Fusion of Palmprint, Palm Vein and Dorsal Hand Vein for Personal Identification

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ABSTRACT

Security is one of the major concerns of human beings in the 21st century. Many forensic and governmental sections now have trusted biometric systems to provide high levels of security for them. Lots of researchers have also worked on many different biometric modalities to both ensure the security and the convenience of the end-users. Nowadays, concerning the magnificent potentials of hand based biometrics, they are a trending choice for a wide range of applications since it is commonly accepted by the society and is not considered to be intrusive while it can offer plenty of features that are abundant to identify humans on a large scale. This thesis uses three different hand-based biometric modalities, namely palmprint, palm vein, and dorsal hand vein to create a secure, efficient, and accurate multimodal hand-based biometric system. Additionally, four different feature extraction methods, namely Principal Component Analysis (PCA), Local Binary Patterns (LBP), Scale Invariant Feature Transforms (SIFT) and Speeded-Up Robust Features (SURF), are exploited to perform person identification. Experiments are conducted on the CASIA palmprint database, Tongji palm vein database, and Bosphorus dorsal vein database. Unimodal and multimodal experimental results are presented on all databases. Moreover, we propose a new multimodal method on palmprint, palm vein, and dorsal hand vein biometrics employing Feature-Level Fusion and Decision-Level Fusion techniques. Finally, the results are presented on six different datasets obtained from the aforementioned palmprint, palm vein, and dorsal vein databases.

Keywords: Person Identification, Biometrics, Palmprint Biometrics, Palm Vein Biometrics, Dorsal Vein Biometrics, Information Fusion.

ÖZ

21. yüzyılda insanlığı etkileyen en önemli şeylerden biri de güvenliktir. Birçok adli tıp ve devlet biriminin yüksek seviyede güvenlik sağlamak için güvenilir biyometri sistemleri vardır. Çoğu araştırmacı, güvenliği sağlamak ve kullanıcıların hayatını kolaylaştırmak için farklı biyometrik özellikler üzerinde çalışmışlardır. Bugünlerde, ele dayalı biyometrik özelliklerin yüksek potansiyeli göz önüne alındığında, el biyometrisinin geniş çaplı uygulamalar için tercih edilen bir seçenek olduğu gözlemlenmektedir. Ayrıca, el biyometrisi geniş çapta insan tanıma işlemi için birçok özellik içerir, toplum tarafından yaygın olarak kabul edilir ve güvenilirdir. Bu tezde, güvenilir, etkili ve doğru çalışan ele dayalı çoklu bir biyometri sistemi yaratmak için avuçiçi, avuçiçi damarları ve el üst damarları kullanılmıştır. Ana Bileşenler Analizi (PCA), Yerel ikili Örüntü (LBP), Ölçekten Bağımsız Öznitelik Dönüşümü (SIFT) ve Hızlandırılmış Sağlam Öznitelikler (SURF) gibi dört değişik öznitelik çıkarma yöntemi de insan tanıma için kullanılmıştır. Deneyler, CASIA avuçiçi veritabanı, Tongji avuçiçi damar veritabanı ve Bosphorus el üst damarları veritabanı üzerinde yapılmıştır. Tekli ve çoklu biyometriğe dayalı deney sonuçları tüm veritabanları üzerinde sunulmuştur. Buna ek olarak, Öznitelik-Seviyesi Kaynaşımı ve Karar-Seviyesi Kaynaşımı teknikleri kullanılarak, avuçiçi, avuçiçi damarları ve el üst damarları birleştirilip, yeni çoklu bir yöntem önerilmiştir. Son olarak, bahsedilen avuçiçi, avuçiçi damarları ve el üst damarları veritabanlarından elde edilen altı farklı veri kümesi üzerinde sonuçlar sunulmuştur.

Anahtar Kelimeler: Insan Tanıma, Biyometri, Avuçiçi Biyometrisi, Avuçiçi Damar Biyometrisi, El Üst Damar Biyometrisi, Bilgi Kaynaşımı.

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LIST OF ABBREVIATIONS

AE	Auto Encoder
BSIF	Binarized Statistical Image Features
CNN	Convolutional Neural Networks
DL	Deep Learning
DWT	Discrete Wavelet Transform
IITD	IIT Delhi Touchless Palmprint Database
LBP	Local Binary Patterns
NIR	Near-Infrared
PolyU II	PolyU Multispectral Palmprint Database
RELM	Regularized Extreme Learning Machine
SIFT	Scale-Invariant Feature Transform
SVM	Support Vector Machine
THUPALMLAB	Tsinghua 500PPIpalmprint Database
WLD	Weber Local Descriptor

Chapter 1

INTRODUCTION

In recent years, with the ever-growing development of digital systems, more users are attracted to digital-based financial platforms and e-commerce. One of the most important challenges of these systems is security. Traditional methods of user authentication like knowledge-based and token-based methods had been used exhaustively up to now, but these old-fashioned methods cannot accommodate all the security requirements that are necessary for the ubiquity of brand-new online systems [1]. Biometric-based systems that are inherently more secure have been suggested as an alternative to automatically authenticate users [2]. Biometrics is an interdisciplinary concept which studies human biological unique traits by statistical analysis ways [3]. Human biometric traits can be categorized into extrinsic traits (fingerprint, palmprint, iris, etc.) and intrinsic traits (palm vein, dorsal hand vein, etc). While intrinsic traits are mostly subcutaneous and lie under human vessels which makes them generally more robust against counterfeits and identity thefts, extrinsic traits are more vulnerable to spoofing attacks since they are naturally more accessible [4].

1.1 Statement of the Problem

We used three biometrics in this thesis, namely, palmprint, palm vein, and dorsal hand vein and combined them for person identification. The main idea of choosing these three biometric modalities was to create an accurate biometric system which also provides high levels of security. To this end, we included Palmprint trait in our system since it is a well-known biometric trait which accurate systems can be built based on it. However, Palmprint has a significant vulnerability against spoofing attacks. For instance, if someone holds a glass of water, his or her Palmprint will get left over the glass and it can be copied and replicated to attack a Palmprint-based biometric system. As a result, we decided to include not just one but two vein-based modalities to provide the security that we intended to have since vein-based systems are harder to be attacked and they also provide liveness detection. In this thesis, palm vein and dorsal hand vein modalities were both selected to be accompanied by palmprint.

1.2 Background on Hand-based Biometrics

Up to now, researchers have discovered several biometric traits that had been proven to be unique among individuals and are potentially suitable for human identification with hand-based biometrics, i.e. palmprint, palm vein, dorsal hand vein, hand geometry, etc. Hand-based traits have some innate attributes that make them slightly a better choice in comparison with other characteristics for the sake of their persistence over time, non-invasiveness due to not requiring very private information and substantially being acceptable by the public, and their feature-rich essence, thus leading to high-accuracy authentication [5, 6].

The acquisition of hand biometric information is also possible to be contact-less; therefore, this will enable self-positioning and convenience which also makes the procedure more secure as previous handprints on the acquisition devices cannot be replicated to perform spoofing attacks [7]. Also, since the users do not have to touch any surfaces, the operation is hygienic as well and potential contamination, grease, or water may not alleviate the ground truth of the presented biometric information [8].

Figure 1 illustrates a few different samples images of hand-based biometrics.

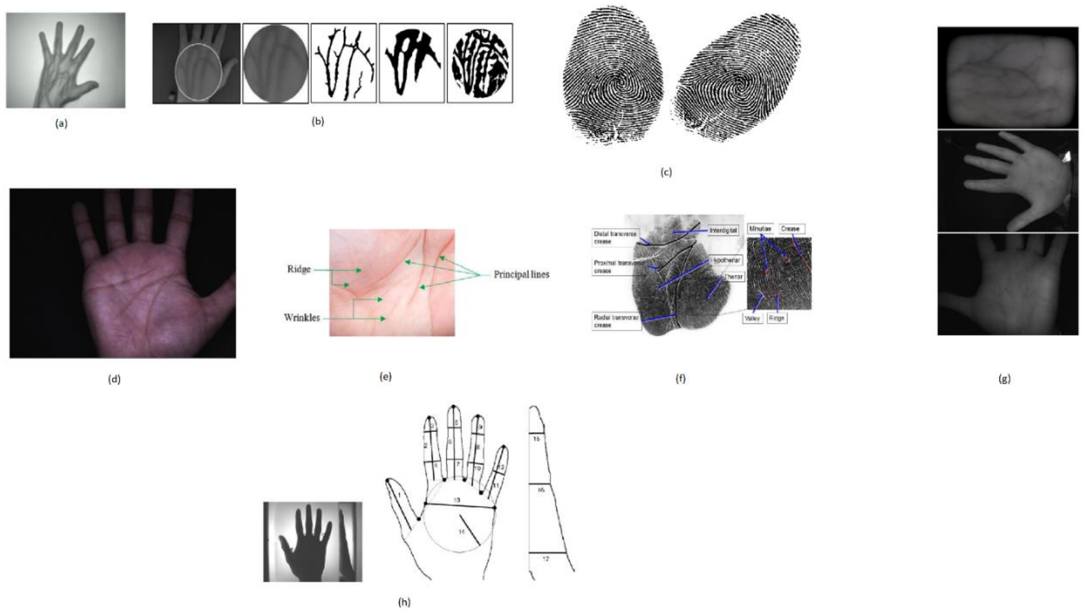


Figure 1: Sample images of different hand-based biometrics including (a-b) dorsal hand vein samples, (c) two distinct fingerprint samples, (d-e-f) raw and cropped palmprint samples, (g) palm vein samples, (h) hand geometry samples.

1.3 Background on Multimodal Hand-based Biometrics

The amalgamation of two or more biometric sources is called multimodal biometrics. Utilization of these systems can yield robustness, accuracy, and a decline in identity theft. Recently, these systems have gained lots of attention from the research community due to some challenges that unimodal systems are facing for identification [9].

Unimodal setups are cost-efficient because the information can be gathered by just one sensor, hence making the acquisition procedure easier, more user-friendly, and less computationally expensive. However, using only one biometric characteristic to identify an individual, generally limits the universality and the number of features that can be extracted and used for further processes. What is more, in real-life applications, noisy information, partial occlusions, high intra-class variations, and inter-class similarities have intrigued researchers to exploit a collection of traits and fused them to fabricate a vigorous authentication system to be used for commercial, forensics, and personal purposes [10, 11].

Figure 2 illustrates a general multimodal biometric system with the necessary steps required for a typical system to operate.

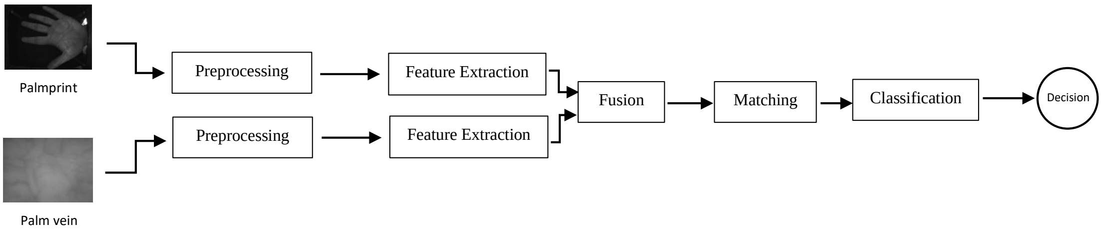


Figure 2: A general multimodal biometric system based on palmprint and palm vein

1.4 The Work Done in This Thesis

We used four feature extraction methods, namely PCA, LBP, SIFT and SURF to acquire necessary information that were inside the three selected biometric modalities (i.e. palmprint, palm vein, and dorsal hand vein) to perform person identification experiments. Additionally, sample images of the selected biometric modalities were obtained from three publicly available databases. CASIA database was chosen for Palmprint, Tongji database for palm vein, and Bosphorus database for dorsal hand vein.

The rest of the thesis is organized as follows. Literature review is discussed in Chapter 2. Four feature extraction methods used in this thesis are described in Chapter 3. Our proposed method is explained in Chapter 4. Details of the exploited databases in this thesis are expanded in Chapter 5. Results of the conducted experiments are illustrated and explained in Chapter 6. Finally, Chapter 7 concludes the thesis with our findings.

Chapter 2

LITERATURE REVIEW

During the last two decades, researches have worked on many human biometric traits and have published many articles around this subject. Specifically, face and fingerprint have attracted more attention than any other biometric characteristics in the literature. This study is focused on hand-based biometric traits namely, palmprint, palm vein, and dorsal hand vein. Each one of these traits has its pros and cons that are discussed in the following sections.

2.1 Palmprint

Palmprint matching is a pattern recognition problem that relies on the unique palm surface features and yet another popular modality among researchers which enables high accuracy identification of individuals through a very easy and convenient acquisition procedure [8, 12]. Palmprint contains some of fingerprint intrinsic characteristics such as friction ridges, persistent and rich features, easy self-positioning, and non-invasiveness which makes it a desirable choice for personal identification [7].

There exist two different approaches in capturing palmprint samples from the users discussed in the literature based on whether users touch the sensors or keeping their hands at a distance in the acquisition stage. Contact-based methods can acquire user samples more accurately and prevent pose variations to some extent, but some factors like grease, water, and pressure level of the hand can create spurious lines and wrinkles which can lead to misidentification, let alone the contamination problems that can cause hygiene issues for users. An alternative is to use a camera at a distance to capture palm images. This way, the acquisition procedure would be less constrained and even low cost and widespread cameras can collect user palm images. However, variations in holding out the hand and posing increase intra-class variations hence raise the need for more intense preprocessing and invariant robust feature extraction algorithms which in time reduces the overall performance of the system [6, 7].

Palm images that had been taken by low-resolution cameras with lower than 200dpi of precision are only suitable for extracting first-level features like lines and creases. On the other hand, more discriminant second-level features such as minutiae and ridges which are more reliable and potentially may result in more accurate matches can only be extracted from images with a resolution of more than 500dpi. Choosing the right resolution depends on the levels of accuracy and precision required for the task ahead. For instance, although, some forensic cases usually have to deal with degraded and distorted palm images left on the crime scenes which consequently can constraint the outcome of the biometric systems, with the help of robust and highly discriminative features, identifications suitable for a lawsuit can be conducted by utilizing second-level features [13].

Two main palmprint recognition techniques have been introduced by previous research studies, Holistic-based and Local-based techniques that are discussed in the following subsections [7].

2.1.1 Holistic-based Palmprint Recognition Techniques

Images in the holistic-based techniques are projected to another sub-space subsequent to feature extraction of the whole image to minimize the dimensionality of the feature vector. As for the shortcomings of the technique, blur, noise, and variations in the lightning induce palmprint distortions [7].

2.1.2 Local-based Palmprint Recognition Techniques

Local-based recognition techniques are divided into three sub-categories as Coding-based methods, Local-texture-descriptor-based methods, and Deep Learning-based methods. These categories are explained in the following subsections.

2.1.2.1 Coding-based Methods

In Coding-based methods, with the application of multiple filters on the palm images, orientation, phase, and magnitude of filter responses from the palm lines are coded into a simple and efficient representation. Later on, the results will be encoded into templates and then a global matching technique such as Hamming Distance is employed to compare templates for recognition and identification. Feature vectors in coding-based methods are small in size and to that end enable fast authentications. Nonetheless, as Hamming Distance algorithms that are used for matching, are sensitive to variations in rotations which makes them incapable of dealing with unconstrained contactless databases [7, 12].

2.1.2.2 Local-texture-descriptor-based Methods

Local-texture-descriptor-based methods try to code a one-dimensional feature vector which represents the biometric template given by the user with common descriptors that are robust against orientation, and geometric transformations. Finally, distance measure algorithms such as Euclidian Distance, Chi-Squared Distance, etc. are exploited for template matching. Among the most commonly implemented methods in the literature based on local-texture-descriptor, Scale-Invariant Feature Transform (SIFT), and Local Binary Patterns (LBP) can be mentioned.

Local-texture-descriptor-based methods can match unconstrained database images slightly better than coding-based methods since they account for pose variations but indeed, this will make their feature vector size relatively large and making the whole recognition and identification process slower accordingly. In short, because of the long comparison time, this method is not feasible for large-scale identifications [7, 12].

2.1.2.3 Deep Learning-based Methods

In Deep Learning-based methods, Convolutional Neural Networks (CNNs) which are often entangled with supervised trained classifiers (e.g. Support Vector Machine (SVM) which is a supervised machine learning model) is utilized for extracting the palm image features. Later on, distance measure algorithms or some other classifiers compare the extracted biometric templates for matching. Unfortunately, classifiers used in this method are not originally trained for extracting palm specific features and they must be prepared in a supervised learning procedure [12].

2.1.3 Comparison of Several Palmprint Recognition Studies

All in all, palmprint is a biometric trait that has strong stability and has features that are persistent and do not change noticeably over time thus accurate biometric systems can be built using palmprints. In Table 1, a few state-of-the-art research methods are compared based on their identification rates.

Deshpande et al. [9] investigated palmprint recognition with the Discrete Wavelet Transform (DWT) feature extraction method to create an accurate palmprint recognition system based on the iterative weights optimization algorithm. Hezil and Boukrouche [11] investigated a multimodal biometric system with ear and palmprint using local texture descriptor methods which included some unimodal experiments on palmprint as well. The related results to palmprint unimodal experiments are provided in Table 1. Genovese et al. [12] researched on a touchless palmprint recognition system and developed a novel method based on Convolutional Neural Networks (CNNs) with interpolation of Gabor filter responses. Genovese et al.'s proposed method not only yielded more uniform and accurate results than other conventional methods but also worked well against heterogeneous databases. Almaghtuf and Khelifi [14] investigated palmprint recognition with the SIFT feature extraction method on full and partial palmprint databases. The key idea in Almaghtuf and Khelifi's research study is to remove false matched keypoints of the SIFT algorithm to increase the genuine recognition rates. Gumaei et al. [15] investigated a fast method to perform palmprint recognition based on Auto Encoder (AE) and Regularized Extreme Learning Machine (RELM) techniques. The main concept of Gumaei et al.'s proposed method is to cut down on the number of features that are describing a palmprint without degrading the quality and the accuracy of the whole system to provide more recognition speed.

Table 1: Accuracy of palmprint methods in literature

Reference No	Database(s)	Feature Extractor(s)	Accuracy
[9]	Lab-made database COEP	Proposed Modified DWT	Lab-made database: 99.25% COEP: 99.20%
[11]	IITD	LBP WLD BSIF	LBP: 88.23% WLD: 66.46% BSIF: 97.73%
[12]	CASIA	PalmNet-Gabor CNN	99.77%
[14]	IITD PolyU II PolyU M_B THUPALMLAB	SIFT-SGR	IITD: 99.28% PolyU II: 97.67% PolyU M_B: 99.93% THUPALMLAB: 97.50%
[15]	MS-PolyU	AE and RELM with NGist Descriptor	Blue: 100% Green: 99.93% Red: 99.93% NIR: 99.70%

2.2 Palm Vein

Palm vein is invisible interior biometric information that has attracted lots of attention because of the high levels of security that it can offer and the number of details that can be extracted and exploited for human identification [16].

The network of blood vessels is captured using near-infrared (NIR) camera and near-infrared illumination because it is not fully visible to the human eyes as they lie under human skin. NIR light is absorbed by the blood hemoglobin, thus result in a dark pattern indicating vein structures. These structures are believed to be unique even among identical twins [1, 17].

Using palm vein for identification has lots of benefits including security, accuracy, user-acceptance, ease of acquisition, cost-efficient, and the last but not the least, liveness detection. Palm vein is secure because vein structures are subcutaneous and are not easily accessible like other external biometric traits let alone the fact that they can only be extracted using NIR illumination. Consequently, in general, it has anti-counterfeit attack robustness which makes it harder for intruders to forge their access [17].

Vascular patterns are a feasible choice to devise accurate systems since they contain a rich amount of details to produce plentiful features such as geometrical parameters of vein vessels like angle, length, and minutiae that can perform well in identification systems [17].

Acquiring palm vein samples does not need a complicated procedure and can be conducted via a low-cost camera while the hand is illuminated with NIR light in a contactless sheltered environment; therefore, it is fast, simple, and convenient for the end-users. Besides, since the acquisition is contactless, environment conditions like wet hand surface, pollution, and scattering will not have any impact on the acquired samples and also contaminations will not be an issue for the users [16].

Palm vein can only be detected when the blood that is flowing in veins absorb the NIR light. Without blood flow and the liveness of the provided sample vein patterns will disappear. This fact will neutralize lots of intruder’s plans to attack vein-based systems with photos and not live samples [1].

With all that being said, despite the benefits of using palm vein for classification and identification, it has some shortcomings that limit the performance of those systems. For instance, veins are not evenly positioned under the skin and the thickness of hand tissues varies in different parts. Skin scattering and optical blurring also have an adverse effect on vein detection. Subsequently, veins in the thinner parts are less detectable than in the thicker parts [1, 16].

In the literature, the issue of captured vein images being low-contrast has been discussed quite a lot and multiple solutions had been proposed to tackle this issue but still, it seems the problem persists and is open for further researches. Because palm vein images are captured with NIR illumination and with conventional camera sensors that only take 8-bit photos, typically images appear darker with low-contrast, and the full luminance dynamic range will be lost, but if too much illumination is used the images would become saturated. Another solution for having a uniform illumination is to customize the light for capturing each sample but since it contains modifications in the light sources for each acquisition, it is time-consuming [1].

Contrast enhancement techniques are yet another solution for low-contrast palm vein images that usually take place in the preprocessing stages. Even still, these methods are not very successful in recovering all the details that had been lost in the low-contrast images because of underexposure or overexposure in the images. Some conventional contrast enhancement techniques are Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Circular Gabor Filter (CGF), Local Ridge Enhancement (LRE), and High-Frequency Emphasis Filtering (HFE) [1, 17].

The utilization of contrast enhancement methods is quite common in vein-based systems and it seems to be a fair reaction to deal with contrast problems. However, these techniques will sometimes produce spurious vein patterns that disrupt the performance of identification systems [17].

Algorithms designed for palm vein detection must account for variations in the hand positioning and lightening conditions. Therefore, they have to ignore negligible features and avoid using spuriously created vein structures while detecting genuine veins.

Conventional palm vein-based biometric techniques are divided into four categories as Geometry-based methods, Statistical-based methods, Local-invariant-based methods, and Appearance-based methods. These methods are explained in the following subsections.

2.2.1 Geometry-based Palm Vein Recognition Methods

These methods use point, line, curvature, and generally vascular structure features to represent palm veins and they are dependent on the estimation of palm vein point data which must be calculated and extracted accurately in the region of interest segmentation stage in advance to perform precise pattern recognition and classifications. On one hand, skin scattering and blurring, and on the other hand, not very powerful vein detection capabilities under NIR illumination with low-contrast images will result in poor performance when using geometry-based methods for identification. They are also vulnerable to variations in the scaling, rotation, and hand displacements [17, 18].

2.2.2 Statistical-based Palm Vein Recognition Methods

Discriminative vein structures represented and recognized with mathematical statistics mean is used for pattern recognition in statistical-based methods. There exist two approaches that are commonly adopted in the literature, namely local and global statistics-based methods [18].

Local statistics-based methods consist of local discriminative features that are suitable for pattern comparisons. Among these methods, Local Binary Patterns (LBP), Local Derivative Pattern (LDP), Weber Local Descriptors (WLD), and their variations have extensively been utilized. Local statistics-based methods also suffer from variations in the scaling, rotation, and displacements and would not perform well under those conditions [18].

On the other hand, Global statistics-based techniques exploit statistical information of invariant features and moments that are robust against scaling, rotation, and displacements. Nonetheless, texture information from some samples is not rich enough to produce highly accurate and distinguishable features for identification [16, 18].

2.2.3 Local-invariant-based Palm Vein Recognition Methods

Palm vein features that are locally invariant and robust against rotations and displacements are extracted using these methods. Scale-Invariant Feature Transform (SIFT) is a popular local-invariant-based method. Although it exhibits outstanding performance in touchless-based systems that the acquired samples usually include some pose variations while a specific hand holder is not utilized, it suffers from low speed. Additionally, the SIFT algorithm does not perform well when the resolution of samples is low [16, 18].

2.2.4 Appearance-based Palm Vein Recognition Methods

Appearance-based methods that are also referred to as subspace methods take the image as a whole and use extracted coefficients of the subspace of veins as features for performing classification and pattern recognition. Principal Component Analysis (PCA) is a well-known example of these methods [18].

2.2.5 Comparison of Several Palm Vein Recognition Studies

Overall, despite all the challenges and problems that were discussed in the literature, selecting palm vein for creating a biometric system seems to be satisfactory and principled as it provides security, user convenience, and high accuracy if meticulously designed. Table 2 depicts some state-of-the-art methods along with the accuracy achieved using different feature extraction algorithms.

Ahmad [4] investigated palm vein recognition through ways that preserved the privacy of users by using templates that were non-invertible which could prevent identity theft and could also be stored in small storage. Ahmad’s Wave Atom Transform (WAT) method was accurate while being lightweight with privacy-preserving templates. Thapar [19] investigated contactless palm vein recognition with Deep Learning feature extraction methods on several trending palm vein databases. Zhang [20] investigated palmprint and palm vein recognition based on Deep Convolutional Neural Network (DCNN) on a newly created large-scale lab-made palm vein database (Tongji). Super Vector Machine (SVM) classifier was used for identification and Euclidian Distance method was utilized for recognition in Zhang's proposed method to create a palmprint and palm vein recognition system which was more accurate than its predecessors.

Table 2: Accuracy of palm vein methods in literature

Reference No	Database(s)	Feature Extractor(s)	Accuracy
[4]	PolyU	Wave Atom Transform (WAT)	98.78%
[19]	CASIA	CNN-based PVSNet	85.16%
[19]	IITI	CNN-based PVSNet	97.47%
[19]	PolyU	CNN-based PVSNet	98.78%
[20]	Tongji	DCNN-based $PalmR_{CNN}$	100%

2.3 Dorsal Hand Vein

In most of the vein-based biometric systems, the fundamental steps are pretty much the same that consists of the acquisition, feature extraction, classification, and matching. Dorsal hand vein-based systems are not an exception and all the steps used for creating these systems and different algorithms that researchers had used for enhancing the quality of images in the preprocessing stage and extracting and representing features for the identification phase had been already discussed in the previous sections.

Dorsal hand vein has to be captured in the presence of near-infrared illumination and CCD cameras that ensures the liveness of the samples. Liveness detection is major merit that has motivated numerous researchers to choose this biometric characteristic to study. Dorsal vein patterns that are not fully visible to human eyes are difficult to be replicated and forged, hence, it provides high security and anti-counterfeit capacity. Even so, NIR illumination makes captured images appear dark and with low-contrast that in time will restrict the performance of the identification system and makes it hard for feature extraction methods to represent and describe vein patterns to perform matching. In palm vein systems, researchers had used contrast enhancement techniques to improve the quality of the captured palm vein images, likewise, dorsal hand vein systems include a preprocessing stage to unify the illumination of acquired images and reduce the noise and contrast problems caused by near-infrared light.

Deep Convolutional Neural Network (DCNN) is one of the feature extraction techniques that is extensively used in literature for representing dorsal hand veins which yields promising outcomes. However, DCNN requires large-scale databases to train its models and has lots of difficulties when dealing with small-size datasets which sometimes is the case with a dorsal hand vein. A way to address this problem is through using already trained models and transferring their knowledge to other systems, but this method has lots of implementation complexities that prevent researchers from adopting and deploying this approach in their systems [21].

2.3.1 Comparison of Several Dorsal Hand Vein Recognition Studies

Different state-of-the-art techniques from literature are provided in Table 3 to illustrate the potential of dorsal hand vein-based systems and enable a quick comparison between different models.

Wang et al. [21] investigated dorsal hand vein recognition based on Deep Convolutional Neural Network (DCNN) with a novel Minutiae-based Weighting Aggression (MWA) method instead of other conventional methods since the features extracted with DCNN models from a network of blood vessels are sparse and hard to be accurately classified with a pre-trained DCNN model. Gupta et al. [22] investigated hand geometry and dorsal hand vein images taken with near-infrared (NIR) illumination to perform biometric identification. Gupta's method includes a quality estimation stage that reduces the number of spurious features by putting less emphasis on pixels that contain hair or skin texture. Yüksel et al. [23] developed a Dorsal Hand Vein database with near-infrared (NIR) light and utilized three hand recognition schemes that were quite different in nature. Independent Component Analysis (ICA) and Non-negative Matrix Factorization (NMF) considered the whole image and applied two different subspace methods. The third scheme, Line Edge Map (LEM), is based on distances between the contours representing the hands, hence, it is shape-based.

Table 3: Accuracy of dorsal hand vein methods in literature

Reference No	Database(s)	Feature Extractor(s)	Accuracy
[21]	Lab-made database	DCNN	96.81%
[22]	Palm Dorsal GPDS Vein	Multi-scale matched filter and variational	98.15%
[23]	Bosphorus	Independent Component Analysis (ICA)	97.33%
[23]	Bosphorus	Non-negative Matrix Factorization (NMF)	89.67%
[23]	Bosphorus	Line Edge Map (LEM)	78.00%

2.4 Multimodal Systems

To escalate the system performance and accuracy of unimodal biometric systems, multimodal systems had been proposed. Unimodal biometric systems have limited functionality since there are a certain number of features that can be extracted from a biometric trait and thus enhancing the accuracy and security of systems requires more efforts and more sophisticated algorithms and techniques which makes them not feasible or even slow to be used in real case scenarios. In addition, sometimes an individual cannot present a specific trait because of an injury or a disability that also restricts the functionality and the universality of the biometric system [3].

By combining different biometric characteristics, more features will be available for extraction and representation which would help the matching and classification algorithms to perform better and grant more accurate conclusions on the identity of an individual. Furthermore, when users are challenged to present more than one biometric information, ingenuine models and attackers would have a hard time to infiltrate those systems and replicate all the necessary information to bypass the security protocols [11].

In order to create hybrid systems, the results and features from single-mode biometrics should be fused together and this fusion must depict more efficient outcomes comparing with their former single modality origins. There are currently four types of fusions in literature, namely, Sensor-Level Fusion, Feature-Level Fusion, Score-Level Fusion, and Decision-Level Fusion [11].

Table 4 demonstrates state-of-the-art methods and algorithms used on different modalities which further shows the power of multimodal systems over unimodal systems.

Hezil and Boukrouche [11] investigated a multimodal biometric system with ear and palmprint using local texture descriptor methods fused with Feature-Level Fusion that attained a one-hundred percent recognition rate. Gupta et al. [22] investigated hand geometry and dorsal hand vein images taken with near-infrared (NIR) illumination to perform biometric identification. Gupta et al.'s method includes a quality estimation stage that reduces the number of spurious features by putting less emphasis on pixels that contain hair or skin texture. Additionally, results from the ear and palmprint modalities were fused together at the Score-Level Fusion.

Table 4: Accuracy of multimodal methods vs unimodal methods in literature

Reference No	Database(s)	Feature Extractor(s)	Modality	Accuracy
[11]	IIT Delhi-2 ear	Local Binary Patterns (LBP)	Ear	95.02%
[11]	IIT Delhi Palmprint	Local Binary Patterns (LBP)	Palmprint	88.23%
[11]	IIT Delhi-2 ear and IIT Delhi Palmprint	Local Binary Patterns (LBP)	Multimodal Ear & Palmprint	98.64%
[11]	IIT Delhi-2 ear	Weber Local Descriptor (WLD)	Ear	89.59%
[11]	IIT Delhi Palmprint	Weber Local Descriptor (WLD)	Palmprint	66.46%
[11]	IIT Delhi-2 ear and IIT Delhi Palmprint	Weber Local Descriptor (WLD)	Multimodal Ear & Palmprint	96.03%
[11]	IIT Delhi-2 ear	Binarized Statistical Image Features (BSIF)	Ear	98.90%
[11]	IIT Delhi Palmprint	Binarized Statistical Image Features (BSIF)	Palmprint	97.73%
[11]	IIT Delhi-2 ear and IIT Delhi Palmprint	Binarized Statistical Image Features (BSIF)	Multimodal Ear & Palmprint	100%
[22]	Palm Dorsal GPDS Vein	Multi-scale matched filter and variational	Palm dorsal vein	98.15%
[22]	IITK-Pdv	Multi-scale matched filter and variational	Hand Geometry	90.66%
[22]	GPDS Vein and IITK-Pdv	Multi-scale matched filter and variational	Multimodal Palm dorsal vein and Hand Geometry	99.34%

Chapter 3

FEATURE EXTRACTION METHODS

The most complicated and difficult stage of biometric systems is the feature extraction method design. In this stage which happens right after preprocessing, we tend to find, localize, and represent the inherent features and information which lies in the captured images of the biometric traits. Some feature extraction methods try to represent the information by mathematical statistics means while others may try to extract texture information and make comparisons between similarities and differences of pixels or image frames. Choosing the right feature extraction method depends on many aspects such as the database being created in a controlled or uncontrolled environment, the scale of the database whether it is large or small, computational time and space complexity restrictions, the biometric modality used, etc. Consequently, when the researchers finish with previous steps they will be forced to choose feature extraction techniques that are suitable for their work. The methods have to bring high performance to their system and must be easy to implement and deploy.

In this research, we decided to choose PCA among appearance-based feature extraction methods and LBP among texture-based methods and the last but not the least, SIFT and SURF from texture-based scale-invariant techniques. They will all be explained in the following sections.

3.1 Principal Component Analysis (PCA)

PCA is one of the famous appearance-based methods that are also referred to as subspace methods that take the image as a whole and use extracted coefficients of the subspace of the images as features for performing classification and pattern recognition.

PCA is based on correlations and dependencies between image features so it is really important to specify the features that are excessively related to each other as they are biased, and thus tend to lower the final functionality [24].

Eigenvector and eigenvalues which are a prominent part of the PCA algorithm are produced using the covariance matrix. Eigenvalue depicts the fundamental integrants of the samples and eigenvector is a vector consisting of all eigenvalues. After creating the eigenvector, sorting the items according to their values in descending order has to be done as the greatest values indicate more important features and correlations. After rearranging data, all non-zero eigen vector values can be used to differentiate samples and find similarities or differences between enrolled images using a wide range of distance measurement techniques such as Manhattan distance or Euclidean distance methods [25].

PCA summarizes data from a full set of variables into fewer variables by performing a specific alteration on them. The transformation is utilized in a way that linearly correlated variables alter into uncorrelated variables. Correlation indicates that there is redundancy in data. Data redundancy can be decreased; thus, information can be packed. For instance, if there is a pair of variables in the variable set which are highly correlated, then one variable can be removed from the pair because one variable can be shown as the linear combination of the other. In such situations, PCA transfers the variance of the secondary variable into the first variable by rotation and translation of original axes and projecting data over new axes. The area of projection is defined using eigenvalues and eigenvectors. So, the first few transformed points (A.K.A Principal Components) are rich with information, whereas the last features carry mostly noise with negligible data in them. This transferability hold the first few principal components; thus, decreasing the number of variables significantly with the least loss of data. Stages of PCA algorithm are described one by one in the following subsections.

3.1.1 Standardization of the Data

The first stage in the PCA algorithm is to perform the standardization of the data. It is evident that skipping on standardization will presumably result in biased results. Standardization is all about comparing the data in a way that all the variables and their contents lie within a similar range. An example related to the standardization of data is when there are two variables in a dataset; one has values differing between 10-100, and the other one has values between 1000-5000. In such circumstances, it is evident that the production estimated by handling these predictor variables will be biased since the variable with a greater area will have a more visible influence on the outcome. Hence, standardizing the data into a similar range is essential. Standardization is carried out by deducting each variable value in the data from the mean and dividing it by the overall deviation in the dataset. It can be measured as follows:

$$Z = \frac{Variable\ value\ -\ mean}{Standard\ deviation} \tag{3.1}$$

where Z is the standardized variable, and in this way, all the variables in the data are balanced across a standard and comparable scale.

3.1.2 Computing the Covariance Matrix

PCA identifies the correlation and dependencies between the features in a dataset. A covariance matrix reveals the correlation between the diverse variables in the dataset. It is necessary to identify heavily dependent variables because they carry biased and redundant information, which decreases the overall performance of the image. Mathematically, a covariance model is a p × p matrix, where p describes the dimensions of the dataset. Each entry in the pattern describes the covariance of the identical variables. Covariance matrix (C) is calculated as follows, where Z is standardized vector.

$$C = ZZT \tag{3.2}$$

3.1.3 Calculating the Eigenvectors and Eigenvalues

Eigenvectors and eigenvalues are the mathematical constructs that are calculated from the covariance matrix to discover the principal components of the dataset. Eigenvalues, on the other hand, represent the scalars of the eigenvectors. Hence, eigenvectors and eigenvalues will be used to obtain the principal components of the dataset.

3.1.4 Computing the Principal Components

Once the eigenvectors and eigenvalues are calculated, they have to be sorted in descending order, because the eigenvector with the highest eigenvalue is the most important and thus forms the first principal component. The principal components of lesser importance can be excluded in order to decrease the dimensions of the data. The last step in calculating the Principal Components is to form a model known as the feature matrix that holds all the essential data variables that possess maximum information about the data.

3.1.5 Reducing the Dimensions of the Dataset

The final step in applying PCA is to re-arrange the primary data with the final principal components, which describes the maximum and the essential information of the dataset. The maximum number of nonzero eigenvectors that can be used is equal to the number of images minus one in the training stage.

3.2 Local Binary Patterns (LBP)

LBP feature extraction method is considered to be one of the most famous texture-based algorithms that can classify and recognize patterns between multiple images to a great degree of accuracy. Basically, this algorithm calculates pixel values according to their neighboring pixels and recreates a pattern in the processed images that makes them suitable for comparisons. LBP has some windows that will traverse the whole image and replace the central pixel of the windows based on the binarized values of its neighboring pixels. The window sizes can be 3x3 or 5x5 or etc. Whenever that a neighbor value is greater than the central pixel value that pixel will be assigned 1 and if not it will be assigned 0. Also, when the windows overflow the image edges the neighboring pixel values will be assumed to be 0. Then, the binarized values will form a decimal number that will replace the central pixel value and represent its intensity. This process will continue until all the pixels of the image are traversed [26, 27].

Figure 3 shows a 5x5 sample LBP window. This method consists of one anchor point or so-called central pixel along with sixteen neighboring pixels. The neighboring pixels have to be binarized starting from 1 to 16. The zeros inside the matrix indicate the neutrality effect of those pixels on the result. In this thesis, we have exploited a 5x5 LBP window because it was producing a better outcome rather than other combinations.

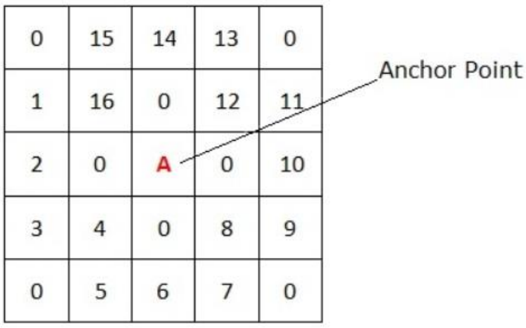


Figure 3: Sample 5x5 LBP Window

To perform identification or recognition based on LBP, processed images are compared with each other using similarity or different measurement techniques like it was explained in the PCA.

The first computational level of the LBP is to build a central image that illustrates the original image in a better way by highlighting the prominent components of the image. To do so, the algorithm uses a sliding window based on the parameters such as radius and adjacency. Figure 4 shows LBP procedure on a palmprint image.

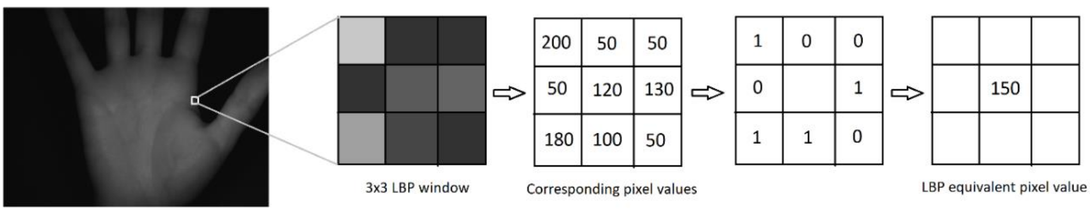


Figure 3: Local Binary Patterns (LBP) procedure.

The LBP procedure can be described as follows. A section of the sample image is selected as a window of 3x3 pixels. It can also be described as a 3x3 matrix (including the intensity of each pixel, which is from 0 to 255). Then, it is required to hold the central value of the matrix to be applied as a threshold. This value will be used to set new values from the eight neighbors. For each neighbor of the central-value (threshold), a new binary value is initiated. For values similar to or higher than the threshold 1 and for values below the threshold 0 will be set. At the end of this stage, the matrix will carry only binary values. By concatenating each binary value from their locations on the matrix (e.g., 10001101) and then transforming this binary value to a decimal value, the new central value of the matrix which is genuinely a pixel from the original image will be calculated. The LBP stages above result into a new model that represents the characteristics of the original image in a better way. Figure 5 shows different possible number of adjacent blocks that can be selected.

Using the model created in LBP feature extraction for each pixel as shown in Figure

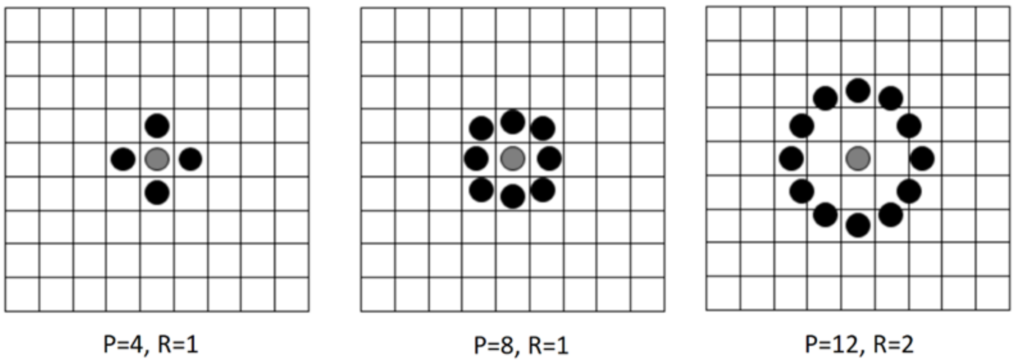


Figure 4: Model of LBP transformation pixels. P and R represent the distance of the sampling points from the center pixel and the number of the sampling points to be used, respectively.

4, the image can be split into multiple grids. The histogram of each region can be obtained as follows: each histogram (from each grid) will carry only 256 positions (0~255), since the image is in grayscale, serving the occurrences of any pixel intensity Then, it is required to concatenate each histogram to generate a new and larger histogram.

In the recognition stage, histograms built based on the previous instructions are used to draw each model from the training dataset. So, given an input image, previous steps must be completed again for this new image to create a histogram that represents the image. Consequently, to find the model that matches the input image, it is required to match two histograms to return the image with the most resembling histogram. Different distance measures can be utilized to compare the histograms (calculate the distance between two histograms), for example, Euclidean distance, chi-square, absolute value, etc. In this thesis, Manhattan distance is used. The output of the algorithm is the ID from the model with the closest histogram.

3.3 Scale Invariant Feature Transformation (SIFT)

SIFT is a powerful invariant-based feature extraction method that can perform well in the presence of uncontrolled environment conditions such as pose variations. The author, David G. Lowe, has come up with a method to obtain distinctive key points and features from an image that are robust to image scale and variations, and also matching between images and object recognition can be done with the help of these features. This distinctiveness among key points is achieved by assembling a high-dimensional vector representing the image gradients within a local region of the image [28].

The algorithm can be broken down into four major steps:

1. Feature point (keypoint) detection
2. Keypoint localization
3. Orientation assignment
4. Feature descriptor generation.

A keypoint is a characteristic of an object that only is meaningful at a certain scale or orientation. Figure 6 shows one hundred strong keypoints of the image.

SIFT includes a feature detector and a feature descriptor. The detector extracts from an image a collection of frames or key points. These are oriented disks attached to structures of the image. The frames are covariant, in a way that they track image rotations and scalings. The effect of such transformations can then be undone by canonization, which is by warping the frames to a canonical disk. The descriptor is the statistics of the gradients of the frame. As a result of canonization, the descriptors are invariant to translations, rotations, and scalings of the image. Because of their statistical nature, they are also pretty robust to other sources of noise as well [28].

Figure 5: One hundred strong keypoints within the image

The highly discriminative key points that are extracted using the SIFT algorithm can be used to accurately match images from a large database of key points. The key points have been shown to be invariant to image rotation and scale and robust across a range of distortion, noise, and illumination [28].

Despite the spectacular performance of the SIFT method, it has some drawbacks that have to be considered and dealt with accordingly. Image gradient magnitude and orientations are sampled around the keypoint location, which uses the scale of the key point to select the level of Gaussian blur for the image. The orientation of the histogram is also used for the same reason. But generally, it does not work well with lighting changes and blur. Additionally, the SIFT keypoint and feature detection algorithm is computationally expensive and takes a long time to be extracted, therefore; it is not meant to be used for real-time purposes and only works for greyscale images. Another yet challenging problem of SIFT is that some keypoint pairs may mistakenly mismatch with each other which will later increase the false acceptance rate (FAR) of the biometric system substantially [28].

Figure 7 is a sample of the way that the SIFT algorithm finds the keypoints and matches them together.

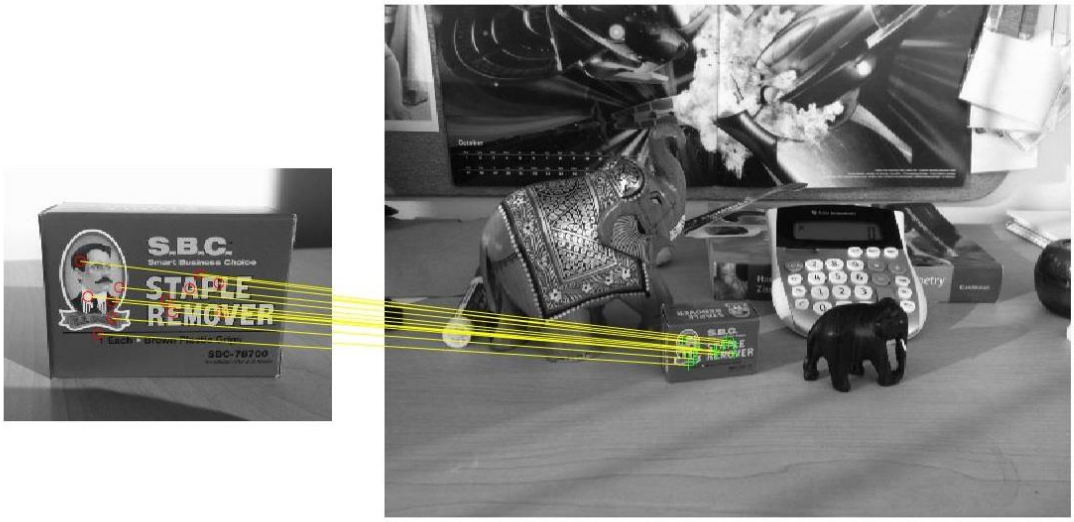


Figure 6: Matched points between an object and its recognized figure in a larger image

3.4 Speeded Up Robust Features (SURF)

In the previous section, the SIFT algorithm introduced, and among its drawbacks, low speed was very noticeable. SURF algorithm is mostly similar to its predecessor, SIFT with some small changes that have made the method to detect and match the keypoints way faster. This will enable the method to be used in real-time scenarios that require a short time for the matching process to be performed. SURF utilizes square-like filters as an estimation of Gaussian smoothing, while the SIFT method integrates cascaded filters to identify scale-invariant points. SURF can have a fast computation of operators using box filters [29].

In SIFT, Lowe [28] approximated Laplacian of Gaussian (LOG) with Difference of Gaussian for finding scale-space. SURF goes a little further and approximates LoG with Box Filter. Below Figure 8 shows a demonstration of such an approximation. One big advantage of this approximation is that, convolution with box filter can be easily calculated with the help of integral images. And it can be done in parallel for different scales. Also the SURF rely on determinant of Hessian matrix for both scale and location.

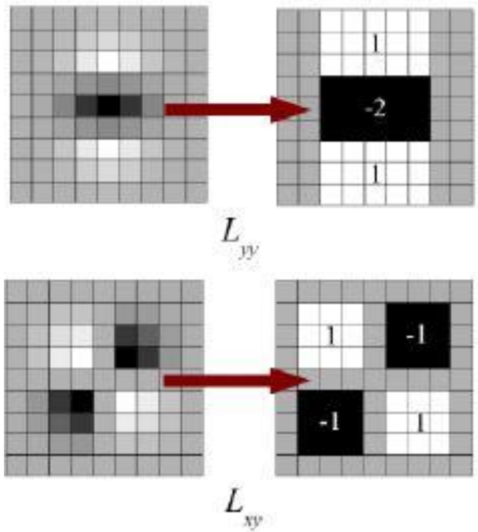


Figure 7: Demonstration of Laplacian of Gaussian approximation

Like SIFT method, SURF also has orientation assignment step. For orientation assignment, SURF uses wavelet responses in horizontal and vertical direction for a neighborhood of size 6s. Adequate Gaussian weights are also applied to it. Then they are plotted in a space as given in Figure 9. The dominant orientation is estimated by calculating the sum of all responses within a sliding orientation window of angle 60 degrees. Interestingly, wavelet response can be find out using integral images very easily at any scale. For many applications, rotation invariance is not required, so there is no need of finding this orientation, which speeds up the process.

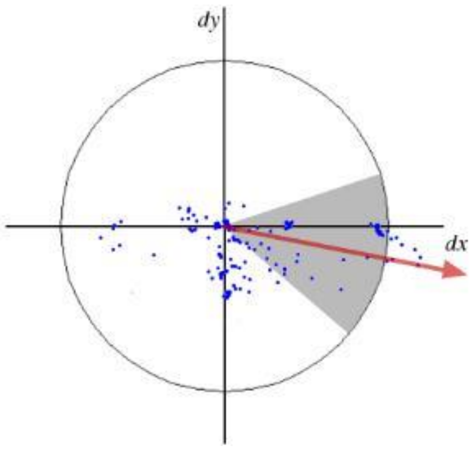


Figure 8: SURF orientation assignment illustration

Similar to SIFT, SURF also has feature description step, and thus SURF uses Wavelet responses in horizontal and vertical direction (again, use of integral images makes things easier). A neighborhood of size 20sX20s is taken around the keypoint where s is the size. It is divided into 4x4 subregions. For each subregion, horizontal and vertical wavelet responses are taken and a vector is formed like this:

$$v = \left(\sum dx, \sum dy, \sum |dx|, \sum |dy|\right) \tag{3.3}$$

The SURF feature descriptor vector will have total of 64 dimensions. The lower the dimension, the higher the speed of computation and matching, but higher feature descriptor vector dimension provides better distinctiveness of features. Figure 10 shows detected keypoints with SURF algorithm along with their orientation assignment on a sample picture.

Figure 9: SURF keypoints with their orientation assignments

Another important improvement in SURF method over SIFT method is the use of sign of Laplacian (trace of Hessian Matrix) for underlying interest point. It adds no computation cost since it is already computed during detection. The sign of the Laplacian distinguishes bright blobs on dark backgrounds from the reverse situation. In the matching stage, we only compare features if they have the same type of contrast as shown in Figure 11. This minimal information allows for faster matching, without reducing the descriptor's performance.

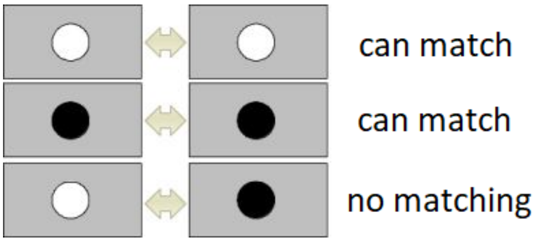


Figure 10: Contrast checking of SURF algorithm in matching stage

Overall, SURF adds a lot of features to improve the speed in every step. Analysis shows it is three times faster than SIFT while performance is comparable to SIFT. SURF is good at handling images with blurring and rotation, but not good at handling viewpoint change and illumination change.

Chapter 4

PROPOSED METHOD

The proposed method employed in this thesis has four fundamental parts namely, pre-processing, feature extraction, matching, and classification. Figure 12 shows a graphical depiction of the sequential steps. Detailed mechanism of the adopted stages is given below.

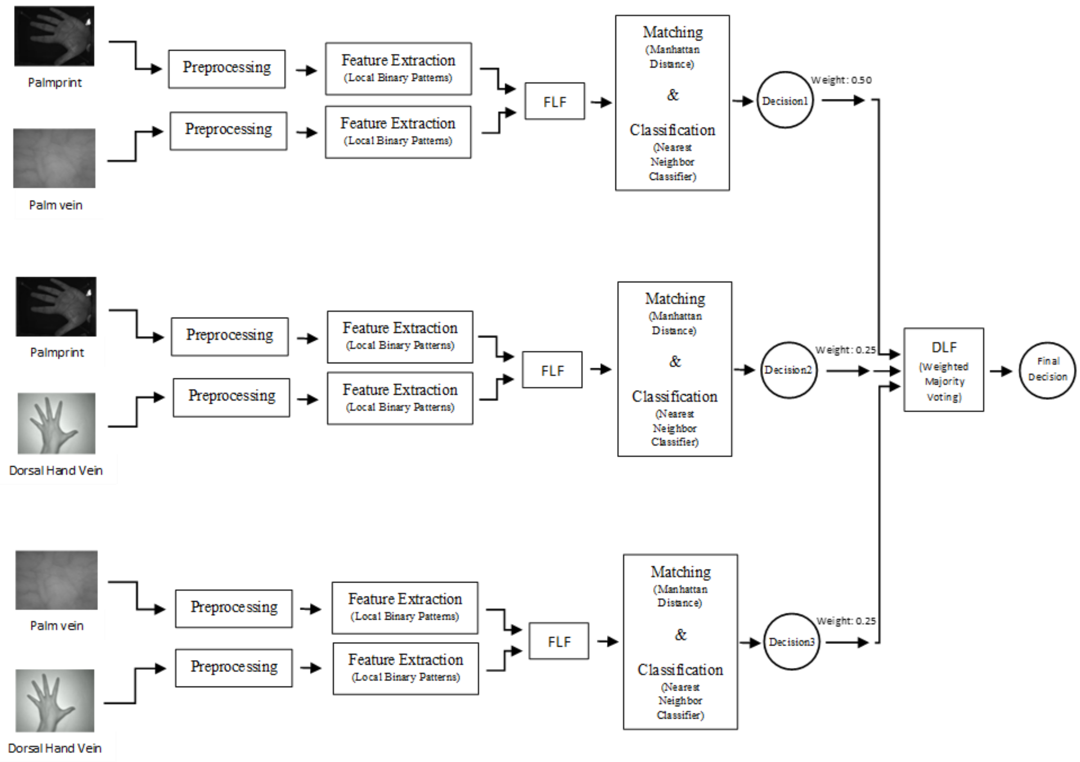


Figure 11: Block diagram of the proposed method.

4.1 Preprocessing

Pre-processing is a significant phase in any biometric system. In this study, pre-processing algorithms are employed according to each feature extraction method that is going to be used to reduce noise, blur, and adjust the size of images to a proper scale and make the input images ready for the next step which is feature extraction.

Next, based on the feature extraction method selected in this phase, training and testing images will both undergo certain operations for their inherent features to be extracted as biometric templates.

Later on, these templates will be matched together using Euclidian Distance or Manhattan Distance measurement techniques according to the selected feature extraction method for finding the percentage of individuals who have been identified truly by the system.

All the above stages are somewhat common between unimodal biometric systems to perform matching and identification. In this thesis study, since three different biometric modalities have to be considered and matched together, the results from each modality must be fused with others to come up with a unanimous decision to determine the success or failure of the identification. Among the available fusion techniques, Feature-Level, and Decision-Level Fusions are selected and utilized to combine the unimodal results.

4.2 Feature Extraction

In image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

In this research, we decided to choose PCA among appearance-based feature extraction methods and LBP among texture-based methods and the last but not the least, SIFT and SURF from invariant-based techniques.

4.3 Feature-Level Fusion

Many multimodal biometric systems have used Feature-Level Fusion that is accomplished before matching extensively to combine feature sets extracted from different sources. The amalgamation of two or more feature sets in the Feature-Level fusion will result in a new consolidated feature vector that can represent the information of an individual more comprehensively and remove some limitations of a unimodal system [30].

Feature-level Fusion does not require the biometric system to be modified or normalized. However, it is still hard to be performed especially when the nature of utilized biometric modalities that are to be combined are very different from each other. In that case, multi-dimensional feature vectors can be created to combine different varieties. Additionally, Feature-Level Fusion encodes features together instead of primary training features and that creates some insubstantial, noisy, redundant data, and ignores some relationships between features that impact the performance of the system adversely [11, 31].

4.4 Matching and Classification

Biometric matching and classification refer to the process of the degree of match (usually in the form of a match score) between two biometric signatures, one usually collected at the biometric enrollment stage and the other collected at the biometric verification or identification stage. Biometric matching is a critical component in biometric recognition systems. Biometric recognition systems encompass both biometric verification systems (that compare a presented test biometric signature to an enrolled signature corresponding to a claimed identity) and biometric identification systems (where a presented test biometric signature is compared to several stored signatures in order to determine the identity of the test subject).

4.5 Decision-Level Fusion

Decision-level Fusion which is also called abstract-level fusion is the easiest fusion that can be implemented to combine the individual decisions resulted from matchers succeeding the matching stage among all other fusion techniques. The fusion at the Decision-Level is carried out by the help of some rules such as AND, OR, Bayesian, and Majority voting. The most common method is majority voting to evaluate the final decision since it is not obligatory to have prior knowledge about the individual matchers [30].

Decision-Level Fusion only yields straight to the point final decision about the combination of the biometric modalities and does not provide lots of other information and that makes it undemanding to implement [30].

Another decision-making technique that can be used with this fusion method is the weighted majority voting. This compound technique first collects the decisions coming from different matchers, then, based on the veracity and precision of individual decisions it assigns a weight to each of them to escalate the accuracy of the final decision.

Chapter 5

DATABASES

Three benchmark databases for each selected biometric modality, namely palmprint, palm vein, and dorsal hand vein, are used in this thesis. The number of subjects and samples per individuals in all three databases are different, to that end, a collection of images from the benchmark databases were selected to create a more homogeneous and balanced dataset of images to carry out experiments specifically for multimodal observations. In the following sections, all three databases are discussed in detail.

5.1 Tongji Contact-less Palm Vein Dataset

Tongji is a large-scale contact-less palm vein database created by researchers of the Tongji University in Shanghai, China. There was not an abundance in publicly available large-scale palm vein databases while the researchers were working on their palm-vein-based biometric systems. Therefore, they decided to construct a large-scale database of individuals' palm vein images using their convenient contact-less self-manufactured acquisition device. With irradiation of NIR light to palm surfaces, some black lines appear which represent veins under the palm skin. Then a camera can take the picture of NIR illuminated palm surfaces to acquire the essential samples [20].

The database embraces 12,000 palm vein images from 600 different palms taken in two distinct sessions with a two-month time interval between each session. 300 volunteers including 192 males and 108 females had presented their biometric information for the creation of this database. Most of the samples (235 individuals) belong to subjects aged between 20 to 30 and the rest belong to people between 30 to 50 years old. Each subject's palm was captured 10 times in each session. That is to say, 40 images were collected from two palms of each subject. The resolution of taken images is 800 × 600 pixels [32].

Two sample images from the Tongji Palm Vein database is provided in Figure 13.

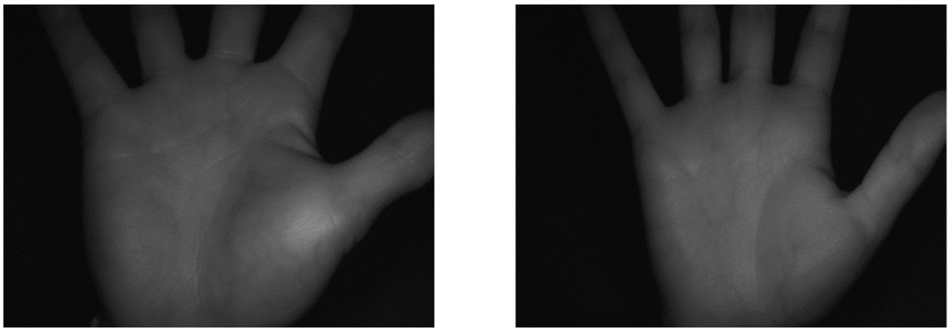
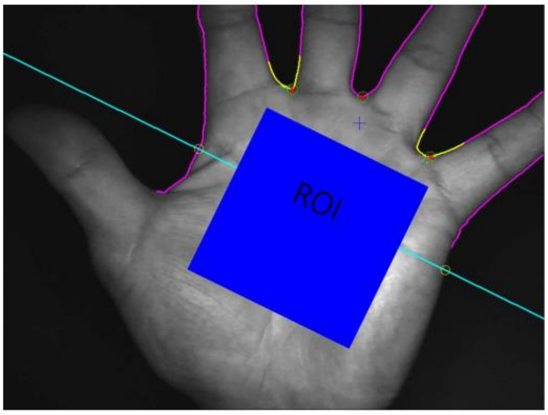


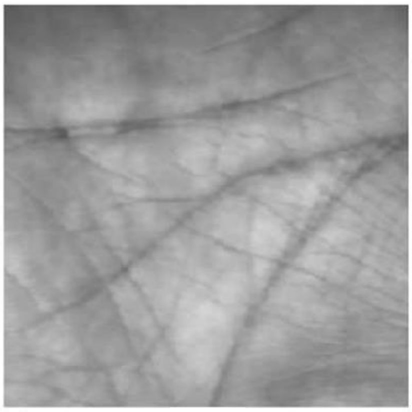
Figure 12: Sample images from the Tongji Palm Vein Database.

Since the hand images of Tongji palm vein database are taken in a contact-less manner, pose variations of different samples of each individual result in high intra-class variations which can restrict the efficiency of the feature extraction stage. Therefore, palm vein images have to be carefully aligned and their ROI have to be extracted to be ready for further operations. For that reason, a ROI of 128 × 128 has been extracted from original palm vein images to account for geometrical transformations by the authors [20].

Figure 14 depicts the way that researchers extracted the region of interest on the whole palmprint image.



(a)



(b)

Figure 13: ROI extraction. (a) Obtained keypoints for ROI extraction. (b) The final extracted ROI palm vein image.

5.2 Bosphorus Hand Vein Database

Bosphorus hand vein database, created by researchers at the Boğaziçi University located on the European side of the Bosphorus strait in Istanbul, Turkey, contains 1575 images of 100 individual's dorsal hand veins (41 female and 59 male subjects). To capture database images, the researchers have illuminated subject' hands with two IR lights and then used a near-infrared CCD camera equipped with an infrared lens for acquisition. The resolution of images is 300 × 240 pixels stored in 8-bit grey-scale format with .bmp extension [23].

Images in the database have been taken under different circumstances to provide cover for different scenarios in real-life applications. Most of the images have been acquired from the left dorsal hand of volunteers except a small set comprising 3 samples per each subject from the right dorsal hand under normal circumstances. Similarly, there is a set of 3 samples per each subject taken under normal conditions from the left dorsal hand. Additionally, researchers have made the volunteers hold a bag weighted 3 kilograms for one minute, applied a pack of ice to the back of their hands, and in another case, they have made subjects to squeeze an elastic ball for one minute before the acquisition of some samples distinctively to create variety but in the same way by taking 3 samples from each subject. There is also another set devoted to 25 number of volunteers that had come back after 3-5 months after the first acquisition stage to give their hand vein biometric information to create a dataset with a time interval from the first group [33].

Figure 15 shows a few sample images from the Bosphorus Hand Vein database.

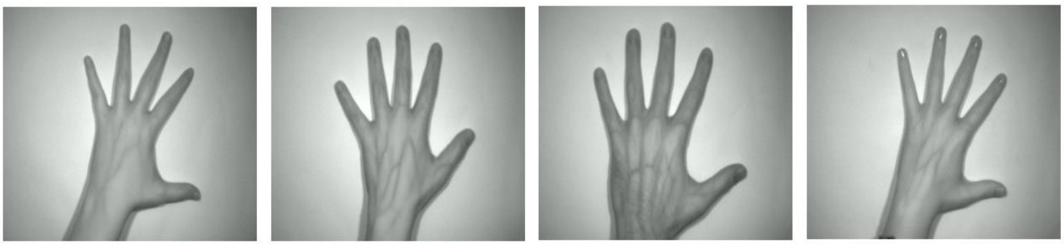


Figure 14: Sample images from the Bosphorus Hand Vein Database

5.3 CASIA Multi-Spectral Palmprint Image Database

CASIA Multi-Spectral Palmprint Image Database V1.0 (or CASIA-MS-Palmprint-V1.0 for short) comprises 7200 palm images from 100 individuals. The Chinese Academy of Sciences' Institute of Automation (CASIA) created the multi-spectral palmprint database captured under six different electromagnetic spectrum wavelengths ranging from the visible light spectrum to infrared i.e. 460nm, 630nm, 700nm, 850nm, 940nm, and white light. Images are all 8-bit grey-scale with a resolution of 768 × 576 pixels with JPEG extension [34].

Six groups of LEDs were utilized to irradiate the subject' palm hands and the reflection of the lights representing the structure of palm was captured with a NIR CCD camera in a sheltered environment to prevent illumination variations with no hand-holder in a contact-less manner to avoid possible contaminations and provide better hygienic practices. The database images were taken from subjects in two separate sessions with a one-month time interval. In each session, 3 images for each mentioned electromagnetic spectrum wavelength were taken from the left palm of volunteers and similarly 3 images from their right palms while allowing some pose variations in capturing images [35].

Figure 16 illustrates a few sample images from the CASIA-MS-Palmprint database.

Figure 15: Sample images from CASIA-MS-Palmprint Database

Chapter 6

EXPERIMENTAL RESULTS

6.1 Description of Experimental Setups

Experiments were conducted on a Computer running a Core-i7 CPU using both MATLAB and Python programming languages to code feature extraction methods. PCA and LBP based methods were implemented using MATLAB while SIFT and SURF based methods were coded in Python by interpolating OpenCV Python Library V4.3.0.

Two virtual datasets from palmprint, palm vein, and dorsal hand vein databases were created to perform experiments. There are 100 individuals in both datasets that each of them has three different samples from all three databases.

For building the first dataset, from the CASIA palmprint database, three left-hand palmprints were selected among images that were captured with the help of 460nm electromagnetic spectrum wavelength lights from the first session of the acquisition stage. And, from the Tongji palm vein database, for each subject, three samples were selected from the first session. Finally, from the Bosphorus dorsal hand vein database, three samples were chosen among left dorsal hand vein images of subjects taken under normal conditions.

Similarly, for building the second dataset, from the CASIA palmprint database, three right-hand palmprints were selected among images that had been captured with the help of 460nm electromagnetic spectrum wavelength lights from the first session of the acquisition stage. And, from the Tongji palm vein database, for each subject, three samples were selected from the second session. Finally, from the Bosphorus dorsal hand vein database, three samples were chosen among right dorsal hand vein images of subjects taken under normal conditions.

After the creation of virtual datasets, we needed to decide on which samples should be used for training and which samples should be used for testing. To cover all possible scenarios and define the best compound of training and testing sets, we tested all possible combinations of the samples and named the subsets accordingly to facilitate their usage and increase readability. Table 5 demonstrates different training sets used in the experiments.

Table 5: Different Training and Testing Sets used in the experiments

Set No	Training Sample Numbers	Testing Sample Number	Virtual Dataset No
Set #1	Sample 1 & Sample 2	Sample 3	Dataset 1
Set #2	Sample 1 & Sample 3	Sample 2	Dataset 1
Set #3	Sample 2 & Sample 3	Sample 1	Dataset 1
Set #4	Sample 1 & Sample 2	Sample 3	Dataset 2
Set #5	Sample 1 & Sample 3	Sample 2	Dataset 2
Set #6	Sample 2 & Sample 3	Sample 1	Dataset 2

6.2 Uni-modal Experiments

For this thesis, four different feature extraction methods are selected, that is to say, PCA, LBP, SIFT, and SURF. These four algorithms have been tested on three modalities i.e. palmprint, palm vein, and dorsal hand vein. For each selected biometric modality one database has been assigned. As a result, we have conducted twelve different unimodal experiments on each database using all four feature extraction methods to test out their potential and capabilities and to determine the future steps and decisions.

In the following tables, the results of all the experiments have been provided. Some database names are used in the tables that each of them is related to a specific biometric trait:

- Tongji database is related to palm vein
- Bosphorus database is related to dorsal hand vein
- CASIA database is related to palmprint.

Table 6 indicates three unimodal experiments conducted on all three biometric modalities, namely, palm vein, dorsal hand vein, and palmprint using the PCA algorithm. While the PCA algorithm has performed very well on the Tongji database (i.e. palm vein images), it has had a hard time identifying Bosphorus database images related to dorsal hand vein samples because the images inside the Bosphorus database have a low resolution and the presence of near-infrared light to indicate veins has made them blurred and has further decreased their quality. The results of identification rates of the PCA algorithm on palmprint images are again not very impressive and peaked at about 51% for the first set of training and testing samples.

Table 6: Unimodal experimental results using PCA algorithm

Experimental Setup	Set #1	Set #2	Set #3	Average 1-3	Set #4	Set #5	Set #6	Average 4-6
Unimodal PCA on Tongji	82%	90%	83%	85%	61%	73%	67%	67%
Unimodal PCA on Bosphorus	14%	16%	15%	15%	21%	28%	27%	25.33%
Unimodal PCA on CASIA	51%	46%	46%	47.66%	42%	46%	27%	38.33%

Table 7 depicts the outcome of the LBP algorithm on all three modalities. LBP has shown outstanding performance on the Tongji database with one hundred percent accuracy. Similarly, CASIA database samples were identified to a satisfactory rate and topped at 82%, but again the dorsal hand vein image identification results are still very low with the LBP method since the Bosphorus database images have been degraded while captured using the near infrared light and the image blurs prevent the necessary features to be extracted using the LBP extraction technique.

Table 7: Unimodal experimental results using LBP algorithm

Experimental Setup	Set #1	Set #2	Set #3	Average 1-3	Set #4	Set #5	Set #6	Average 4-6
Unimodal LBP on Tongji	100%	100%	100%	100%	100%	100%	100%	100%
Unimodal LBP on Bosphorus	21%	21%	23%	21.66%	26%	30%	32%	29.33%
Unimodal LBP on CASIA	74%	82%	66%	74%	74%	79%	62%	71.6%

Table 8 demonstrates the experimental results of the SIFT feature extraction method on our selected unimodal biometric traits. The algorithm has shown more consistency in results than the other two previous methods and almost all database samples have been identified to a satisfactory degree. CASIA database images have a higher resolution and the samples belonging to this database had been better identified by the SIFT algorithm since more keypoints can be found in larger images in comparison with low-resolution images. The experimental results related to the Tongji database with SIFT is similar to PCA but lower than LBP. However, SIFT has proved to be efficient on the Bosphorus database while PCA and LBP were not able to have better results than 29.33% on average of the identification rate.

Table 8: Unimodal experimental results using SIFT algorithm

Experimental Setup	Set #1	Set #2	Set #3	Average 1-3	Set #4	Set #5	Set #6	Average 4-6
Unimodal SIFT on Tongji	85%	87%	87%	86.33%	71%	81%	77%	76.33%
Unimodal SIFT on Bosphorus	70%	66%	77%	71%	69%	77%	82%	76%
Unimodal SIFT on CASIA	97%	96%	93%	95.33%	91%	97%	92%	93.33%

Table 9 is related to all unimodal experiments conducted on all three modalities using the SURF feature extraction algorithm. The results for palm vein and palmprint identifications are higher than those in the SIFT table, but the dorsal hand vein identification rates are a bit lower than the previous method. Also, the SURF algorithm was way faster than the SIFT algorithm and the experiments with SURF were less computationally expensive which was a noticeable change while conducting the experiments.

Table 9: Unimodal experimental results using SURF algorithm

Experimental Setup	Set #1	Set #2	Set #3	Average 1-3	Set #4	Set #5	Set #6	Average 4-6
Unimodal SURF on Tongji	91%	97%	96%	94.66%	81%	89%	82%	84%
Unimodal SURF on Bosphorus	49%	51%	56%	52%	60%	64%	72%	65.33%
Unimodal SURF on CASIA	100%	99%	92%	97%	95%	97%	92%	94.66%

6.3 Multimodal Experiments with Feature-Level Fusion

After conducting all the unimodal experiments, it was about time to choose a fusion technique to accumulate the results and create the multimodal hybrid system. All three modalities were fused together using Feature-Level Fusion within the selected feature extraction algorithms to again determine the best method out of the experiment results.

Figure 17 illustrates the block diagram of the Feature-Level Fusion stages conducted in our tests.

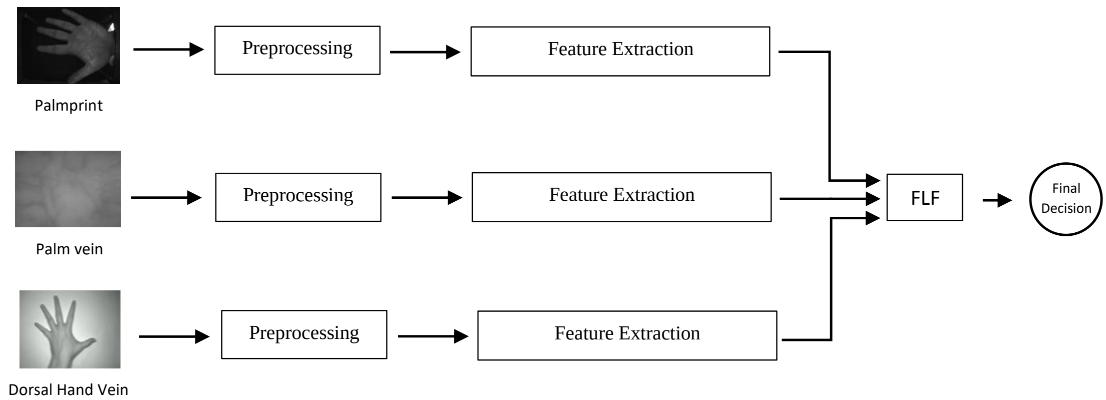


Figure 16: Feature-Level Fusion Block Diagram

Table 10 shows multimodal experiment results using PCA, LBP, SIFT, and SURF with Feature-Level Fusion on all datasets. The table depicts that the PCA method has the worst results among all and is not a feasible choice for performing Feature-Level Fusion in creating a multimodal system based on it with respect to our selected modalities. On the other hand, LBP has shown significant results and all the outcomes of the LBP-based experiments seem to be stable and well above all others. SIFT and SURF methods are also appropriate with SURF performing better than SIFT in this area with close results on the first virtual dataset but with a slight reduction in performance in the second virtual dataset in comparison with LBP.

Table 10: Multimodal experiments using all four algorithms with feature-level fusion

Experimental Setup	Set #1	Set #2	Set #3	Average 1-3	Set #4	Set #5	Set #6	Average 4-6
Multimodal PCA	42%	43%	36%	40.33%	45%	52%	36%	44.33%
Multimodal LBP	98%	100%	100%	99.33%	98%	99%	95%	97.33%
Multimodal SIFT	85%	87%	87%	86.33%	71%	81%	77%	76.33%
Multimodal SURF	91%	97%	96%	94.66%	81%	89%	82%	84%

6.4 Multimodal Experiments with Decision-Level Fusion

To further test out all the possibilities of our system, we decided to perform Decision-Level Fusion on three modalities as well with the majority voting to fuse the decision results of individual decisions to form a multimodal system.

Figure 18 illustrates Decision-Level Fusion stages performed in our tests.

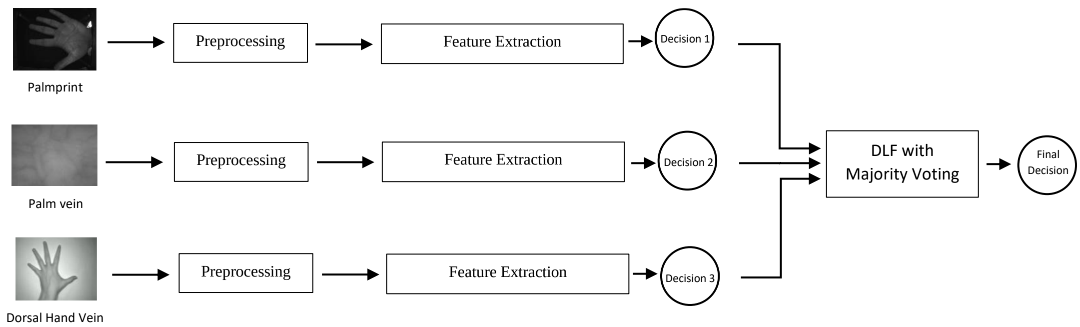


Figure 17: Decision-Level Fusion Block Diagram

As indicated in Table 11, the PCA feature extraction method still falls behind other methods and LBP, SIFT, and SURF methods are at a close range to each other with some fluctuations within different testing sets.

Table 11: Multimodal experiments using all four algorithms with Decision-Level Fusion

Experimental Setup	**Set #1**	**Set #2**	**Set #3**	**Average 1-3**	**Set #4**	**Set #5**	**Set #6**	**Average 4-6**
Multimodal PCA	66%	60%	54%	60%	53%	58%	51%	54%
Multimodal LBP	78%	80%	75%	77.66%	82%	86%	79%	82.33%
Multimodal SIFT	85%	87%	87%	86.33%	71%	81%	77%	76.33%
Multimodal SURF	91%	97%	96%	94.66%	81%	89%	82%	84%

6.5 Proposed Multimodal Experiments with Feature-Level Fusion Incorporated with Weighted Decision-Level Fusion

After witnessing the results from Feature-Level Fusion and Decision-Level Fusion techniques, we decided to escalate the stability and accuracy of our system with not just one fusion technique and combine both Feature-Level and Decision-Level Fusions together to form our proposed method.

First, we again tested Feature-Level Fusion on a combination of modalities by selecting each time two distinct traits and calculating their identification results using a distinct feature extraction technique. There are four different selected feature extraction techniques in this thesis and there is a three possible combination of different mixtures of databases which results in twelve different experiments that we conducted to determine the best feature extraction method among all of them.

As a result, three separate identification experiments were conducted on combinations of the databases. Each time, two distinct modalities were chosen and all the template features in the feature extraction stages were fused together to form a consolidated template using Feature-Level Fusion to produce an independent decision. Then, all three independent decisions resulted from the experiments were combined through a Decision-Level Fusion to form the final identification decision concerning the impact of each decision taken from the first fusion-level.

Figure 19 is related to the block diagram of the Feature-Level Fusion with Decision-Level Fusion on the distinctive decisions that are resulted from the Feature-Level Fusions with Majority Voting.

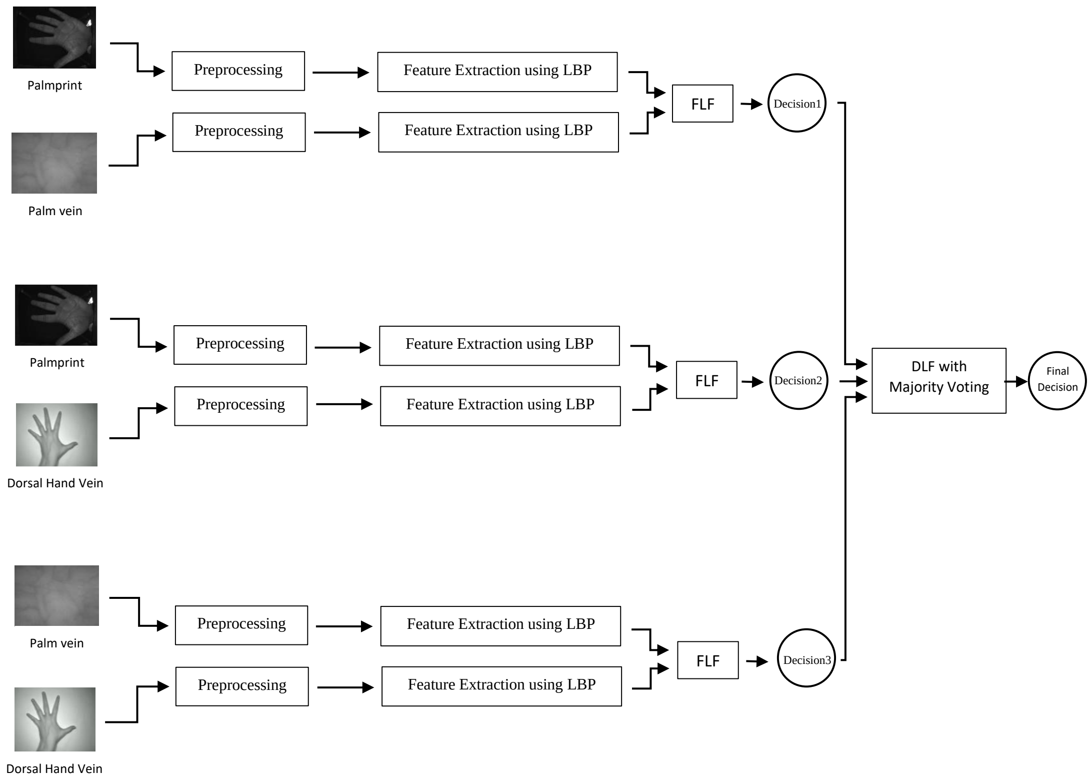


Figure 18: Feature-Level Fusion with Decision-Level Fusion Block Diagram

According to Table 12, the LBP feature extraction method has the highest results among all, and therefore; we selected this method to continue our work. Then, the decisions produced by each matcher considered through a Decision-Level Fusion to form the final identification decision based on the LBP method.

Table 12: Experiments to determine the best feature extraction method with Decision-Level Fusion

Experimental Setup	Set #1	Set #2	Set #3	Average 1-3	Set #4	Set #5	Set #6	Average 4-6
Multimodal PCA Tongji & Bosphorus	14%	18%	18%	16.66%	21%	28%	27%	25.33%
Multimodal LBP Tongji & Bosphorus	92%	98%	96%	95.33%	95%	98%	95%	96%
Multimodal SIFT Tongji & Bosphorus	85%	87%	87%	86.33%	71%	81%	77%	76.33%
Multimodal SURF Tongji & Bosphorus	91%	97%	96%	94.66%	81%	89%	82%	84%
Multimodal PCA Tongji & CASIA	49%	47%	47%	42.33%	43%	47%	31%	40.33%
Multimodal LBP Tongji & CASIA	100%	100%	100%	100%	99%	100%	97%	98.66%
Multimodal SIFT Tongji & CASIA	85%	87%	87%	86.33%	71%	81%	77%	76.33%
Multimodal SURF Tongji & CASIA	91%	97%	96%	94.66%	81%	89%	82%	84%
Multimodal PCA Bosphorus & CASIA	42%	44%	37%	41%	41%	49%	32%	40.66%
Multimodal LBP Bosphorus & CASIA	63%	71%	65%	66.33%	72%	79%	71%	74%
Multimodal SIFT Bosphorus & CASIA	85%	87%	87%	86.33%	71%	81%	77%	76.33%
Multimodal SURF Bosphorus & CASIA	91%	97%	96%	94.66%	81%	89%	82%	84%

After choosing the right feature extraction method, we decided to put a weight on different decisions to come up with better results. Figure 20 shows the block diagram of this procedure. Basically, it was witnessed that the decision that is produced from the palmprint and palm vein modalities have more accurate results and have more veracity than other combinations; therefore, more decision weight was put on this modality to come up with a more complimentary performance at the end.

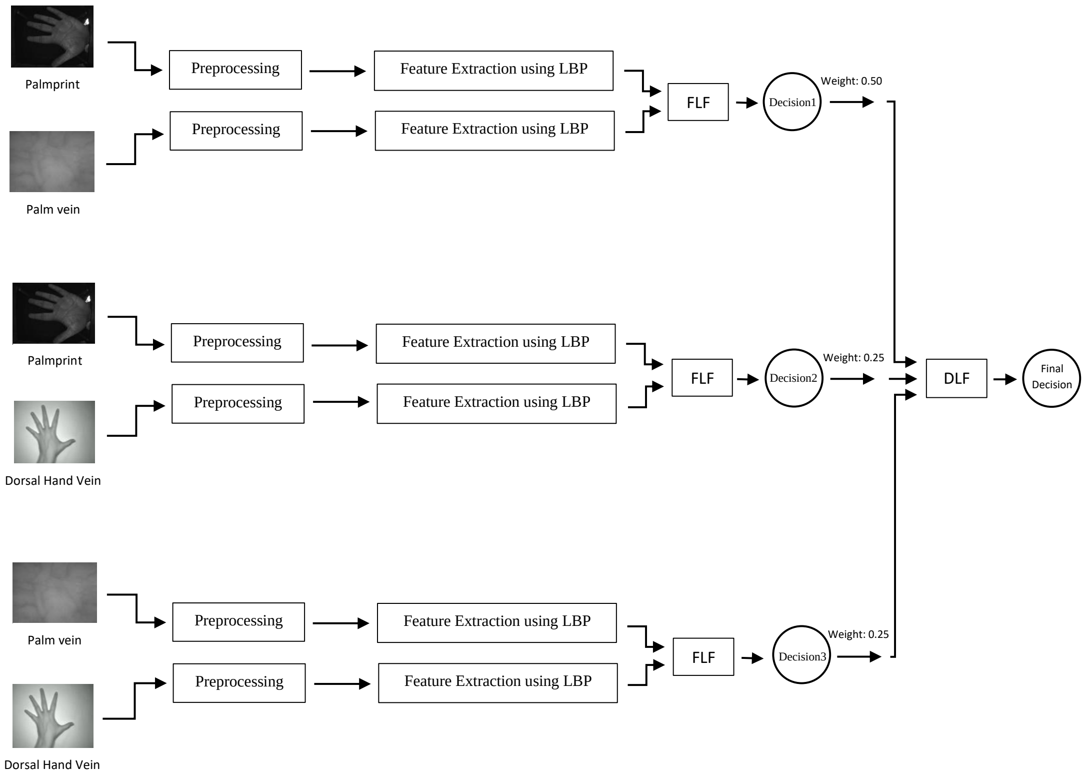


Figure 19: Block Diagram of Feature-Level Fusion with Weighted Decision-Level Fusion of our multimodal proposed system

The first row of Table 13 is the plain combination of Feature-Level Fusion with Decision-Level Fusion where the distinct decisions from feature-fused individual matches were combined together using Majority Voting in the Decision-Level stage to form the final decision. Decision one (D1) belongs to the Feature-Fusion of palmprint and palm vein. Decision two (D2) is related to palmprint and dorsal hand vein, and the last decision (D3) has come from palm vein and dorsal hand vein. The subsequent rows belong to experiments that had a specific weight on the individual Feature-Fused matcher decisions. It is evident that when decision one (D1) which is related to palmprint and palm vein combination has a greater impact in terms of decision weights the final results are more impressive. Also, according to Table 12, the palmprint and palm vein combination has yielded better results in LBP comparing with other mixtures. As a result, when the decision one (D1) is set to have

0.5 weight and the other two decisions (D2 and D3) left to have 0.25 weight, the best possible result, i.e. 99.66%, of the identification rate achieved.

Table 13: Results of our proposed method, Multimodal experiments with Feature-Level Fusion combined with Decision-Level Fusion along with weighted decisions.

Experimental Setup	**Set #1**	**Set #2**	**Set #3**	**Average 1-3**	**Set #4**	**Set #5**	**Set #6**	**Average 4-6**
Multimodal LBP	98%	99%	99%	98.66%	99%	99%	99%	99%
Multimodal LBP Weights: D1: 0.33 D2: 0.33 D3: 0.33	95%	98%	98%	97%	99%	99%	99%	99%
Multimodal LBP Weights: D1: 0.50 D2: 0.25 D3: 0.25	99%	100%	100%	99.66%	99%	100%	100%	99.66%
Multimodal LBP Weights: D1: 0.25 D2: 0.50 D3: 0.25	77%	82%	82%	80.33%	86%	91%	81%	86%
Multimodal LBP Weights: D1: 0.25 D2: 0.25 D3: 0.50	94%	98%	98%	96.66%	96%	98%	97%	97%
Multimodal LBP Weights: D1: 0.40 D2: 0.30 D3: 0.30	98%	100%	100%	99.33%	99%	100%	100%	99.66%

Chapter 7

CONCLUSION

In this thesis, a hand-based biometric identification method is proposed to identify individuals based on their hand features, namely, palmprint, palm vein, and dorsal hand vein. The purpose behind this work is to combine all the merits of all three biometric modalities and overcome the limits of unimodal systems to bring more robustness, stability, universality and security to biometric systems. Palmprint is a powerful method for human identification since it includes rich distinctive features that are unique among all individuals but it is not as secure as vein-based biometrics. Palmprint biometric trait can be replicated because it is visible to human eyes and hand leftover patterns can be fetched among object surfaces to perform spoofing attacks to unimodal palmprint-based systems. Consequently, we had an idea to amalgamate hand veins that are harder to be forged and replicated with already high-performance palmprint-based biometrics to increase its security while ensuring its accuracy. Our method uses Feature-Level Fusion along with weighted Decision-Level Fusion to combine the results from unimodal biometrics and form a fully functioning multimodal system. Our proposed method uses three biometric modalities that had never been combined together. The proposed method creates a unified system and has shown significant results that are comparable to the state-of-the-art multimodal systems that are using different biometric modalities and also unimodal systems with 99.66% of accuracy in the identification of individuals.

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