reflections and these occlusions can lead to higher false non-match rates.

1.2.2 Recognition of Identical Twins Using Face Biometric

Absence of the factors, such as universality, uniqueness, permanence, and acceptability lead to a weak recognition system with high error rates. Therefore all the factors must be available at the same time in order to get a good distinguishing system. In all the cases, the face trait meets the aforementioned factors perfectly which makes it a good choice as a biometric trait. However, there is a case of face recognition that represents the main challenges with one of those factors which is identical (monozygotic) twins case [16]. In identical twins case; universality, permanence and acceptability are satisfied, but the factor that represents a serious problem is the uniqueness. It is axiomatic that the identical twins have almost the same face shape, size and features as shown in Figures 7 and 8, so new methods and algorithms should be studied and considered in order to deal with the high similarities in case of identical twins. It is obvious that face recognition for a population without identical twins will be more

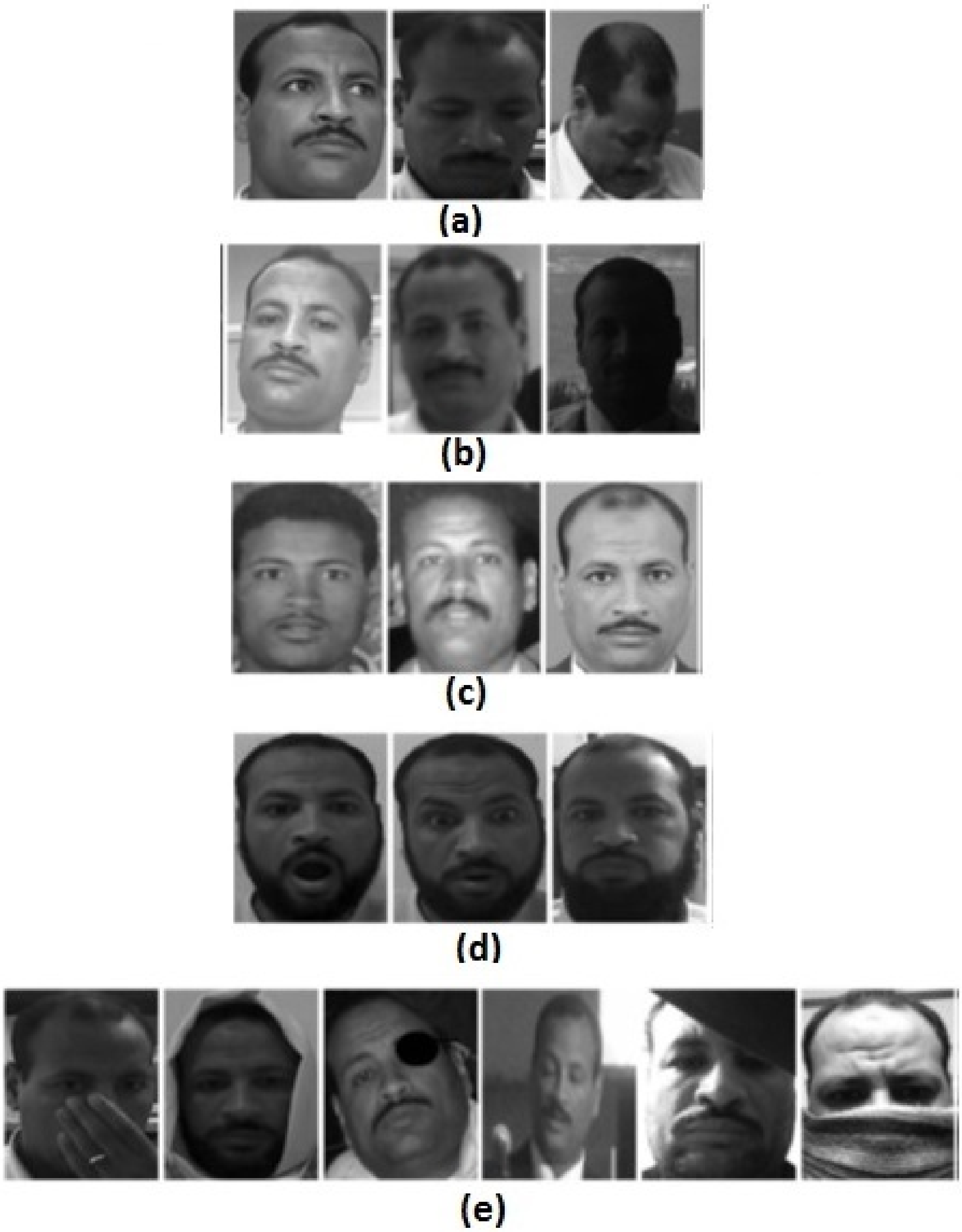

Figure 6: The Challenges in the Context of Face Recognition (a) Pose Variations (b) Illumination Variations (c) Ageing Variations (d) Facial Expressions (e) Occlusions

efficient and easier when constructing a system of identical twins recognition. In other words, algorithms that are able to distinguish the critical challenges such as identical twins should be more powerful in the case of non-twins recognition which is the main goal in this study. In order to distinguish identical twins, we propose two different hybrid biometric approaches which is mainly based on three different types of fusion, namely feature-level fusion, score-level fusion and decision-level fusion. Additionally, Principal Component Analysis (PCA) [17] , Histograms of Oriented Gradients (HOG) [18], Local Binary Patterns (LBP) [19], Local Phase Quantization (LPQ) [20] and Binarized Statistical Image Features (BSIF) [21] are employed as feature extraction algorithms.

Figure 7: Face Images of Identical Twins (Male)

1.3 Unimodal & Multimodal Biometric Systems

Some of the limitations imposed by unimodal biometric systems (that is, biometric systems that rely on the evidence of a single biometric trait) can be overcome by using multiple biometric modalities [22]. Increasing the discriminant information and con-

Figure 8: Face Images of Identical Twins (Female)

straints leads to decrease the error in recognition process. More information can be acquired when using different sources of information simultaneously and the sources of information may be on several types such as multiple biometric traits, algorithms, instances, samples and sensors. Consolidating multiple features that are acquired from different biometric sources in order to construct a person recognition system is defined as multibiometric systems. For example, fingerprint and palmprint traits, or right and left iris of an individual, or two different images that are captured from the same ear trait may be fused together to recognize the person in a more accurate and reliable way than unimodal biometric systems. Due to the usage of two or more biometric sources, many of the limitations of unimodal systems can be overcome by the multimodal biometric systems [23].

Multibiometric systems are able to compensate a shortage of any source using the other source of information. In addition, the difficulty of circumvention of multiple biometric sources simultaneously creates more reliable systems than unimodal systems. On the other hand, unimodal biometric systems have low cost and require less enrollment and recognition time compared to multimodal systems. Hence, when implementing multibiometrics in the business for a specific application such as commercial, forensics and biometric systems that include large population, the tradeoff between the benefits earned and the added cost should be analyzed.

The information used in recognition process can be fused in five different levels namely sensor-level fusion, feature-level fusion, score-level fusion, decision-level fusion and rank-level fusion. Among the aforementioned fusion techniques, the most popular ones are score-level and feature-level fusion. Most of the person identification systems use these fusion techniques because of their simplicity and high performance.

1.4 Research Contribution

The contribution of this PhD thesis is to use frontal face and the symmetry of profile face and ear modalities for identical twins and non-twins identification by different multimodal biometric approaches. Additionally, various challenges are also considered in addition to the high similarity of identical twins such as illumination, expression and ageing. The proposed approaches are based on three fusion techniques on biometric traits. However, the contributions of each proposed scheme are further explained in detail in the following chapters.

1.5 Outline of the Dissertation

The rest of the thesis is organized as follows. Chapter 2 discusses the related studies in recognition of twins by using different methods and different biometric traits in addition to some researches about symmetry of traits. Chapter 3 presents the details of the feature extraction methods and fusion techniques that are applied in this work. The proposed method 1 that recognizes identical twins using frontal face under different challenges are detailed in Chapter 4. Chapter 5 presents the hybrid approach (the proposed method 2) that exploits the symmetry of different sides of biometric traits for recognition purposes. Finally, we conclude this study in Chapter 6.

Chapter 2

LITERATURE REVIEW

2.1 Related Work of The Proposed Method 1

Identical twins were used in some studies in the literature especially by analyzing their faces, fingerprints, irises and speech [24]. Jain et al. in 2002 [25] used the minutia-based automatic fingerprint matching and successfully distinguished the fingerprint images of identical twins. However for non-twins matching, the accuracy was higher than the case of identical twins. In other words, the similarity between the fingerprints of identical twins was much higher than the case of non-twins. As a result, False Accept Rate (FAR) of identical twins was about 4 times higher than that of non-twins.

Adapted Gaussian Mixture Models (GMMs) were implemented to investigate the performance of speaker verification technology for distinguishing identical twins in 2005 [26]. The tests were applied using long and short duration of speaking by GMM-UBM scoring procedure as baseline scores in the experiments. Acquired scores were subjected to Unconstrained Cohort Normalization (UCN) and labeled as UCN scores. Using UCN, EER decreased from 10.4% to 1% (short) and from 5.2% to around 0% (long). Competitive code algorithm was developed in 2006 in order to distinguish individuals who have the same genetic information such as identical-twins using palmprints as biometric trait [27]. The authors proved that using the three principle lines of palmprint is not enough to distinguish identical twins since it is genetically related.

Genetically unrelated features in palmprint were also used in that study and the genuine accept rate was found to be about 97%.

Hollingsworth et al. in 2010 [28] proposed to evaluate the human ability to determine the degree of similarity between iris images and whether they belong to identical twins or not. Using 3 seconds to display each image, 81% accuracy was acquired using only the appearance of iris and 76% accuracy using only the appearance of periocular. Increasing the time of displaying each image of iris and periocular improved the accuracy to 92% and 93%, respectively. Demographic information such as gender and ethnicity and/or some facial marks were included to face matching algorithms in 2010 [29] with a view to improve the performance of the system. When comparisons between the matching results of rank-one matching accuracy of the state-of-the-art commercial face matcher (face VACS) with the proposed facial marks matcher were performed, the accuracy increased from 90.61% (face VACS) to 92.02% (proposed facial marks matcher).

Recognition experiments on identical twins in 2010 [30] showed that the multimodal biometric systems which combine different instances of the same biometric traits lead to perfect matching compared with the unimodal systems. Using a commercial minutiae-based matcher such as VeriFinger and the iris feature representation method based on ordinal measure, the EER's of finger fusion and the fusion of right and left irises were both 0.49%. On the other hand, discriminating facial traits were determined by observation of humans in 2011 [31]. In that study, 23 people participated in the recognition experiments in which maximum, minimum, and average success rates were 90.56%, 60,56% and 78.82% respectively. Additionally, they performed automated system matching with uncontrolled face images and obtained low success rates.

In [32], some experiments are conducted on 3D Twins Expression Challenge ("3DTEC") dataset using state-of-the-art face recognition algorithms. The presented results indicate that 3D face recognition of identical twins in the presence of varying facial expressions is far from a solved problem.

Three different commercial face matchers in addition to Local Region Principle Component Analysis (LR-PCA) were used in 2011 [33] for distinguishing identical twins. Experiments were run under several conditions such as expression, light control, and presence of glasses. The best performance with a minimum EER (from 0.01% to 0.12%) was acquired by Cognitec matcher under ideal conditions. On the other hand, the accuracy of identical twins matching was increased by cascading of appearance-based verifier and motion-based verifier in 2012 [34] compared with the results of using both of them separately. Six face expressions were examined using motion-based matchers, Simple Spare Displacement Algorithm (SDA) and Dense Displacement Algorithm (DDA). The best performance was acquired by motion-based matcher which was increased from 93.3% to 96% after applying cascading approach.

Paone et al. in 2014 performed some experiments that were implemented with different conditions on face images of identical twins [35]. The primary goal of these experiments is to measure the ability of some algorithms to distinguish two different faces that have large similarity such as identical twins (monozygotic). Three of the top submissions to Multiple Biometric Evaluation (MBE) 2010 face track algorithms [36] were used in addition to four commercially available algorithms. Measuring the performance of all algorithms and comparing the results in order to determine the best algorithm with the lowest error rate were done. The experiments were only applied on frontal faces without wearing glasses and all EER results were demonstrated in that study. Consequently, these results are used in our experiments for comparison purposes in Chapter 4.

2.2 Related Work of The Proposed Method 2

Some studies have found that the left and right ear are close to symmetric for many subjects but more researches are needed to find ways of exploiting this fact in automatic recognition systems [37].

Many biometric traits such as face, ear and palmprint are symmetric. The mirror images of symmetrical traits encode discriminative features, which are a benefit for recognition performance. Xiaoxun and Yunde [38] proposed a method for ear and face recognition based on a Symmetrical Null Space Linear Discriminant Analysis (SNLDA) with the odd/even decomposition principle. They introduced mirror images in order to construct the two orthogonal odd/even eigenspaces, and the discriminative features are then, respectively, extracted from the both eigenspaces under the most suitable situation of the null space. Two images of different sided ears are combined as a single image before mirror transformation. The method using the concatenated image showed about 2% enhancement in the performance compared to the method using the right or left ear separately.

The symmetry of human ears was analyzed and presented by Abaza and Ross [39] in 2010. They performed experiments to analyze the symmetry of ear from a biometric perspective by conducting three different analysis. In the first one, they used a symmetry operator which evaluates symmetricity by assigning a symmetry measure for each point in the edge map of the image. In the second analysis, they used the Iannerelli system to study the geometrical symmetry between individual regions in the right and left ears. In the third analysis, Shape From Shading (SFS) and Eigen-Ear (PCA) techniques were used to study the symmetrical characteristics of the ear. They conducted several experiments using the WVU (West Virginia University) database. These experiments suggested the existence of some degree of symmetry in the human ears that can perhaps be systematically exploited in the future design of commercial ear recognition systems. Finally, scores were generated using probe and input samples of the same side of the ear (right-right) in addition to scores of the left side of ear as input and the mirrored right side of ear as the stored sample. Then, match scores of both sets by the Weighted Sum Rule are fused. The performance of the rank-4 was improved about 3% using that fusion. The authors in [40] conducted experiments to test ear symmetry. Two different angles of view have been examined which are 30 degree off the center (for 88 subjects) and 45 degree off the center (for 119 subjects). The right ear of the subject is used as the gallery, and the left ear is used as the probe. PCA approach and ICP-based approach are used for feature extraction. They found that most people's right and left ears are symmetric to a good extent, but some people's right and left ears have different shapes.

Few researchers have used facial symmetry to handle pose variations in real time and in an uncooperative image acquisition environment. Passalis et al. [41] introduced a novel 3D face recognition method that used facial symmetry to handle pose variations, and solved the missing data problem by using facial symmetry on occluded areas. For evaluation purposes, they used the most challenging databases in terms of pose variations and missing data. Their method achieves 20% enhancement on recognition rate.

Kirby and Sirovich [42] added mirror images into the characterization of human faces, and derived a new expansion form based on the K-L expansion. They also proved that the reconstruction errors of samples outside the training set are reduced by providing reflected images.

Symmetrical Principal Component Analysis (SPCA) for face recognition was proposed by Yang and Ding [43] using symmetrical face images. Even and odd symmetrical principal components are extracted based on combining PCA with the odd/even decomposition principle. The experiments that were applied on face recognition after introducing mirror images, demonstrated that SPCA achieves higher recognition rate than PCA, and SPCA utilities mirror images and exploits more information.

The first work that studies the impact of facial asymmetry on recognition performance was proposed by Liu et al. [44]. The main objective of that work was to improve the performance of recognition under different expressions. They demonstrated that the symmetry of face may provide helpful features and information for human recognition system. Additionally, they examined the effects of extrinsic factors of facial asymmetry (e.g. taking advantage of self-shadowing such as nose), expression identification (temporal variations of facial asymmetry) and the effective feature combination schemes for optimal face classification.

On the other hand, palmprint is increasingly adapted as one of the effective modalities for the biometrics identification. There exists a degree of similarity between left and right-hand human palms. Kumar and Wang [45] introduced a novel approach in this field such that their approach explores on the possibility of matching left with the right palmprint images in order to achieve more accurate matching for the left-to-right matches. Palmprint matching was done from a Convolution Neural Network (CNN). CNN is essentially a kind of neural network which uses multiple layers (convolution pattern) to connect each neuron. They noted that left to right palmprint matching can generate different results than right to left palmprint matching. Consequently, the matching using CNN achieves outperforming results (EER = 9.25%) compared to other methods.

Identical twins are distinguished in [46] using samples of one side of ear as training and the other as test. The accuracies of left (training)-right (test) and right (training)-left (test) cases were 54.78% and 53.4%, respectively.

Chapter 3

FEATURE EXTRACTION AND FUSION APPROACHES

3.1 Feature Extraction Approaches

In this study, two different categories of feature extraction techniques are used, namely appearance-based and texture-based techniques.

Appearance-based techniques are based on mapping the high-dimensional face image into a lower dimensional sub-space in order to generate a compact representation of the entire face region in the acquired image. This sub-space is defined by a set of representative basis vectors, which are learned using a training set of images. The most commonly used appearance-based technique for facial feature extraction is Principal Component Analysis (PCA) [1].

3.1.1 Principal Component Analysis

Principal Component Analysis (PCA) is implemented as an appearance-based techniques as it is one of the earliest method that was used for automated feature extraction. PCA uses the training data to learn a subspace that accounts for as much variability in the training data as possible. This is achieved by performing an Eigen value decomposition of the covariance matrix of the data [1].

The aim of PCA is to acquire eigenvectors of the covariance matrix (C) as $C\mathrm{w} = \lambda\mathrm{w}$ where w is the set of eigenvectors related to the eigenvalues λ and

$$C = XX^T = \frac{1}{N}\sum_i \sum_j (\overline{X}_{i_j} - \overline{m})(X_{i_j} - \overline{m})^T, \tag{3.1}$$

$$X = [X_1 - m,\ X_2 - m,\ \ldots,\ X_N - m] \tag{3.2}$$

with X_i representing the training images vector of the ith image and

$$m = \frac{1}{N}\sum_{i=1}^{N} X_i. \tag{3.3}$$

where m is the average of the training set and N is the number of training samples.

On the other hand, texture-based approaches try to find robust local features that are invariant to pose or lighting variations. Scale Invariant Feature Transform (SIFT), Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Local Phase Quantization (LPQ) and Binarized Statistical Image Features (BSIF) are implemented as texture-based approaches in this study and these methods are also used in many recognition/classification problems [47–50].

3.1.2 Histogram of Oriented Gradients

Histogram of Oriented Gradients (HOG) descriptors [51] used in computer vision and image processing for the purpose of object detection, count occurrences of gradient orientation in localized portions of an image. Calculation of the classic HOG descriptor begins by dividing an image under the detection window into a dense grid of rectangular cells. For each cell, a separate orientation of gradients is calculated. The gradient magnitude $|G|$ and the orientation of the gradient θ for an image $I_{X,Y}$ are calculated as in Equation 3.4:

$$|G| = \sqrt{I_X^2 + I_Y^2}, \quad where$$
$$I_X = I * D_X, \quad I_Y = I * D_Y,$$
$$D_X = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}, \quad D_Y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}, \tag{3.4}$$

where * is the convolution operator and $\theta = atan2(I_Y, I_X)\, radians$, that returns a value in the interval (-π, π].

The angle transformed into degrees is α=θ*180/π, that gives values in the range (-180, 180] degrees. For the 'signed' gradient, it is needed to translate the range of the gradient from (-180, 180] to [0, 360) degrees. This is performed as in Equation 3.5:

$$\alpha_{signed} = \begin{cases} \alpha, & \text{if } \alpha \geq 0 \\ \alpha + 360, & \text{if } \alpha < 0 \end{cases} \tag{3.5}$$

The histogram consists of evenly spaced orientation bins accumulating the weighted votes of gradient magnitude of each pixel belonging to the cell. Additionally, the cells are grouped into blocks and for each block, all cell histograms are normalized. The blocks are overlapping, so the same cell can be differently normalized in several blocks. The descriptor is calculated using all overlapping blocks from the image detection window.

3.1.3 Scale Invariant Feature Transform

Scale Invariant Feature Transform (SIFT) is considered as one of the most common local representation techniques that are used in pattern recognition. The stable keypoints can be used to overcome the pose variation problem. However, SIFT can extract a quite large number of keypoints (in hundreds), consequently, it is challenging task to find the correspondences between the keypoints of different images [52,53]. Computation of stable features of SIFT consists of four main steps namely scale-space extrema detection, keypoint localization, orientation assignment and keypoint description in a local neighborhood at each keypoint.

In scale-space extrema detection, multiple scales and image locations by using a Difference-of-Gaussian function are searched. An approximation to the scale normalized Laplacian *L(x, y, σ)* of Gaussian *L(x, y, σ)* with an input image *I(x, y)* [54] is represented as in Equation 3.6:

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y), \tag{3.6}$$

where * is the convolution operation in the coordinates of each pixel (x, y). Furthermore, different scales of image are obtained by the scale parameter σ and

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}, \tag{3.7}$$

and the difference-of-Gaussian function convolved with the image is shown in Equation 3.8:

$$\begin{aligned} D(x,y,\sigma) &= (G(x,y,k\sigma) - G(x,y,\sigma)) * I(x,y), \\ &= L(x,y,k\sigma) - L(x,y,\sigma) \end{aligned} \tag{3.8}$$

where k is a constant multiplicative factor.

3.1.4 Local Binary Patterns

Local Binary Patterns (LBP) algorithm has been used as one of the most common and successful texture-based techniques in recent years. Image analysis and feature extraction are active research topics in computer vision with a wide range of important applications, e.g., human-computer interaction, biometric identification, surveillance and security [55]. The original LBP operator labels the pixels of an image with decimal numbers, called Local Binary Patterns or LBP codes, which encode the local structure around each pixel [19, 56].

The image is divided by LBP into different equal size blocks that are nonoverlapped. For each block, LBP texture descriptors are performed separately in order to extract the local features. Then, histogram is extracted for each block in order to hold information of the objects on a set of pixels. Finally, a single global feature vector is produced by concatenating the extracted features of each. LBP is checking a local neighborhood surrounding a central point R which is sampled at P points and checks whether the surrounding points are less or greater than the central point to classify textures. The LBP value of the center pixel in the P neighborhood on a circle of radius R can be calculated by Equation 3.9:

$$LBP_{(P,R)} = \sum_{p=0}^{p-1} S(g_p - g_c)2^p, \tag{3.9}$$

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

where g_p and g_c are the gray-value of surrounding points and the center pixel, respectively.

3.1.5 Local Phase Quantization

Local Phase Quantization (LPQ) descriptor was proposed by Ojansivu and Heikkilä [20] in 2008 to tackle the relative sensitivity of LBP to blur, based on quantizing the Fourier transform phase in local neighborhoods. The blurred image is represented as a convolution of a centrally symmetric Point Spread Function (PSF) and the original image. The Fourier representation of the blurred image is shown in Equation 3.10:

$$G(u) = F(u) \otimes H(u), \tag{3.10}$$

where *G(u)*, *F(u)* and *H(u)* are the discrete Fourier transforms (DFT) of the blurred image *g(x)*, the original image *f(x)*, and the PSF *h(x)*, respectively, and *u* is a vector of coordinates $[u,v]^T$.

Considering only the phase of the spectrum, the relation turns into a sum $\angle G = \angle F + \angle H$. If the PSF is centrally symmetric, the transform H becomes real valued and the phase angle $\angle H$ must be equal to 0 or π as given by Equation 3.11:

$$\angle H(u) = \begin{cases} 0, & H(u) \geq 0 \\ \pi, & H(u) < 0 \end{cases} \tag{3.11}$$

Furthermore, the shape of H for a regular PSF is close to a Gaussian or a sinc function, which at least makes the low frequency values of H positive. At these frequencies, $\angle H = 0$ causes $\angle G = \angle F$ to be a blur invariant property. This phenomenon is the basis of the LPQ method.

The phase of each pixel is computed within a predetermined local radius. Then, the image is quantized by checking the sign of the imaginary and real segment of the local phase. Meanwhile, the quantized neighborhood of each pixel is reported as an 8 digit binary number [57]. Given an image, the LPQ value is first computed for every pixel. Next, local histograms with 265 bins are computed within a sliding window. Afterwards, the concatenated histogram descriptor is computed for different window sizes and with different radii for the neighborhood of each pixel.

3.1.6 Binarized Statistical Image Features

Binarized Statistical Image Features (BSIF) was proposed by Kannala and Rahtu [21] in 2012. It was implemented for texture classification and human recognition using face images. Based on LPQ and LBP, the main idea of BSIF is to automatically learn a fixed set of filters from a small set of natural images, instead of using filters that are manually constructed such as in LPQ and LBP. The learning process to construct statistically independent filters has three main steps:

1- Mean subtraction of each patch.

2- Dimensionality reduction using PCA.

3- Estimation of statistically independent filter using Independent Component Analysis (ICA).

The values of each bit within the BSIF descriptor is computed by quantizing the response of a linear filter. Each bit in the string is associated to a particular filter and the number of bits determines the number of filters used. The set of filters is learned from a training set of natural image patches by maximizing the statistical independence of the filter responses. Given an image patch X of size $l \times l$ pixels and a linear filter W_i of the same size, the filter response s_{i} is obtained by Equation 3.12:

$$s_i = \sum_{u,v} W_i(u,v)X(u,v) = w_i^T x, \tag{3.12}$$

where vectors w and x contain the pixels of W_{i} and X. Furthermore, the binarized feature b_{i} is obtained by Equation 3.13:

$$b(i) = \begin{cases} 1, & s_i > 0 \\ 0, & otherwise \end{cases} \tag{3.13}$$

As in LBP, the binary code word is then mapped to a real value between 0 and 2^{x} for x different filters. Finally a histogram is created from the mapped values in the BSIF image for describing the local properties of the image texture.

3.2 Fusion Level Approaches

Biometric fusion can be implemented in two different modes, either prior to matching process or after matching process. In this study, fusion techniques from each biometric fusion mode were used such as feature-level, score-level and decision-level fusion techniques. Feature-level fusion represents biometric fusion prior to matching. However, score-level and decision-level fusions are methods of biometric fusion techniques that are implemented after matching process. There are many biometric systems employing fusion of different levels [48, 58–60].

3.2.1 Feature-level Fusion

Consolidating two or more feature sets of different biometric traits of the same user in order to form them as one feature set is a definition of feature or representation-level fusion [61]. Feature-level fusion can be classified into two different classes such as homogenous and heterogeneous feature fusion. A homogeneous feature fusion scheme combines multiple feature sets of different samples of the same biometric trait by using the same feature extraction such as minutia sets of two or more impressions of one finger. On the other hand, heterogeneous feature fusion techniques are used when the feature sets are corresponding to samples that are captured from different biometric traits (or different instances of a single trait) or extracted from different algorithms for feature extraction. The block diagram of feature-level fusion is presented in Figure 9 .

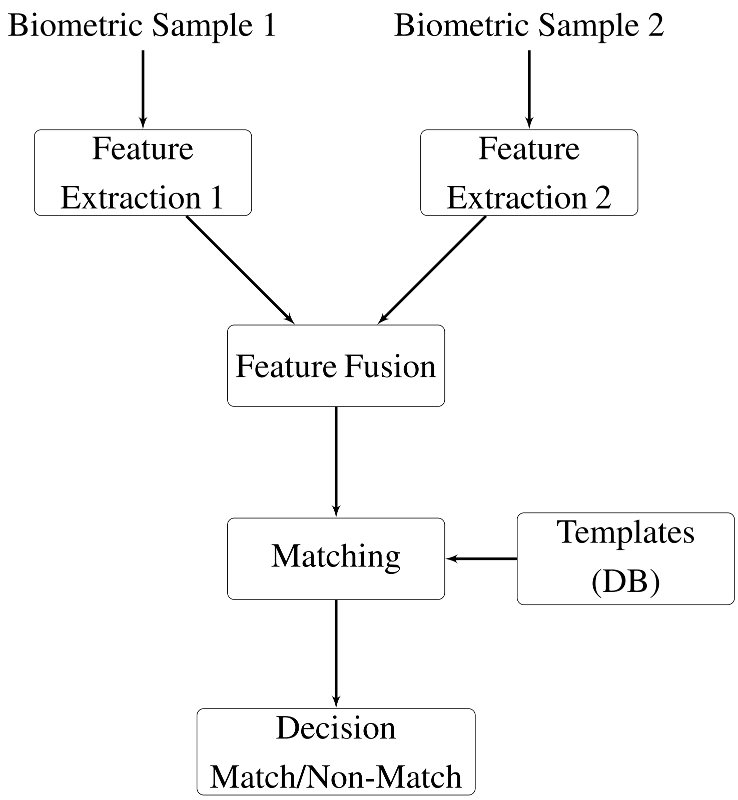

Figure 9: General Block Diagram of Feature-level Fusion

3.2.2 Score-level Fusion

When a final recognition decision can be acquired by combining two or more match scores of different biometric matchers as shown in Figure 10, fusion is considered to be implemented at the score-level [62]. After capturing the raw data from sensors and extracting feature vectors, the next level of fusion is based on match scores. In multibiometric systems, score-level fusion is the most commonly used method because of the scores, which are generated by different biometric matchers, are relatively easy to be accessed and combined. There are many types of score-level fusion such as likelihood-ratio-based fusion and transformation-based fusion. In this work, transformation-based fusion (Sum Rule) is used.

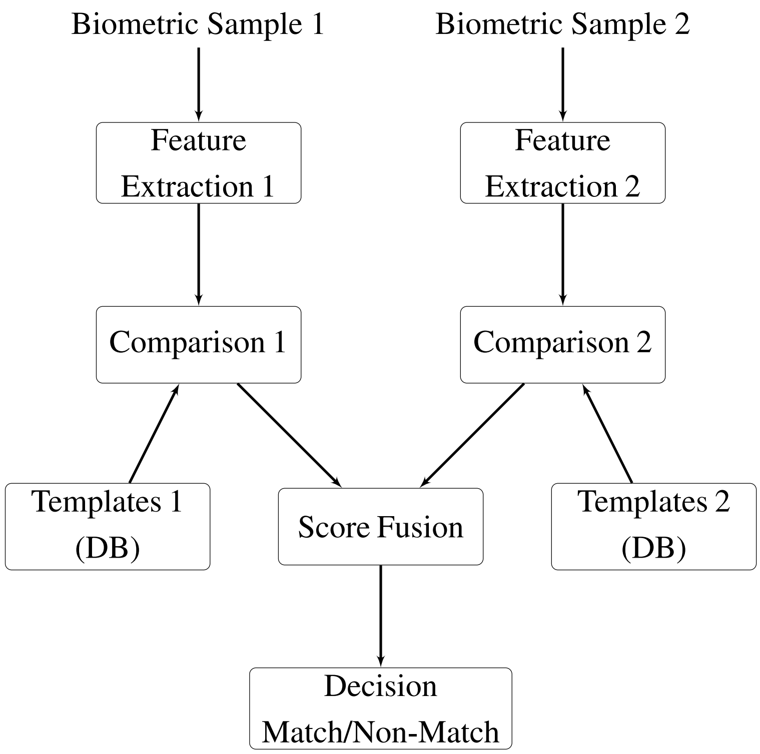

Figure 10: General Block Diagram of Score-level Fusion

3.2.3 Decision-level Fusion

In a multibiometric system, fusion process is conducted at decision-level when only the decision outputs of multiple matchers are available [63] as shown in Figure 11. The decision level fusion rules such as AND and OR rules, Bayesian decision fusion, majority voting, the Dempster-Shafer theory of evidence, and behavior knowledge space are used to integrate the multiple decisions to produce the final decision. In this study, we used a hybrid decision-level fusion strategy which is explained in the next section.

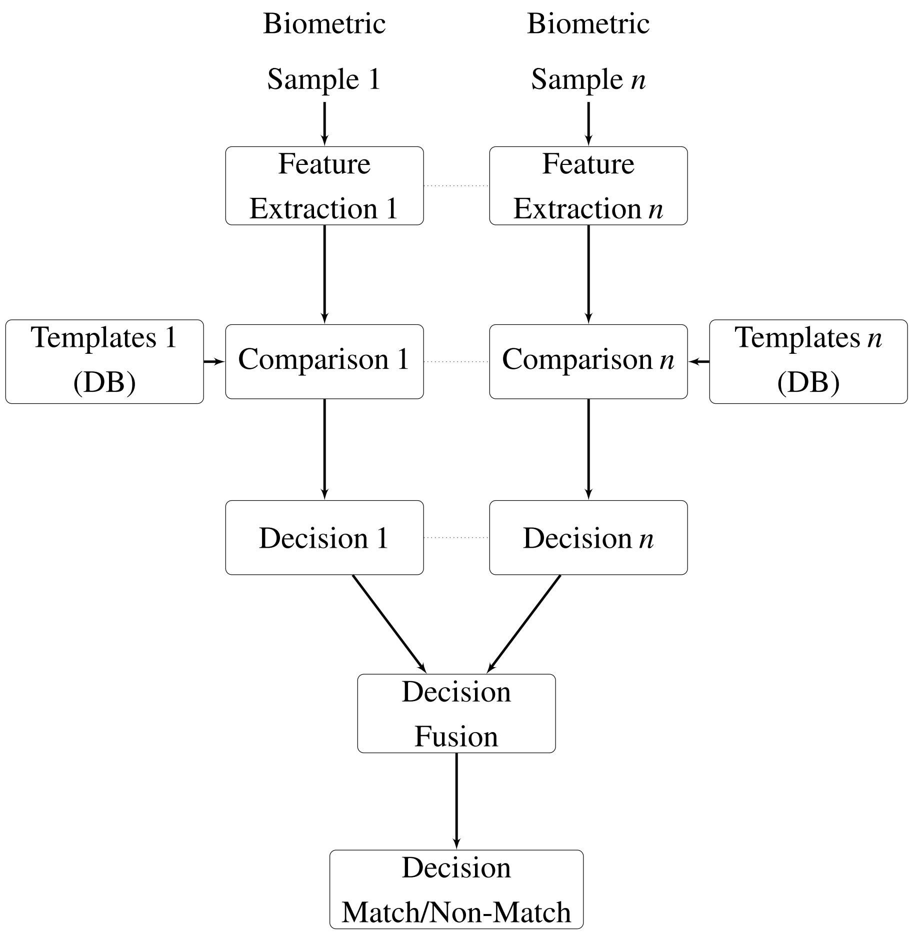

Figure 11: General Block Diagram of Decision-level Fusion

Chapter 4

RECOGNITION OF IDENTICAL TWINS USING FRONTAL FACE

4.1 An Overview of The Proposed Method 1

Distinguishing identical twins using their face images is a challenge in biometrics. The goal of these experiments is to construct a biometric system that is able to give the correct matching decision for the recognition of identical twins. We propose a method that uses feature-level fusion, score-level fusion and decision-level fusion with Principal Component Analysis (PCA), which generates a compact representation of the entire region of the biometric sample in the acquired image (such as the general geometry of the face and global skin color), Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) feature extractors, which try to find robust local features (micro level features such as scars, freckles, skin discoloration, and moles) that are invariant to pose or lighting variations. In the experiments, face images of identical twins from ND-TWINS-2009-2010 database are used. The results show that the proposed method 1 is better than the state-of-the-art methods for distinguishing identical twins. Variations in illumination, expression, gender, and age of identical twins' faces were also considered in this study. The experimental results of all variation cases demonstrated that the most effective method to distinguish identical twins is the proposed method 1 compared to the other approaches implemented in this study. The lowest Equal Error Rates of identical twins recognition that are achieved using the proposed method 1 are 2.07% for natural expression, 0.0% for smiling expression and 2.2% for controlled illumination compared to 4.5%, 4.2% and 4.7% Equal Error Rates of the best state-of-the-art algorithm under the same conditions. Additionally, the proposed method 1 is compared with the other methods for non-twins using the same database and standard FERET subsets. The results achieved by the proposed method 1 for non-twins identification are also better than all the other methods under expression, illumination and ageing variations.

4.2 Description of The Proposed Method 1

A novel method for the recognition of identical twins is proposed and implemented in the experiments of this chapter. The proposed method 1 is based on the output of feature fusion and score fusion of HOG and LBP methods beside the output of the decision fusion of LBP, HOG and PCA approaches as shown in Figure 12 and 13. The proposed method 1 works under verification mode, therefore, the user must claim his/her identity in order to check if he/she is genuine or impostor. On the other hand, if the user is recognized as impostor in any partial decision, the recognized ID will be used, where the system checks not only the template of the claimed ID but also all the stored templates of all the users that are stored in the database. In the case that the user is not recognized and it is not included in the database, the partial decision becomes "unrecognized".

The main steps of the proposed method 1 are presented below:

1. Apply feature-level and score-level fusion using HOG and LBP in addition to decision-level fusion using PCA, HOG and LBP.
2. Partial decisions from each level of fusion will be acquired as follows: If (Partial

Decision=Genuine) Then Ri=1, Else (Partial Decision=(Impostor/ Not Recognized)) Ri=0 (Ri represents partial decision output (1:genuine, 0:impostor/ Not Recognized) for each fusion level).

3. In both decision cases, either genuine or impostor, Partial Decision will present the recognized ID of the individual.
4. If two or more of the fusion levels recognize the input image as genuine based on the claimed ID, the whole system will recognize the user in the final decision as genuine.
5. In the case of only one fusion level recognizes the input image as genuine, the system will check the recognized IDs (ID/ Not Recognized) of other algorithms. If they are not the same, the whole system will recognize the user in the final decision as genuine, otherwise the system will recognize the user as impostor. Table 1 clarifies this step.

Table 1: Combination possibilities of partial decisions

First Partial Decision	Second Partial Decision	Third Partial Decision	Final Decision
Genuine	Genuine	Genuine	Genuine
Impostor (ID:A)	Genuine	Genuine	Genuine
Genuine	Not Recognized	Genuine	Genuine
Genuine	Not Recognized	Impostor (ID:A)	Genuine
Impostor (ID:A)	Genuine	Impostor (ID:B)	Genuine
Not Recognized	Not Recognized	Genuine	Impostor
Impostor (ID:B)	Genuine	Impostor (ID:B)	Impostor

Figure 12 shows the general block diagram of the proposed method 1 while the details related to the second decision-level are presented in Figure 13.

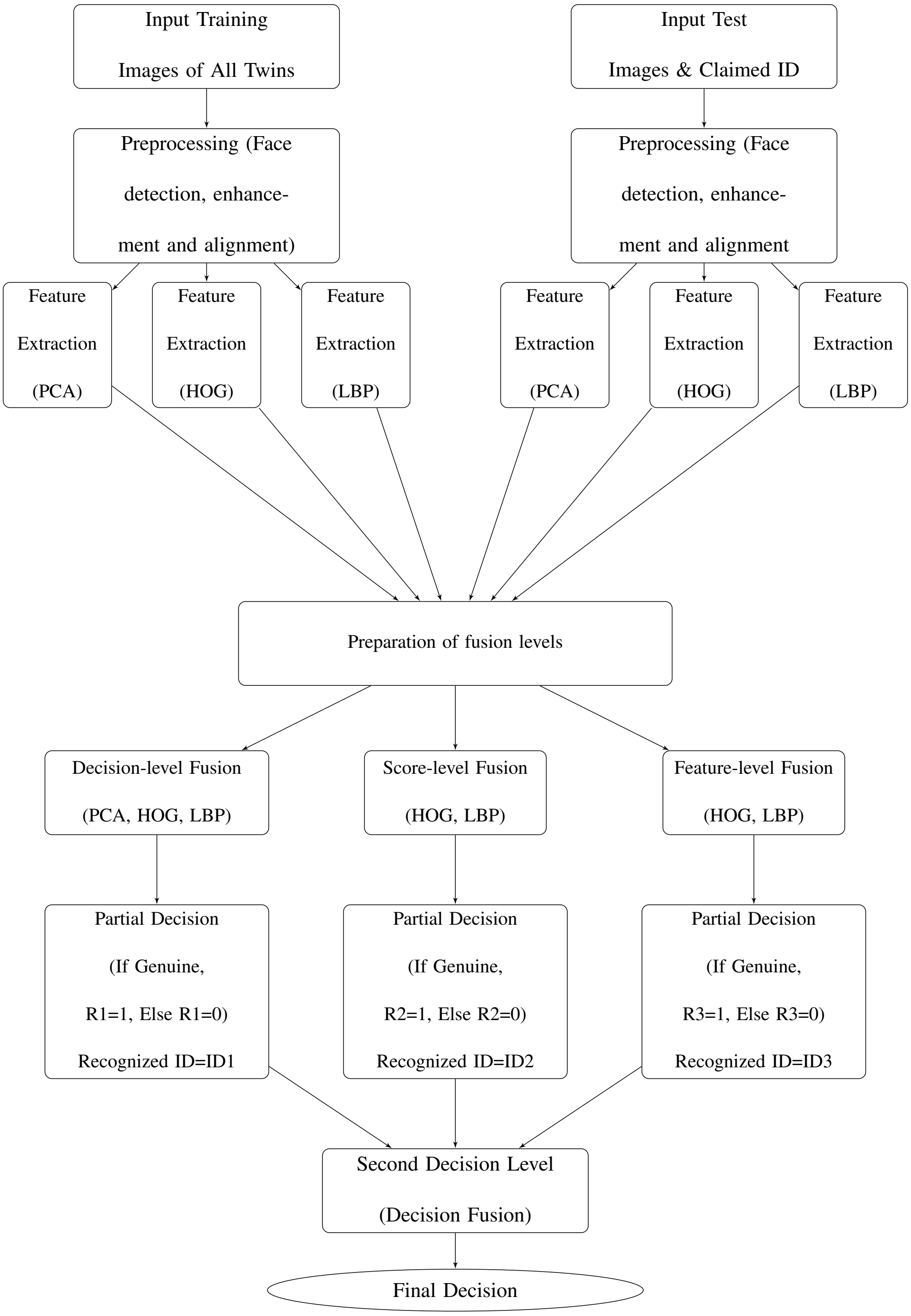

Figure 12: Block Diagram of the Proposed Method 1

4.3 Experiments and Results of The Proposed Method 1

In order to demonstrate the validity of the proposed method 1 in distinguishing identical twins, several experiments have been conducted on ND-TWINS-2009-2010 Dataset

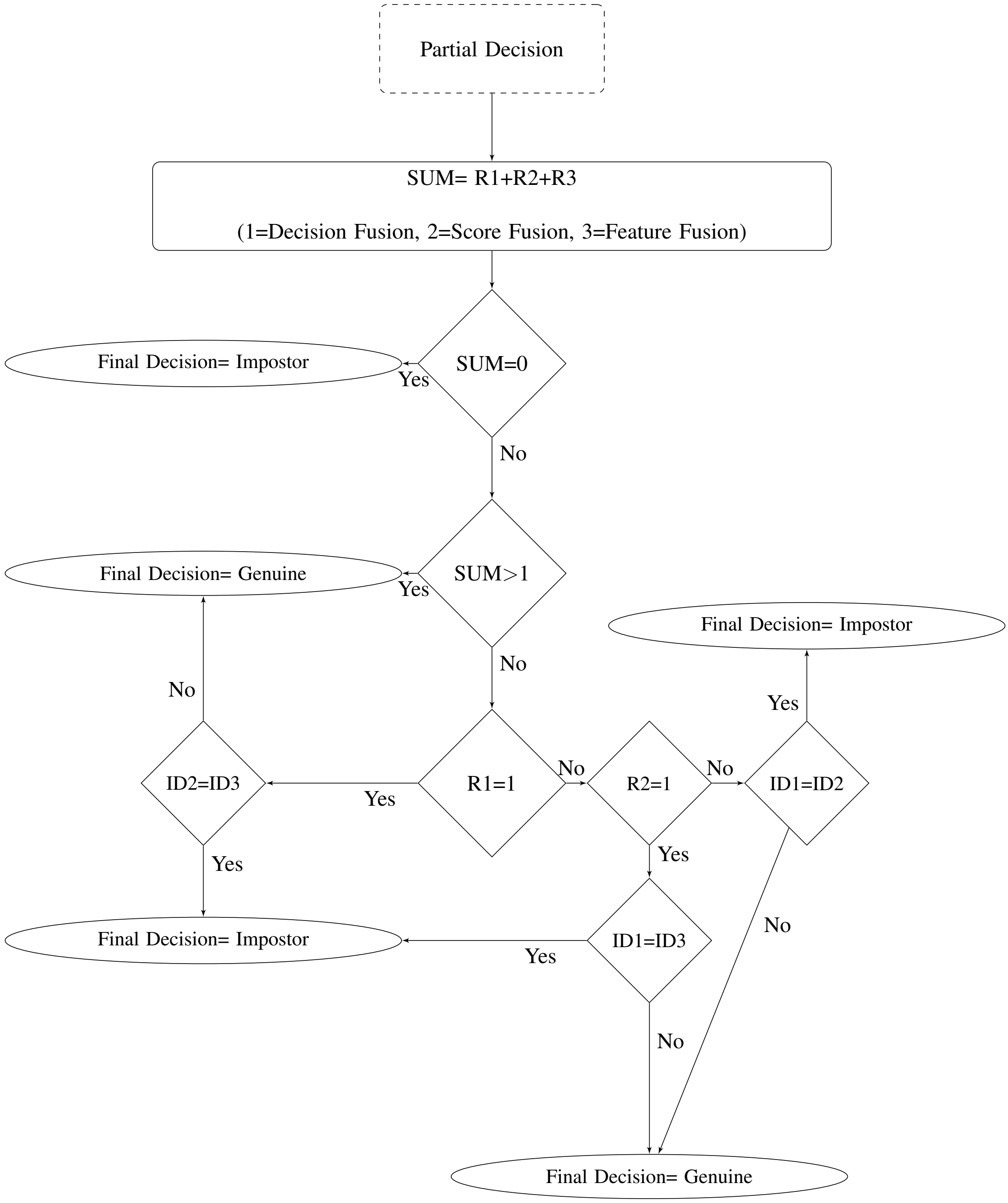

Figure 13: The Second Decision-level of the Proposed Method 1

[16, 64]. The following subsections present the details about the dataset used, the experimental setup and the results of different types of experiments such as expression-based, illumination-based, gender-based and age-based experiments. Additionally, experiments related to the recognition of non-twins are also presented in the following

subsections using ND-TWINS-2009-2010 and FERET [65, 66] datasets.

4.3.1 ND-TWINS-2009-2010 Dataset

ND-TWINS-2009-2010 Dataset contains 24,050 color photographs of the faces of 435 attendees of the Twins Days Festivals in Twinsburg, Ohio performed in 2009 and 2010. All images were captured by Nikon D90 SLR cameras. Images were captured under natural light in ”indoor” and ”outdoor” configurations (”indoor” was a tent). Facial capturing angle varied from -90 to +90 degrees in steps of 45 degrees (zero degrees were frontal). Additionally, images were captured under natural and smiling expression. Example images can be seen in Figure 14 for two different people (identical twins) where each image shows two different samples of the same person. Figure 15 also demonstrates two different images for twins of more than 40 year old women.

4.3.2 Standard FERET Dataset

The standard FERET dataset is a subset of FERET database that contains 1196 gallery images for training and four different subsets of FERET database images under various challenges. The training images that are in category fa (1196 images) are used as gallery images for four probe sets namely fb, fc, duplicate I and duplicate II. The subset fb includes 1195 images with variations in expressions. The subset fc includes 194 images with illumination variations. On the other hand, images with ageing variations are in Duplicate I and Duplicate II subsets. Duplicate I subset consists of 722 facial images which are recorded at different times compared to fa subset images. Duplicate II is a subset of Duplicate I (234 images) which includes images taken at least 18 months later after the gallery image was taken. Duplicate I and Duplicate II subsets are useful for ageing experiments using face recognition methods. The standard FERET

(a)

(b)

Figure 14: Examples of Frontal Faces of Male Subjects Who are Younger than 40. Images in (a) are of the First Twin Under Different Illumination and Expression while Images in (b) are of the Second Twin Under Different Illumination and Expression

subsets are used in this study to compare various face recognition algorithms and the proposed method 1 under different challenges for non-twins. Figure 16 presents some face images of FERET dataset.

Figure 15: Examples of Frontal Faces of Female Subjects Who are Older than 40. Images in (a) are of the First Twin Under Different Expression and Controlled Illumination While Images in (b) are of the Second Twin Under Different Expression and Uncontrolled Illumination

4.3.3 Experimental Setup of The Proposed Method 1

A set of experiments is conducted for identical twins based on their face images by using 352 users (176 identical twins) and 1512 image samples from ND-TWINS-2009-2010 Dataset. Three algorithms, namely Principal Component Analysis (PCA),

Figure 16: Sample Images of FERET Dataset

Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) are implemented for comparison purposes. Additionally, three fusion methods namely feature-level, score-level and decision-level fusion and the proposed method 1 are implemented in order to find the most reliable system that is able to correctly match identical twins by face recognition. The effect of the four conditions (illumination, expression, gender and age) is also examined. All the selected images in the experiments were frontal face images without glasses. Manhattan distance measure is used to measure the similarity between test and train images.

The unimodal biometric systems that are implemented in this study use PCA, HOG and LBP. For PCA, we use the maximum number of non-zero eigenvectors. HOG algorithm uses 64×128 image size, and divides the facial image into 16×16 blocks with 50% overlapping. The images are also processed using LBP by dividing it to 5×5 partitions (segments).

The performance of the proposed method 1 is also measured in the case of non-twins using ND-TWINS-2009-2010 dataset. These set of experiments are conducted by dividing 176 identical twins into two equal groups. The first group contains the first brother/sister of each twin, while the second group contains the second brother/sister of each twin. In that case, each group contains 88 of users who are not twins. By implementing the same type of experiments on these two groups separately, the face recognition performance on non-twins is measured. Using the same database, same users and same samples in the recognition experiments on twins and non-twins, the comparison is more realistic than using different database, since the capturing conditions of images such as illumination, expression, distance to camera, etc. are the same.

On the other hand, standard FERET subsets are also used to evaluate the proposed method 1 in the absence of identical twins. In this study, five different subsets of FERET Database are used namely ”fa”, ”fb”, ”fc”,”duplicate I” and ”duplicate II” subsets. The first subset which is named as ”fa” contains frontal face images with ideal conditions (natural expression and controlled lighting) and it is used for training (gallery) purposes. On the other hand, ”fb” subset includes frontal face images with alternative face expression. In ”fc” subset, the included frontal face images were captured under uncontrolled illumination. ”duplicate I” subset contains probe frontal face images that were obtained anywhere between one minute and 1031 days after their respective gallery matches. Additionally, ”duplicate II” subset includes probe frontal face images that are a strict subset of the ”duplicate I” images and they are those taken only at least 18 months after their gallery entries. ”fb”, ”fc”, ”duplicate I” and ”duplicate II” subsets are used for testing operations.

The performance of all algorithms is measured and reported by Equal Error Rate (EER). EER is defined as the point that False Reject Rate (FRR) and False Accept Rate (FAR) have the same value. EER is also used to compare the efficiency of the implemented methods under different conditions.

4.3.4 Experiments on ND-TWINS-2009-2010 Dataset

We conducted four sets of experiments using ND-TWINS-2009-2010 dataset. These are expression-based, illumination-based, gender-based and age-based experiments. The following subsections present the details of these experiments for the recognition of identical twins and non-twins separately.

4.3.4.1 Expression-Based Experiments

The first set of experiments aim to measure the efficiency of face recognition for identical twins and non-twins under the condition of expression variation. In these experiments, both smiling and natural expressions of the face image that were captured under controlled lighting were used. Tables 2 and 3 show the EER of natural-natural

(N-N), natural-smiling (N-S), and smiling- smiling (S-S) as training-test combination for identical twins and non-twins, respectively. Expression-Based Experiments show that the variation of expression between training and test samples negatively affects the performance of the recognition system where the EER of proposed method 1 is 3.24% under different expression (natural versus smiling) while the EER's under the same expression (natural versus natural and smiling versus smiling) are 2.07% & 0%, respectively.

Figures 17 and 18 demonstrate the ROC curves for Natural-Natural Expression and Natural-Smiling Expression, Controlled-Controlled Illumination and Cont-Uncont Illumination, respectively. The ROC curves show that the proposed method 1 outperforms the fusion of LBP and HOG in feature level and LBP algorithm as unimodal system.

4.3.4.2 Illumination-Based Experiments

Various face images that were captured under same and different lighting conditions are used in the second set of experiments. For these experiments, there are two possibilities: controlled illumination (image acquired under the tent) and uncontrolled illumination (images acquired outdoor in rainy or sunny weather). Using face images that were captured under controlled and uncontrolled illumination, the tests were conducted in three different cases, namely Controlled - Controlled (C-C), Controlled - Uncontrolled (C-U), and Uncontrolled - Uncontrolled (U-U) as training-test combinations. Tables 4 and 5 show the EER results of these experiments performed under illumination conditions for identical twins and non-twins, respectively. Illumination-Based Experiments show that the variation of illumination between training and test

Table 2: EER results of expression-based experiments for identical twins

		EER Results (%) of		
	Expression (Training-Test)	Natural-Natural	Natural-Smiling	Smiling-Smiling
Implemented algorithms	PCA	12.65	24.54	20.83
	HOG	5.60	11.11	4.17
	LBP	2.76	8.80	0
	Score fusion (PCA, HOG, LBP)	3.76	11.11	3.13
	Score fusion (HOG, LBP)	2.30	4.63	2.09
	Feature fusion (PCA, HOG, LBP)	3.53	6.02	4.17
	Feature fusion (HOG, LBP)	2.38	4.17	0
	Decision fusion (PCA, HOG, LBP)	3.37	6.94	0
	proposed method 1	**2.07**	**3.24**	0
Algorithms Implemented in [35]	A	4.50	7.00	4.20
	B	39.40	39.20	40.00
	C	6.70	37.60	7.40
	D	22.20	22.90	19.90
	E	14.40	13.50	13.50
	F	9.40	10.80	9.30
	G	7.70	8.80	6.80

samples reduces the performance of the recognition system where the EER of proposed method 1 is 10.77% under different illumination (controlled versus uncontrolled) while the EER's under the same illumination (controlled versus controlled and uncontrolled versus uncontrolled) are 2.2% & 4.04%, respectively.

Table 3: EER results of expression - based experiments for non-twins

		EER Results (%) of of		
	Expression (Training-Test)	Natural-Natural	Natural-Smiling	Smiling-Smiling
Algorithms	PCA	4.4	6.4	3.6
	HOG	0.8	3.6	0.0
	LBP	0.0	2.8	0.0
	Score fusion (PCA, HOG, LBP)	0.0	2.8	1.2
	Score fusion (HOG, LBP)	0.0	1.2	0.0
	Feature fusion (PCA, HOG, LBP)	0.0	1.6	0.0
	Feature fusion (HOG, LBP)	0.0	0.4	0.0
	Decision fusion (PCA, HOG, LBP)	0.0	2.0	0.0
	Proposed Method	0.0	**0.0**	0.0

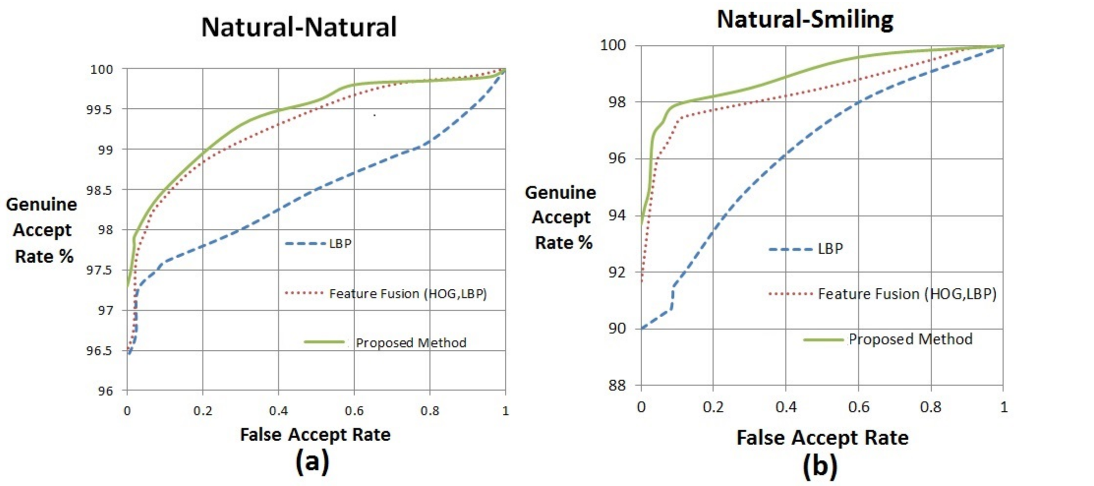

Figure 17: ROC Curves for: (a) Natural - Natural Expression / (b) Natural - Smiling Expression

Table 4: EER results of illumination - based experiments for identical twins (Cont: Controlled Condition, Uncont: Uncontrolled Condition)

		EER Results (%) of		
	Illumination (Training-Test)	Cont-Cont	Cont-Uncont	Uncont-Uncont
Implemented algorithms	PCA	12.01	31.15	14.04
	HOG	6.09	25.77	9.23
	LBP	3.45	12.69	4.08
	Score fusion (PCA, HOG, LBP)	4.40	20.19	9.04
	Score fusion (HOG, LBP)	2.58	13.65	5.77
	Feature fusion (PCA, HOG, LBP)	3.89	21.92	8.27
	Feature fusion (HOG, LBP)	2.58	12.88	**4.04**
	Decision fusion (PCA, HOG, LBP)	3.58	12.50	4.81
	proposed method 1	**2.20**	**10.77**	**4.04**
Implemented algorithms in [35]	A	4.70	5.90	11.50
	B	35.90	40.70	41.40
	C	9.00	34.10	32.30
	D	14.50	20.90	26.50
	E	10.20	13.80	24.00
	F	7.30	12.40	19.40
	G	8.00	7.80	16.20

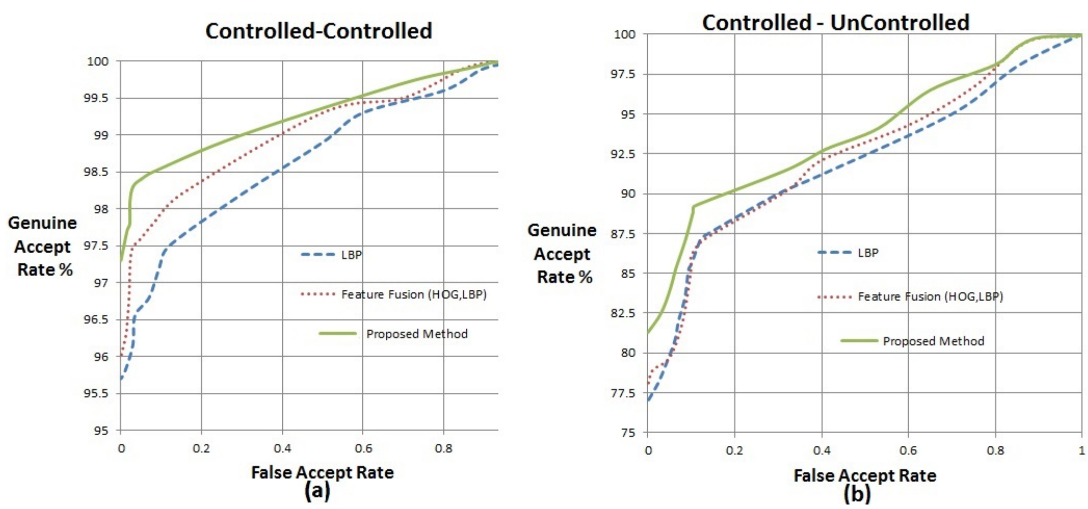

Figure 18: ROC Curves for (a) Controlled-Controlled Illumination / (b) Controlled-Uncontrolled Illumination

Table 5: EER results of illumination - based experiments for non-twins (Cont: Controlled Condition, Uncont: Uncontrolled Condition)

		EER Results (%) of		
	Illumination (Training-Test)	Cont-Cont	Cont-Uncont	Uncont-Uncont
Algorithms	PCA	8.3	17.7	10.8
	HOG	3.7	11.4	5.7
	LBP	1.7	8.5	2.8
	Score fusion (PCA, HOG, LBP)	2.5	9.4	5.7
	Score fusion (HOG, LBP)	0.6	6.3	2.8
	Feature fusion (PCA, HOG, LBP)	1.1	8.2	4.6
	Feature fusion (HOG, LBP)	0.6	8.0	1.7
	Decision fusion (PCA, HOG, LBP)	1.1	6.3	2.3
	proposed method 1	**0.0**	**5.7**	**1.1**

4.3.4.3 Gender-Based Experiments

In the next set of experiments, we separated the subjects used in the previous experiments (expression-based and illumination -based) to male and female face images. The experiments were performed based on gender as female and male in which the facial images are grouped separately. The results based on EER values of identical twins and non-twins are shown on Tables 6 and 7, respectively. Gender-Based Experiments show that the recognition of female is harder than recognition of male where the female normally uses make up which hides most of the discriminate micro features. The EER's of the proposed method 1 are 3.9% & 4.64% for male and female, respectively.

4.3.4.4 Age-Based Experiments

The goal of the last experiment set is to study the effect of age using several algorithms for distinguishing identical twins and non-twins. Therefore, the images are divided into two categories based on age: over 40 years old and 40 years old and younger. The

Table 6: EER results of gender - based experiments for identical twins

		EER Results (%) of	
	Gender	Male	Female
Implemented algorithms	PCA	14.94	17.56
	HOG	11.42	10.81
	LBP	4.91	5.64
	Score fusion (PCA, HOG, LBP)	6.74	9.12
	Score fusion (HOG, LBP)	6.12	5.54
	Feature fusion (PCA, HOG, LBP)	8.88	8.70
	Feature fusion (HOG, LBP)	4.04	5.38
	Decision fusion (PCA, HOG, LBP)	4.55	6.07
	proposed method 1	**3.90**	**4.64**
Implemented algorithms in [35]	A	4.10	8.10
	B	39.40	39.10
	C	7.30	35.10
	D	22.30	21.30
	E	14.10	16.70
	F	9.80	13.10
	G	6.70	11.50

results of these experiments are demonstrated on Tables 8 and 9 for identical twins and non-twins, respectively. Results of Age-Based Experiments are not significantly affected by variation in age where EER's of the proposed method 1 are 3.85% & 4.5% for both cases.

4.3.5 Experiments on Standard FERET Datasets for Non-twins Recognition

In these experiments, proposed method 1 is evaluated using non-twins face images. Table 10 shows the EER results of non-twins recognition using standard FERET subsets. These set of experiments are conducted under three different challenges namely

Table 7: EER results of gender - based experiments for non-twins

		EER Results (%) of	
	Gender	Male	Female
Algorithms	PCA	8.1	8.7
	HOG	4.0	4.3
	LBP	2.2	2.7
	Score fusion (PCA, HOG, LBP)	3.3	3.7
	Score fusion (HOG, LBP)	1.5	1.8
	Feature fusion (PCA, HOG, LBP)	2.1	2.5
	Feature fusion (HOG, LBP)	1.5	1.8
	Decision fusion (PCA, HOG, LBP)	1.7	2.1
	proposed method 1	**0.6**	**0.9**

expression, illumination and ageing variations. The results show that the illumination is the hardest challenge compared to expression and ageing problems.

4.3.6 Results and Discussion

All the experimental results demonstrate that the decision fusion (PCA, HOG, LBP) is better than or comparable with the state-of-the-art methods. However, the proposed method 1 is better than the decision fusion (PCA, HOG, LBP) and it shows superior performance compared to the state-of-the-art methods in this field for all types of experimental conditions including expression, illumination, gender and age variations. The high performance of the proposed method 1 is caused by the usage of a combination of feature-level, score-level and decision-level fusion in one method in addition to the usage of different voting techniques in the second decision level.

Distinguishing identical twins under standard conditions is possible as shown in the experimental results. However, when conditions of the captured images are not ideal,

Table 8: EER results of age - based experiments for identical twins

		EER Results (%) of	
	Age	40 & Younger	Over 40
Implemented algorithms	PCA	14.54	17.10
	HOG	11.89	10.14
	LBP	4.00	5.59
	Score fusion (PCA, HOG, LBP)	7.55	8.51
	Score fusion (HOG, LBP)	6.36	5.16
	Feature fusion (PCA, HOG, LBP)	8.79	8.53
	Feature fusion (HOG, LBP)	3.92	5.36
	Decision fusion (PCA, HOG, LBP)	5.79	5.30
	proposed method 1	**3.85**	**4.50**
Implemented algorithms in [35]	A	9.60	7.40
	B	38.40	39.00
	C	15.50	34.10
	D	24.30	21.60
	E	19.40	21.60
	F	14.50	12.50
	G	13.50	11.00

distinguishing identical twins is a hard challenge. Identical twins represent a very difficult recognition problem and the results achieved for the recognition of identical twins are worse than the results obtained to recognize non-twins.

4.4 Conclusions of The Proposed Method 1

A novel method is proposed for the solution of distinguishing identical twins by using facial images. The proposed method 1 uses feature-level fusion, score-level fusion and decision-level fusion with three feature extraction approaches. PCA, HOG and LBP are implemented as feature extractors and matching is performed using KNN. Var-

Table 9: EER results of age - based experiments for non-twins

		EER Results (%) of	
	Age	40 & Younger	Over 40
Algorithms	PCA	10.3	8.0
	HOG	5.1	3.3
	LBP	3.1	2.9
	Score fusion (PCA, HOG, LBP)	3.9	3.1
	Score fusion (HOG, LBP)	1.7	1.7
	Feature fusion (PCA, HOG, LBP)	2.5	2.7
	Feature fusion (HOG, LBP)	2.1	1.9
	Decision fusion (PCA, HOG, LBP)	1.9	1.7
	proposed method 1	**1.0**	**0.8**

ious experiments are conducted using ND-TWINS-2009-2010 and standard FERET Datasets. The experiments that use ND-Twins-2009-2010 database are performed under different illumination, expression, age and gender conditions using samples of identical twins and non-twins separately. Additionally, the performance of the proposed method 1 is measured using standard FERET Dataset of non-twins' faces under different expression, illumination and ageing conditions. Experiments show that the recognition of identical twins is harder when the conditions of capturing samples are different. Consequently, the degree of difference between images is lower when both training and test samples are acquired under the same conditions such as uniform lighting and natural expression. Results are not significantly affected by variation in age and gender. In addition, the high similarity between identical twins significantly affects the performance of any recognition system compared with the non-twins case. The proposed method 1 is compared with four unimodal and five multimodal systems that are conducted in this work in addition to seven state-of-the-art algorithms.

Table 10: EER results for non-twins using standard FERET subsets under expression, illumination and age variations

		EER Results (%) of			
	Challenge	Expression	Illumination	Ageing	Ageing
	Subset	(fb)	(fc)	(Duplicate I)	(Duplicate II)
Algorithms	PCA	11.4	34.3	23.2	30.7
	HOG	9.5	31.9	13	14
	LBP	3.43	24.9	11.15	12
	Score fusion (HOG, LBP)	5.9	24.2	10.25	10.7
	Feature fusion (PCA, HOG, LBP)	8.7	28.1	11.15	14
	Feature fusion (HOG, LBP)	3.9	24.5	10.75	12
	Decision fusion (PCA, HOG, LBP)	2.9	21.8	8.15	8.7
	Proposed Method	**2.5**	**20.6**	**7.5**	**8**

The lowest Equal Error Rates of identical twins recognition that are achieved using the proposed method 1 are 2.07% for natural expression, 0.0% for smiling expression and 2.2% for controlled illumination compared to 4.5%, 4.2% and 4.7% Equal Error Rates of the best state-of-the-art algorithm under the same conditions. Consequently, all the experimental results demonstrate that the proposed method 1 outperforms all aforementioned techniques under different expression, illumination, gender and ageing conditions for both identical twins and non-twins recognition.

Chapter 5

IDENTICAL TWINS RECOGNITION USING SYMMETRY OF PROFILE FACE AND EAR

Most of the people can match the right side of a biometric trait by comparing the left side of the same trait and vice versa. In other words, bilateral symmetry may help the brain to recognize when the body is in different angles. Therefore, an automated system can also be trained to recognize a user using the other side of the trait that is stored in the database. This can be very useful since most of the biometric traits have right and left sides such as profile face, ear, palmprint, iris, and fingerprint. This type of recognition can be widely used in passive biometric systems such as surveillance and forensics that may suffer to capture the same side of a biometric trait that is stored in the database due to non-cooperation of the user with the system. Capturing the same side of a biometric trait which is stored as a template under some challenges such as inconvenient pose, occlusion or non-uniform illumination may be compensated by using the other side of a trait that is not used and stored in the training phase.

Biometric traits are captured in two different methods; the first method requires direct contact between the user and sensor such as in fingerprint and palmprint biometrics, and the second method captures the trait from a far distance such as in face and ear biometrics. It is clear that the recognition process that uses the mirror of a biometric trait is more effective when the trait is captured from a far distance of sensor. In this study, two different biometric traits that can be captured from a far distance and do not require direct contact with sensor are used for human recognition. Profile face and ear are tested to assess the symmetry of left/right side with the other mirrored side of the same trait of identical twins and non-twins as shown in Fig. 19 and 20.

5.1 An Overview of The Proposed Method 2

Profile face and ear of identical twins and non-twins are used and fused in this work because they have the advantage of acquiring data in a single capture, device and image over the other fusion possibilities which decreases the cost and time of acquiring and collecting biometric data. Therefore, the individual is willing to provide his biometric trait to the sensor of the system with as little inconvenience as possible. Additionally, ear biometrics can work in recognition systems as supplement for other modalities such as profile face. Whenever the face recognition process struggles with profile faces, the ear can serve as a source of information on the identity of people in many biometric applications such as surveillance, forensics and security.

Apart from enhancement of the recognition rate, the main goal of this work is to find to what extent the symmetry of profile face and ear of identical twins and non-twins can be used to recognize people as a standalone biometric system or it can only serve to support and enhance other biometric systems.

Profile face and ear biometric traits that are used in this thesis have four properties for a potential biometrics: universality, uniqueness, permanence and collectability. Both face and ear may not require the cooperation of user (passive biometric traits). Face as a biometric trait is more commonly used compared to ear traits because it is easier

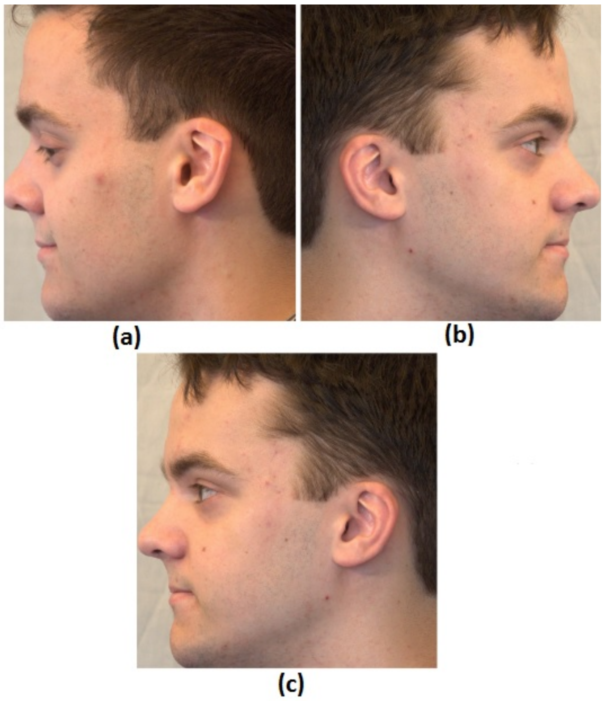

Figure 19: (a) Left Profile Face / (b) Right Profile Face / (c) Mirroring of Right Profile Face (Horizontal Flipping)

to capture the face images than other traits and the number of features that can be extracted from ear is less than the extracted features of the face.

Many challenges may affect human recognition rate such as Ageing and expression variations in which face trait suffers from [1]. Other challenges are common among many traits namely lighting variation, pose variation, and occlusion. The challenge that is considered in this thesis is the extent of ”symmetry” and ”asymmetry” between the left and right side of profile face and ear. The objective is to test to what extent this approach can be exploited in biometric verification and identification process. In other words, the possibility of identifying individuals using unimodal biometric system based on matching symmetry of bilateral traits is measured as demonstrated in Fig.21. Principal Component Analysis (PCA), Scale-invariant Feature Transform (SIFT), Lo-

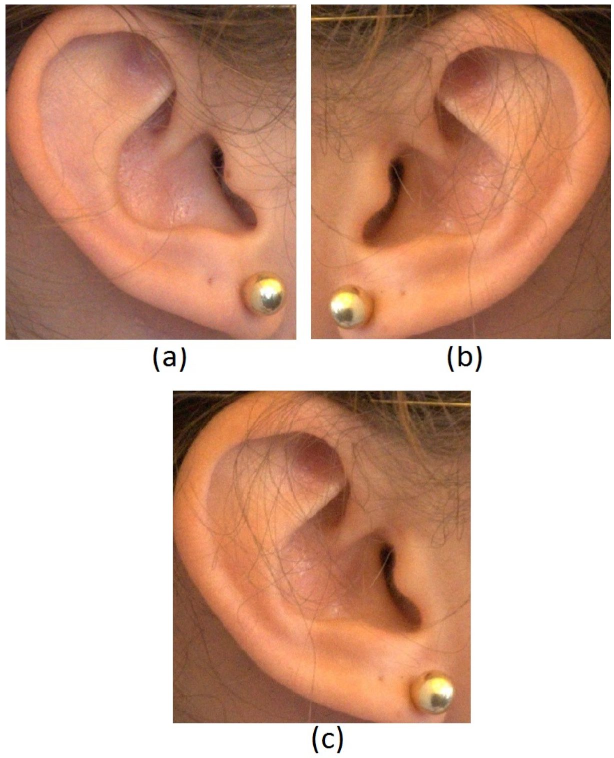

Figure 20: (a) Right Ear / (b) Left Ear / (c) Mirroring of Left Ear (Horizontal Flipping)

cal Binary Patterns (LBP), Local Phase Quantization (LPQ) and Binarized Statistical Image Features (BSIF) algorithms are used in feature extraction process.

The work presented in this chapter is unique in several points with respect to prior works. It is the first study that measures the symmetry of profile face biometric traits either for identical twins or non-twins individuals. Additionally, only one other work [46] has considered identical twins for ear symmetry experiments and we compare five feature extraction approaches to measure the symmetry of profile face and ear biometric systems for identical twins and non-twins users. Moreover, a novel method that uses feature-level and score-level fusion to fuse two bilateral and symmetric traits (profile face and ear) is proposed and implemented.

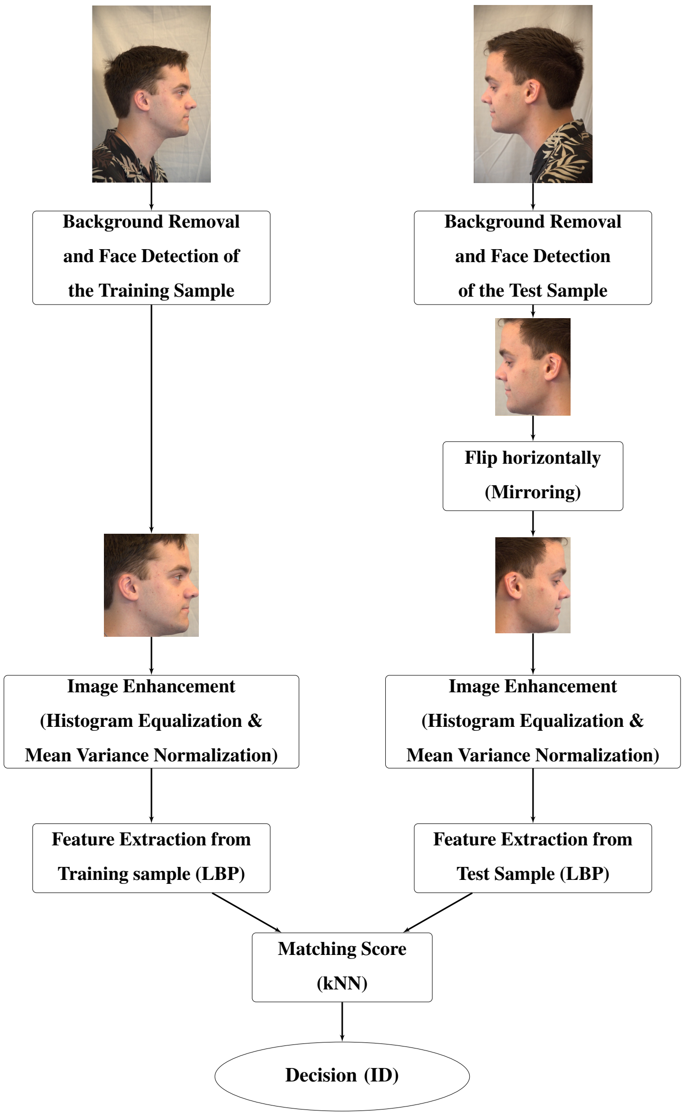

Figure 21: Block Diagram of a Unimodal Symmetric Recognition System Using Left and Right Profile Face Biometric Trait

5.2 Description of The Proposed Method 2

Taking into consideration the symmetric biometric traits, a novel human recognition method is proposed and implemented in this study. The main goal of the proposed method 2 is to conduct the feature-level and score-level fusion approaches on profile face and ear biometrics. The training samples of both traits (ear and profile face) should be acquired from the same side (right or left) in the enrollment phase, however, test samples should be used from the other side (left or right). Consequently, if training samples of profile face and ear are captured from the left side, the test samples should be taken from the right side and then flipped horizontally as shown in Fig. 22.

The proposed method 2 uses the profile face and ear images that are enhanced by histogram equalization and mean variance normalization techniques. Then, using LBP, LPQ and BSIF algorithms, features of left and right sides of the used traits are extracted. Empirically, 5*5 segments of LBP, radii 7 of LPQ and 8-bit code words with 17*17 filter of BSIF are implemented in this study because they show the highest performance of all other tested parameters. Then, for each trait, the extracted features by the three algorithms, which show the highest performance in unimodal experiments, are fused as a single feature vector. These feature vectors are used in the matching stage and the match scores are generated by k-Nearest Neighbor (kNN) classifier for each trait. Lastly, in order to have a final decision on the identity of the individual, as demonstrated in the block diagram of the proposed method 2 in Fig. 22, score-level fusion is used to combine the match scores of profile face and ear biometric traits.

5.3 Experiments and Results of The Proposed Method 2

Validity of the proposed method 2 is demonstrated by conducting several experiments on ND-TWINS-2009-2010 and UBEAR datasets [67]. Figures 23 and 24 show samples of profile face images of ND-TWINS-2009-2010 and UBEAR databases, respectively. Details about the datasets, the experimental setup and the results of different approaches and traits are presented in the following subsections.

5.3.1 UBEAR Database

The UBEAR dataset comprises 4429 profile images from 126 subjects taken from both the left and the right side. The images were captured under different illumination

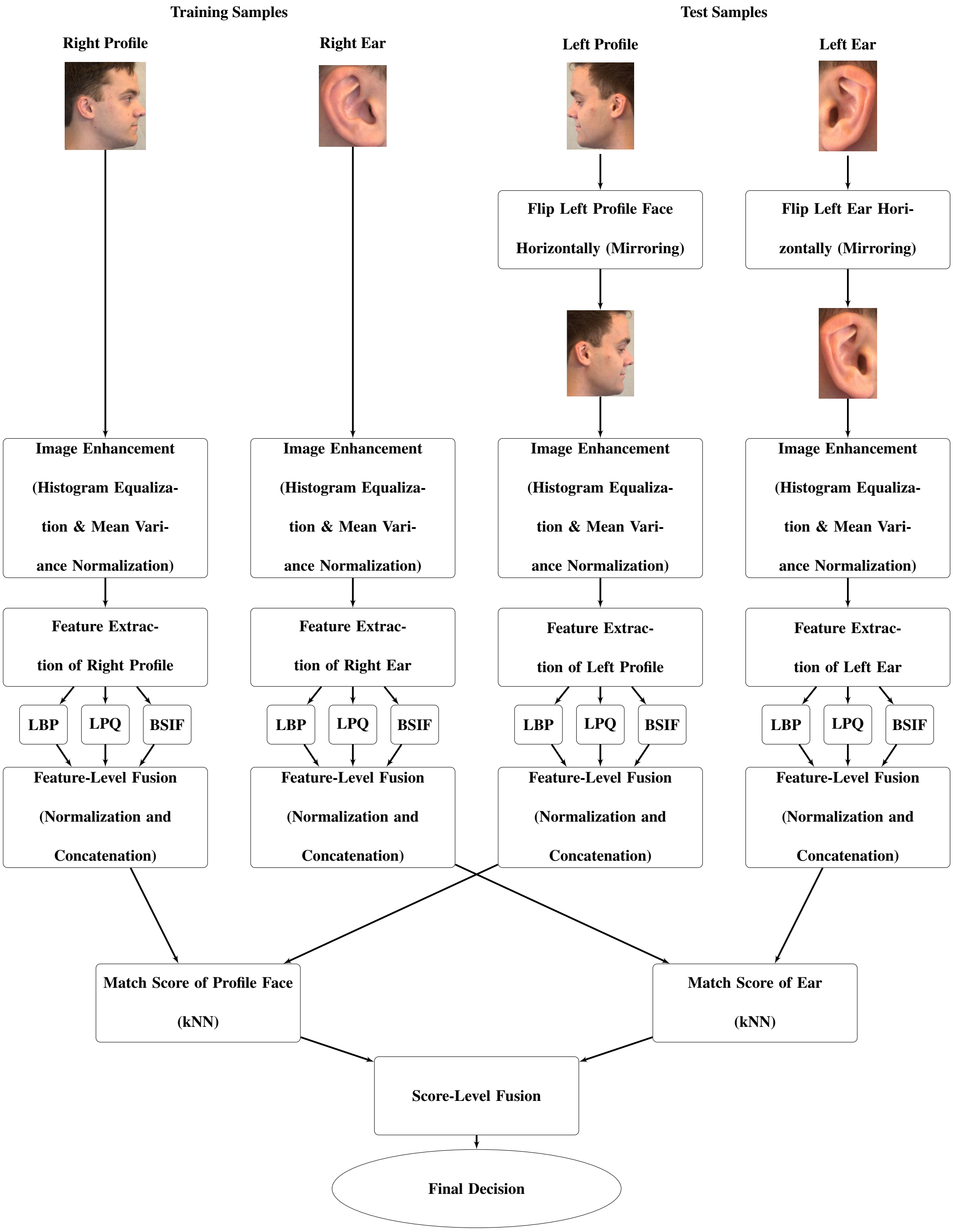

Figure 22: Block Diagram of the Proposed Method 2 (Right Profile Face and Ear as Training Samples) (Left Profile Face and Ear as Test Samples)

conditions. Partial occlusions of the ear are also present on some of the images. This dataset is interesting because images were captured while the subjects were moving. This characteristic is useful for studying techniques for video-based ear recognition

Figure 23: Right Profile Face Samples of Identical Twins (ND-TWINS-2009-2010 Database)

Figure 24: Samples of Right and Left Profile Face Images (UBEAR Database)

where blurring and shearing effects typically appear [37].

5.3.2 Experimental Setup of The Proposed Method 2

Experiments use 92 users from ND-TWINS-2009-2010 Dataset (46 twins) and each user has 16 samples (totally 1472 samples), 4 for each trait (right ear, left ear, right profile face and left profile face). The same number of users and samples are also used from UBEAR database, the samples of UBEAR database are chosen with as minimum as possible of challenges namely illumination, pose and occlusion.

Firstly, the face images from ND-TWINS-2009-2010 and UBEAR Databases with a rotation of +90° (Right) and -90° (Left) are selected. After reading the test samples of profile face and ear, the samples are flipped horizontally in order to rotate the test samples to the same direction of the training samples. Each sample of profile face and ear is tested individually by using PCA, SIFT, LBP, LPQ and BSIF algorithms for feature extraction and kNN is used for matching.

Many unimodal experiments are conducted to measure the symmetry between left and right side of identical twins using ND-TWINS-2009-2010 dataset that is also used to measure the symmetry of non-twins by dividing the 92 users of identical twins into two equal groups. The first group contains the first brother/sister of each twin, while the second group contains the second brother/sister of each twin. In that case, each group contains 46 of the users who are not twins. By implementing the same experiments on these two groups separately, the performance of ear and profile face traits on non-twins is measured. On the other hand, UBEAR database is used only to evaluate the symmetry of non-twins because it does not contain individuals who are twins.

Finally, due to the unsatisfactory recognition rates of unimodal systems that are implemented in this study, score-level fusion in addition to our proposed method 2 are applied as presented in the following subsection.

5.3.3 Experiments On Unimodal Systems

The first and the second sets of experiments aim to measure the recognition rates by using the symmetry of profile face and ear biometric traits. In these experiments, PCA, SIFT, LBP, LPQ and BSIF methods are used as feature extractors. The results of ND-

Twins and UBEAR databases by using symmetry of identical twins and non-twins are shown in Tables 11 and 12 using ear and profile face biometric traits, respectively. BSIF algorithm in unimodal biometric system outperforms all other feature extractors that are implemented in unimodal experiments for ear and profile face biometric traits in addition to identical twins and non-twins cases. Additionally, the performances of PCA and SIFT are low compared to other approaches for both databases.

Table 11: Recognition rates of ear trait using different feature extraction algorithms

Recognition Rate (%) of Identical Twins (ND-Twins Database)						
Sample		Algorithm				
Training	Test	PCA	SIFT	LBP	LPQ	BSIF
RE	LE	26.63	40.21	53.26	54.34	59.78
LE	RE	26.63	42.39	52.17	55.97	58.69
Recognition Rate (%) of Non-Twins (ND-Twins Database)						
Sample		Algorithm				
Training	Test	PCA	SIFT	LBP	LPQ	BSIF
RE	LE	40.39	52.04	62.49	66.30	70.65
LE	RE	40.21	50	64.13	66.30	68.47
Recognition Rate (%) of Non-Twins (UBEAR Database)						
Sample		Algorithm				
Training	Test	PCA	SIFT	LBP	LPQ	BSIF
RE	LE	31.52	40.76	57.06	59.78	63.58
LE	RE	33.15	39.67	55.43	60.86	65.21

5.3.4 Experiments On Multimodal Systems

Different combination scenarios of LBP, LPQ and BSIF algorithms, that show the highest performance in the unimodal experiments, are conducted using score-level fusion. Recognition rates of multimodal systems are presented in Tables 13 and 14 for ear and profile face biometric traits, respectively. Implementing score-level fusion of LBP, LPQ and BSIF algorithm as a multimodal biometric system shows better per-

Table 12: Recognition rates of profile face trait using different feature extraction algorithms

Recognition Rate (%) of Identical Twins (ND-Twins Database)						
Sample		Algorithm				
Training	Test	PCA	SIFT	LBP	LPQ	BSIF
RPF	LPF	30.43	57.6	62.5	65.76	68.47
LPF	RPF	24.45	48.91	59.78	64.13	68.47
Recognition Rate (%) of Non-Twins (ND-Twins Database)						
Sample		Algorithm				
Training	Test	PCA	SIFT	LBP	LPQ	BSIF
RPF	LPF	36.41	70.65	76.08	78.80	81.15
LPF	RPF	41.29	61.95	73.36	75.00	79.89
Recognition Rate (%) of Non-Twins (UBEAR Database)						
Sample		Algorithm				
Training	Test	PCA	SIFT	LBP	LPQ	BSIF
RPF	LPF	32.60	59.23	69.56	70.65	74.45
LPF	RPF	32.60	60.32	68.47	71.19	73.36

formance than the other multimodal systems that use only two of the aforementioned algorithms.

5.3.5 Experiments On The Proposed Method 2

In the next set of experiments, the proposed method 2 that use feature-level and score-level fusion of profile face and ear of identical twins and non-twins is conducted as presented in Figure 22. Table 15 shows the recognition rates of the proposed method 2 using LBP, LPQ and BSIF algorithms. The improvement, in percentages, compared to the highest results of the multimodal experiments, which use score-level fusion of LBP, LPQ and BSIF for each trait separately, are also shown in Table 15. All the experimental results demonstrate that the proposed method 2 is better than all the unimodal and multimodal systems that are implemented in this work and based on the symmetry of bilateral traits.

Table 13: Recognition rates of multimodal systems of ear using score-level fusion

Recognition Rate (%) of Identical Twins (ND-Twins Database)					
Sample		Score-level fusion			
Training	Test	LBP+LPQ	BSIF+LBP	BSIF+LPQ	BSIF+LPQ+LBP
RE	LE	56.52	61.41	61.19	62.5
LE	RE	57.06	60.32	60.32	62.5
Recognition Rate (%) of Non-Twins (ND-Twins Database)					
Sample		Score-level fusion			
Training	Test	LBP+LPQ	BSIF+LBP	BSIF+LPQ	BSIF+LPQ+LBP
RE	LE	67.93	73.36	74.45	76.08
LE	RE	69.02	69.56	71.19	71.73
Recognition Rate (%) of Non-Twins (UBEAR Database)					
Sample		Score-level fusion			
Training	Test	LBP+LPQ	BSIF+LBP	BSIF+LPQ	BSIF+LPQ+LBP
RE	LE	60.32	63.58	65.21	66.84
LE	RE	61.95	66.84	67.39	67.39

Table 14: Recognition rates of multimodal systems of profile face using score-level fusion

Recognition Rate (%) of Identical Twins (ND-Twins Database)					
Sample		Score-level fusion			
Training	Test	LBP+LPQ	BSIF+LBP	BSIF+LPQ	BSIF+LPQ+LBP
RPF	LPF	65.76	69.56	71.73	72.82
LPF	RPF	65.21	69.02	70.65	71.19
Recognition Rate (%) of Non-Twins (ND-Twins Database)					
Sample		Score-level fusion			
Training	Test	LBP+LPQ	BSIF+LBP	BSIF+LPQ	BSIF+LPQ+LBP
RPF	LPF	79.89	82.60	83.15	84.23
LPF	RPF	75.00	80.97	81.52	81.52
Recognition Rate (%) of Non-Twins (UBEAR Database)					
Sample		Score-level fusion			
Training	Test	LBP+LPQ	BSIF+LBP	BSIF+LPQ	BSIF+LPQ+LBP
RPF	LPF	71.73	75.00	76.08	78.26
LPF	RPF	71.73	73.91	73.91	75.54

Table 15: Recognition rates of the proposed method 2

Recognition Rate (%) of Identical Twins (ND-Twin Database)			
Sample			
Training	Test	Proposed Method 2	Improvement
RE+RPF	LE+LPF	75.00	2.18
LE+LPF	RE+RPF	73.91	2.72
Recognition Rate (%) of Non-Twins (ND-Twin Database)			
Sample			
Training	Test	Proposed Method 2	Improvement
RE+RPF	LE+LPF	88.04	3.81
LE+LPF	RE+RPF	83.69	2.17
Recognition Rate (%) of Non-Twins (UBEAR Database)			
Sample			
Training	Test	Proposed Method 2	Improvement (%)
RE+RPF	LE+LPF	79.89	1.63
LE+LPF	RE+RPF	78.80	3.26

5.3.6 Results and Discussion

According to the experimental results, the extent of symmetry on unimodal left and right of profile face and ear is not enough to make it reliable and standalone unimodal biometric system especially in the identical twins case. Therefore, a multimodal system that uses feature-level and score-level fusion of profile face and ear is proposed and implemented.

All the experimental results demonstrate that the proposed method 2 is better than all the unimodal and multimodal systems that are implemented in this work and based on the symmetry of bilateral traits. LBP, LPQ, BSIF algorithms are used in the proposed method 2 as a feature extractor due to the high recognition rates compared to PCA and SIFT feature extractors. Using two level fusion and three algorithms for feature extraction process make the proposed method 2 superior on all other unimodal and multimodal recognition systems that are implemented in this study.

BSIF algorithm in unimodal biometric system outperforms all other feature extractors that are implemented in unimodal experiments for both ear and profile face biometric traits in addition to identical twins and non-twins cases.

We proposed a multimodal biometric system that implements score-level fusion of LBP, LPQ and BSIF. LBP is robust to illumination and pose variation. LPQ is used to remove blurring from images by quantizing the Fourier Transform phase in the local neighborhood pixels. BSIF uses a fixed set of automatically constructed filters from a small set of natural images instead of using filters that are manually constructed such as in LPQ and LBP. Our multimodal system shows better performance than the other multimodal systems that use only two of the aforementioned algorithms.

In general, profile face recognition system in the presence of symmetry is more efficient than ear recognition which means that the right and left profile face are more similar and contains more common discriminative features than right and left ear.

5.4 Conclusions of The Proposed Method 2

In this study, the symmetry of the bilateral profile face and ear biometric traits is explored. PCA, SIFT, LBP, LPQ and BSIF are used to extract the features to assess the degree of symmetry of individuals' biometric traits. Fusion of left profile face and left ear as gallery images and the reflected right side of the biometric traits as probe images (left versus reflected right) and vice versa is applied in this study. Fusion is conducted using two fusion techniques, which are feature-level and score-level fusion, and three feature extraction approaches namely LBP, LPQ and BSIF are used. Experiments show that the unimodal recognition system of symmetry that uses profile face outperforms all other systems of ear. On the other hand, BSIF algorithm is better than the other feature extractors that are implemented in this study. Experiments also demonstrate that the high degree of similarity of identical twins strongly affects the recognition rate compared to non-twins. Lastly, the proposed method 2 significantly improves the recognition rates of symmetric systems compared to the highest results that are acquired by the unimodal and multimodal systems in identical twins and non-twins cases. In general, the results demonstrate that symmetry contains discriminant information for human identification to some extent and the proposed method 2 efficiently exploits these information to enhance the performance of unimodal and multimodal recognition systems that are based on symmetry. On the other hand, in order to construct unimodal recognition of symmetry, more researches and experiments about symmetry are needed. As a future work, more biometric bilateral traits such as palmprint and iris may be tested for identical twins and non-twins. Additionally, further challenges such as pose variation and partial occlusion in addition to symmetry can be considered which make the recognition system more realistic.

Chapter 6

CONCLUSION

Several hybrid approaches of distinguishing identical twins are studied and implemented in recent years and all the experiments proved that the high similarity of identical twins represents critical challenges in biometrics. In this thesis, some experiments are conducted under standard conditions such as controlled illumination, natural expression and low similarity (non-twins) while many others are performed under one or more challenges. The first study for recognizing identical twins employs several feature extractors such as PCA, HOG, LBP and exploits three different level fusions namely feature-level, score-level and decision-level fusion in order to overcome the high similarity of identical twins. Additionally, a novel voting method, which enhances the performance of the whole system, is used in the proposed method 1. The performance of the proposed method 1 exceeds four different unimodal systems and five multimodal systems in addition to the state-of-the-art methods under different challenges such as uncontrolled illumination and facial expressions.

In the second part of this thesis, the symmetry of ear and profile face of identical twins is studied and implemented. There exists only a few studies that focused on the symmetry of those traits despite its high importance for automated surveillance and forensics applications. The proposed method 2 uses three different feature extraction algorithms namely, LBP, LPQ and BSIF in addition to feature-level and score-level fusion to fuse both traits. The proposed method 2 improves the performance compared to other symmetric recognition systems, but further works are strongly required in order to rely on the symmetry recognition as a standalone biometric system.

In general, both of the proposed approaches show high performance not only for identical twins but also for non-twins individuals under the same considered challenges, such as variations in illumination, facial expressions, age and gender.

As a future work, we will study on other powerful feature extraction techniques and classifiers in order to distinguish identical twins under various challenges.

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