A Weighted Score Matching Algorithm for a Multi-modal Biometric System Based on Fingerprint and Hand Geometry

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ABSTRACT

This paper presents a multi-modal biometric system implemented using MATLAB language. The system fused fingerprint and hand geometry at matching score level by applying a proposed modified weighted sum rule. The fingerprint system was tested using five FVC databases and the hand geometry system was tested using COEP database. Hence, the multi-modal system was tested by merging each FVC database with COEP database. The experimental results show significant improvement in the multi-modal system with an average EER of 3.27%; while it is 8.86% and 8.89% for fingerprint and hand geometry systems, respectively.

1. INTRODUCTION

People used a variety of ways trying to obtain safer and more precise methods to identify themselves and protect their personal properties and private information; like using keys, ID card, password or PIN code. However, these traditional security methods do not satisfy the requirements of most companies and governmental agencies at the present time, especially with modern applications that use electronic services operating automatically, like ATMs in banks, e-learning, e-commerce, criminal search tools … and so on. Hence, these applications need effective and stronger protection methods. Biometric systems are becoming popular as a measure to identify a person by what the characteristics of the person are rather than what the person carries. Each biometric system has its advantages and disadvantages, but still offers great convenience and several advantages over traditional security systems [1, 2]. The next sub-section presents a brief summary on biometric systems.

1.1 Single Biometric Systems

A biometric system is defined as "a system which automatically distinguishes and recognizes a person as a unique individual through a combination of hardware and pattern recognition algorithms based on certain physiological or behavioral traits (characteristics) that are inherent to that person" [3]. According to this definition, the biometric system depends on the person's specific (physiological or behavioral) traits. Therefore, system data cannot be shared, lost, stolen or forgotten [1, 4]. Any human physiological or behavioral trait can be used as a biometric trait, but it has to satisfy some basic requirement factors; shown in Table 1 [1].

Biometric systems are generally classified into verification and identification systems. Verification systems confirm or deny the identity of the person using his/her ID code. Therefore,

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the output decision query is only between one person and only one user template, which is stored in the database (one to one matching process). On the other hand, identification systems are used to determine the identity of one person with respect to all user templates in the database (one to many matching process) [1]. Any biometric system should include four main steps:

1. Pre-processing: Improvement of sample quality, elimination of the noise resulting from sensor device type or environment noise and making the sample appropriate for the next step.

2. Feature extraction: Extraction of details of biometric trait that distinguishes between persons.

3. Feature matching: In this step, the similarity score will be estimated to decide whether the extracted features from two biometric traits are matched or not.

4. Decision making: The final step is used to decide whether the sample is accepted or rejected by selecting an appropriate threshold value and comparing it with the similarity score.

Table 1. Comparison of various biometric traits usage basic requirements [5].
Usage basic requirements; High: H, Medium: M, Low: L.

	Universality	Distinctiveness	Permanence	Collectability	Performance	Acceptability	Circumvention
Face	H	L	M	H	L	H	H
Fingerprint	M	H	H	M	H	M	M
Hand Geometry	M	M	M	H	M	M	M
Iris	H	H	H	M	H	L	L
Voice	M	L	L	M	L	H	H
Signature	L	L	L	H	L	H	H

Figure 1 shows the block diagram of how biometric (verification and identification) systems work with the four main steps mentioned above.

Biometric systems offer good recognition performance, but are not free of errors. However, even the most advanced biometric systems are still facing numerous problems; including data, algorithm used and system design, which cause a negative impact on the performance.

The main drawbacks of biometric systems can be summarized in the following points [3]:

- Noisy data because of a noisy environment or a problem during the use of sensor device which makes the feature extraction process more difficult.

- Not all biometric characteristics are universal because of various birth defects and accidents that lead to the absence of the biometric trait in some people; like a cut hand or finger.

- Lack of individuality, where the biometric trait is similar among a group of people, so that the system cannot distinguish between them, as in the case of twins.

- Susceptibility to circumvention as when an impostor presents a fake biometric sample to the system, such as using gummy fingers.

To resolve the previous problems, upgraded hardware could be used, employing liveliness detection techniques, using robust algorithms to improve the quality of the sample and matching process, or using multi-biometric systems and integrating information from different sources [4]. The next sub-section is oriented toward giving a brief idea on the latter solution; multi-biometric systems, which is the focus of our study.
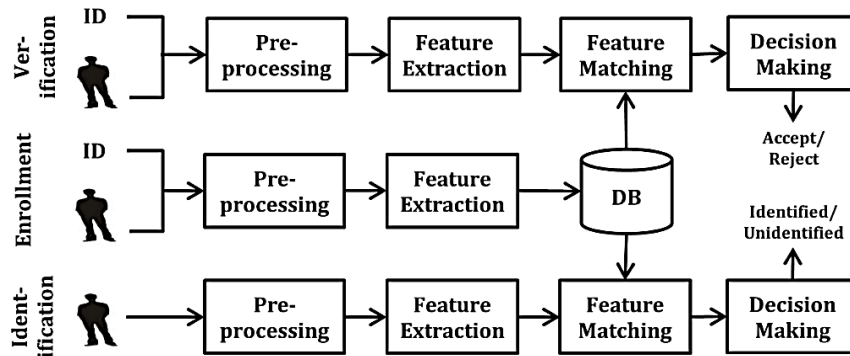
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Figure 1. Biometric (verification and identification) systems.

1.2 Multi-biometric Systems

Multi-biometric systems can offer significant improvement in the performance accuracy of a biometric system, population coverage, preventing spoofed attacks and reducing the failure rate of enrollment data to the system [6]. The term multi-biometric indicates "the presence and use of more than one biometric aspect (modality, algorithm, instance and/or sensor) in some form of combined use for making a specific biometric verification/identification decision" [7]. According to the previous definition, multi-biometric systems are classified into four main categories as shown in Figure 2.
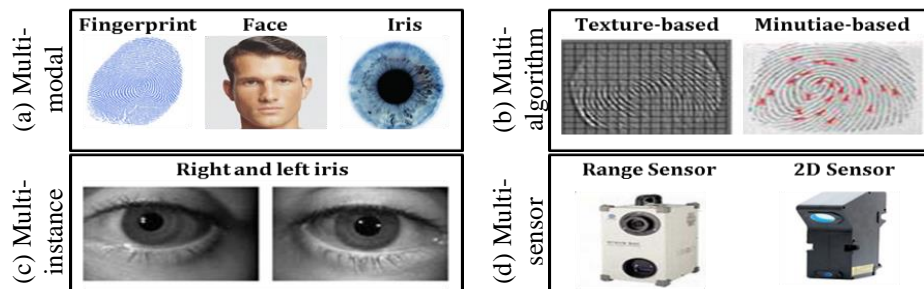

Figure 2. Multi-biometric system categories.

Even though fusing all these categories may offer very high performance results, this procedure was avoided due to increased time consumption and cost effect. Thus, our interest was focused on the multi-modal biometric system which is one of the widely applicable systems.

Different modality of single biometric systems can fuse their information in different levels and produce a multi-modal biometric system. The common fusion levels are [8]:

1. Feature level: Merging feature sets extracted from single systems into one feature set.

2. Score level: In the feature matching step, the similarity scores of each single system are normalized and fused using rules like max and sum rules.

3. Decision level: The simplest method, because it combines the final decisions of each system using rules like AND, OR and Majority voting.

With regard to existing biometric systems used for recognition, there is still room for improvement through development of devices, techniques or algorithms. Therefore, in this paper, a simple and effective multi-modal biometric system based on fingerprint and hand geometry was introduced. We applied the fingerprint system mentioned in our previous paper [9], where the

steps were explained here in more detail. In addition, we adopted the proposed weighted feature matching algorithm in [9] for the proposed hand geometry system and multi-modal biometric system as explained in Section 3.

The remainder of the paper is organized as follows: Section 2 presents the related works. In Section 3, the proposed multi-modal biometric system based on fingerprint and hand geometry at score level fusion is described. Section 4 shows the experimental results of the system with statistics, graphs and tables for illustration. Finally, Section 5 concludes the paper and provides some suggestions for future investigation.

2. RELATED WORKS

2.1 Overview of Fingerprint System

Fingerprint system is one of the most common and reliable systems used for security purposes, because of its uniqueness, universality, invariability and extraction facilities [10]. Figure 3 displays an example of fingerprint surface pattern, which consists of ridge and valley lines. The local ridge lines have a lot of information and form a set of distinct features called minutiae, which is classified into two popular types: ridge ending and ridge bifurcation. These minutiae are used in the biometric system to distinguish between people [9, 11, 12].

Figure 3. Example of fingerprint structure.

Many algorithms have been suggested for enhancement in the specialized literature for fingerprint recognition, either to improve fingerprint image quality, extract the features or match feature approaches [10, 13]. Hong *et al.* [11] published the major article that used Gabor filter to improve fingerprint image quality. They evaluated the goodness index method of minutiae extraction in the verification system. Popovic *et al.* [14] produced directional log-Gabor filter and applied it using low quality images on frequency domain. Chikkerur *et al.* [15] implemented a new algorithm based on short time Fourier transform analysis (STFT).

For feature extraction methods, most studies extracted ridge ending and ridge bifurcation using Crossing Number (CN) concepts [16, 17]. This method depends on the eight-neighbourhood of each ridge pixel [16]. Moreover, Babatunde *et al.* [17] modified the crossing number method to give the same result with lower cost. Xin *et al.* [18] extracted the minutiae from grey-scale images by using Gabor phase field method. Tico and Kuosmane [19] presented a method that validates and deletes many false minutiae, such as spikes, holes, bridges, ladders and spurs. With regard to matching algorithms, Wei *et al.* [20] implemented an algorithm using local ridge line sets to deal with image distortion and false features. They proposed an equation to calculate final matching score for merging two matching algorithms; a graph matching with global orientation field matching. Bengueddoudj *et al.* [21] used local and global structures of the fingerprint to modify the existent minutiae matching algorithm. Jie *et al.* [22] compensated the lack of fingerprint information by improving the effect of orientation field, minutiae, reconnected ridges and recovered missing minutiae.

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2.2 Overview of Hand Geometry System

Hand geometry becomes popular as a biometric trait and is applied in various identification systems of real-world applications. Each human has special hand geometry features that can be useful in distinguishing between persons; such as different shape of the hand, size of the palm, length and width of the fingers [23, 24]. Hand geometry is considered for low-medium security, but with advantages of low computational cost algorithm, low resolution images, high user acceptance and low storage size [2, 25]. Some hand geometry sensor devices came with pegs to fix the position of the user's hand. Others do not rely on these devices as they are captured using a camera in different positions making them more challenging, especially in the field of research, investigation and crime scenes [26]. Many research studies about hand geometry systems have been conducted using different numbers of features or different algorithms.

Saxena *et al.* [2] proposed a new threshold algorithm for hand segmentation. It depends on 21 features from palm width, finger length and width. The system was tested using 6 different distance functions and compared between 96 users with 5 images for each user. Kang and Wu [27] presented a segmentation method to extract fingers from hand images using the principle of a modified Otsu. Al-Ani and Abd Rajab [26] implemented a method for feature extraction using a two-dimensional discrete cosine transform. Their research depended only on extracting the length and width of fingers. In addition, they evaluated the system performance by calculating matching metric correlation. Furthermore, Fierrez *et al.* [28] implemented a system with 17 features extracted from fingers and palm. The features were grouped into 8 sets; each set consisted of a combination of several features. Xiong *et al.* [29] studied the problem of applying hand in the biometric system without using any pegs to determine hand position. They produced an elliptical model to get optimal alignments of hands and improved the traditional geometry measurement methods to extract about 37 features from fingers. Yildirim and Tulay [30] introduced a new approach to identify the hand by its pattern. They classified and recognized patterns using general regression neural networks.

2.3 Overview of Multi-modal Biometric System

There are many studies in multi-modal biometric systems field. These studies vary in terms of the biometric characteristics selected, the level of the fusion or the algorithm used. Jain and Ross [31] developed a multi-modal system using fingerprint, face and hand geometry. They compared between user-specific threshold and their proposed user-specific weight methods which were used for fusion of the biometric traits. Charfi *et al.* [32] suggested fusion between hand shape and palmprint in verification system. They extracted the features by improving Scale Invariant Feature Transform algorithm. The system was tested on IITD hand database and fused at score level using max, min, product and sum rules. Abdolahi *et al.* [33] implemented a novel fusion method to combine iris and fingerprint at decision level. This method depended on Hamming distance, fuzzy logic and weighted code.

Dehache and Souici-Meslati [34] proposed a multi-modal verification system using two traits: fingerprint and signature. They classified the single modes by neural multi-layer perception and fused their matching scores using the support vector machine approach. Meghanathan *et al.* [35] proposed an integration weight optimization technique to improve the performance of biometric models. This technique reduced the computational complexity and used a small number of training samples. They applied their technique using fingerprint and voice. The system used sum rule to fuse the scores and was tested using FVC2002 database for fingerprint and ELSDSR database for voice. Mohi-ud-Din *et al.* [36] presented a multi-modal system based on palmprint and fingerprint using two levels of fusion; feature level and score level. Directional energy-based feature vectors were used to fuse feature vector for each module in one vector, while the sum and product rules were applied in score level fusion.

3. THE ARCHITECTURE OF THE PROPOSED MULTI-MODAL BIOMETRIC SYSTEM

The proposed multi-modal system was implemented at score level fusion based on two models; fingerprint and hand geometry, as shown in Figure 4. The fingerprint was suggested for its strength and uniqueness, while hand geometry was suggested for its speed. The human body has various biometric traits; our focus was on hand, because different traits can be obtained from it using one sensor device, such as fingerprints, palm prints, vein patterns and hand geometry [23]. Hence, there will be no extra inconvenience to the user when using the system, while the accuracy of the system may be increased due to the addition of several features [37].
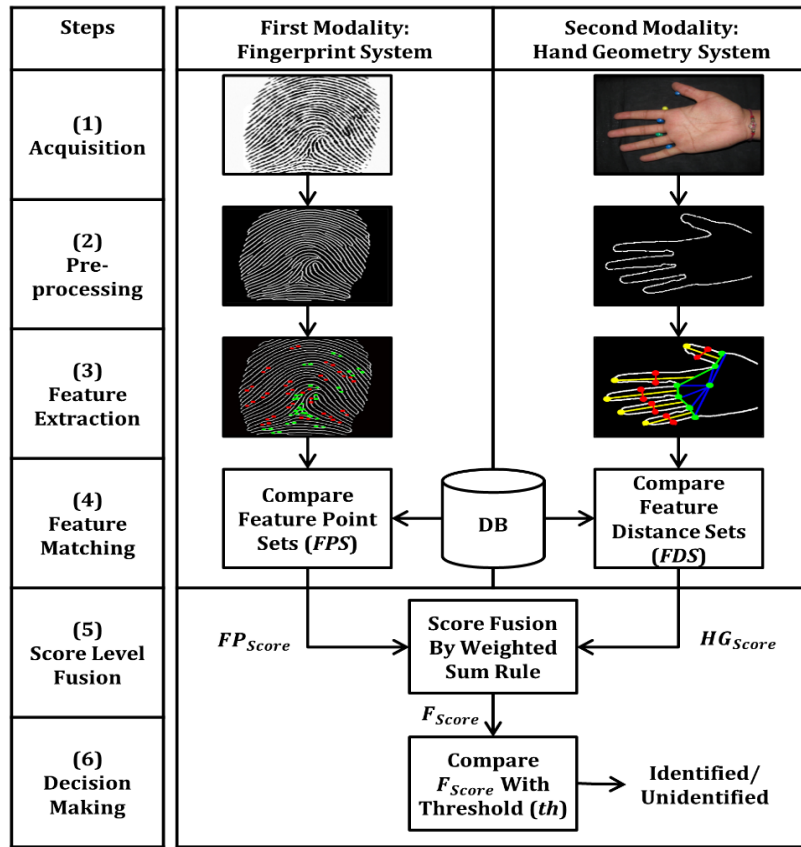

Figure 4. Overview of the proposed multi-modal biometric system.

3.1 The First Modality: Fingerprint System

Although very effective solutions are currently available, there is still need for improvement. In this work, the fingerprint system in our previous paper [9] is implemented; where the weighted feature matching algorithm was modified for more accurate results. Hence, the feature point weight table has been updated. The detailed steps of the proposed fingerprint system [9] is explained in the following subsections.

3.1.1 Pre-processing

When you take fingerprint images by a sensor device, this may result in several image qualities due to the noise in the environment. Therefore, the goal of pre-processing is improving fingerprint image quality and facilitating feature extraction [38]. The basic idea to enhance the image is taken from the classical Gabor filter technique [11]. It was used for contextual enhancement using local characteristics information on fingerprint; i.e., ridge orientation and ridge frequency to correct

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ridge endings and bifurcation [39, 40]. Figure 5 displays the pre-processing steps in the proposed fingerprint system.
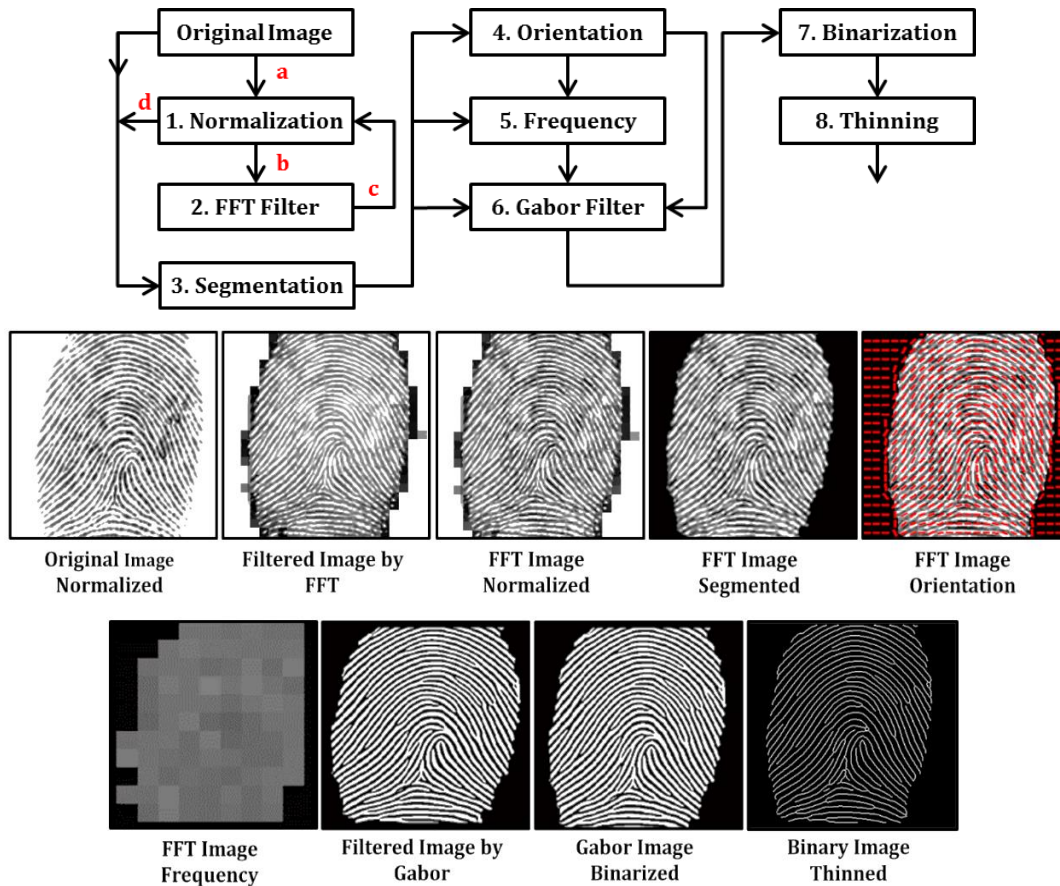

Figure 5. Pre-processing steps in fingerprint system with an example.

We propose to change the classic technique by applying an adaptive histogram equalization algorithm in the normalization step and adding a new step to filter the image using Fast Fourier Transform (FFT) filter. This filter will connect the broken ridges and fill the holes [39]. Image enhanced by FFT filter is used as an input for Gabor filter technique instead of using the normalized image, as it is more accurate and clear. In this way, we combine the advantages of the two filters to get an image with better quality. In addition, images are segmented in a good way. Figure 6 displays some results to clarify the difference between classic and proposed filters.

In our system, the segmentation process will create two masks; the first one (I_{mask1}) will be used to isolate the foreground region from the background region. The second mask (I_{mask2}) which is smaller than I_{mask1} will play a role in the feature extraction process. Furthermore, in the last step, two thinning images were created using morphological thinning operation for the feature extraction process:

1. Using binary image (I_{Binary}) to create a thinned image ($I_{Thinned1}$), which is used to extract ridge ending points.

2. Inverted binary image ($\sim I_{Binary}$) was applied to create a second thinned image ($I_{Thinned2}$), which is used to locate the positions of the ridge bifurcation points.

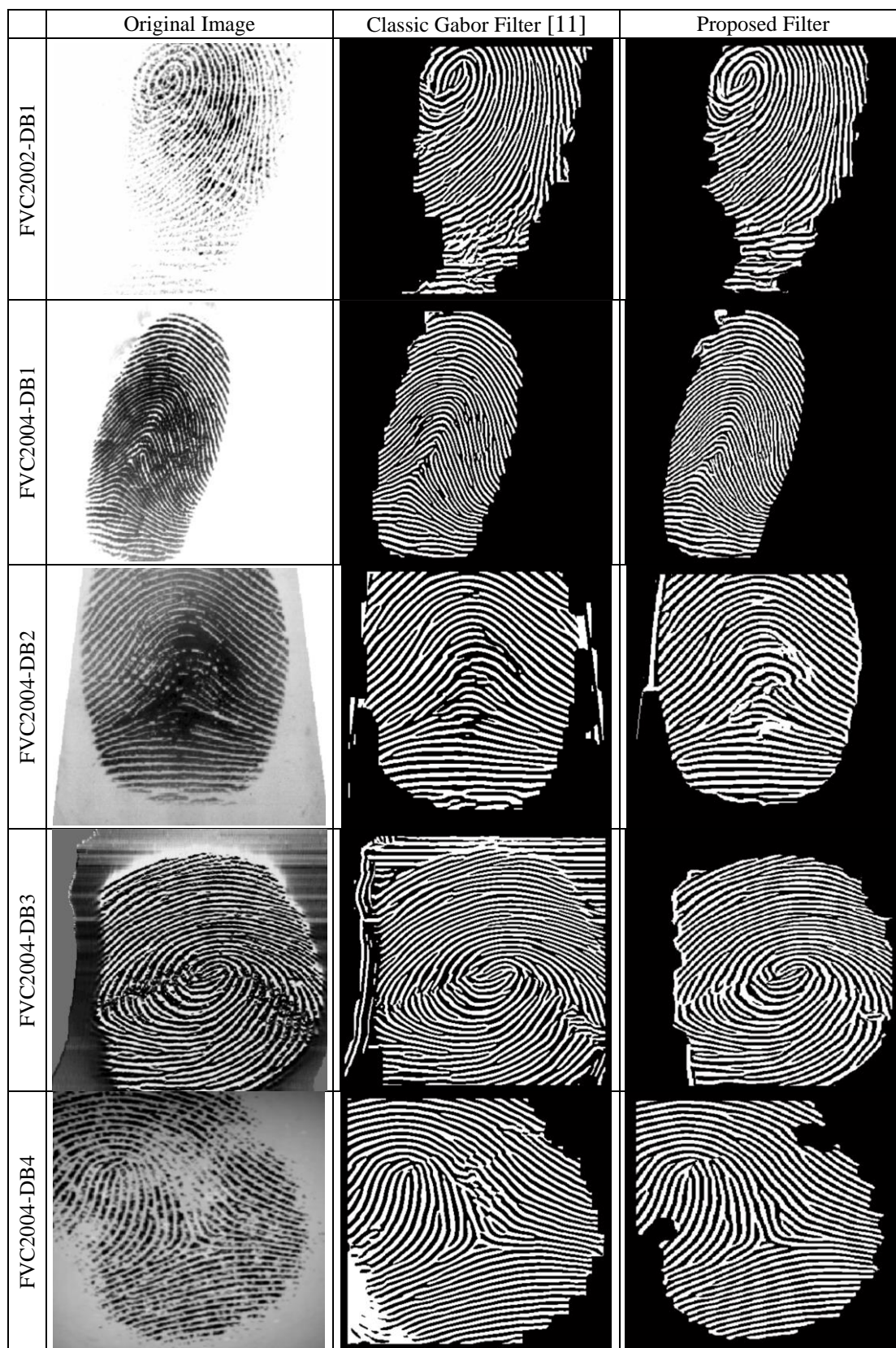|	Original Image	Classic Gabor Filter [11]	Proposed Filter
FVC2002-DB1			
FVC2004-DB1			
FVC2004-DB2			
FVC2004-DB3			
FVC2004-DB4			

Figure 6. Some results from pre-processing steps in the fingerprint system.

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3.1.2 Feature Extraction

After the fingerprint image is enhanced, fingerprint features represented in minutiae and ridge points can be extracted easily [20]. The combination between these points was suggested to give more information about the fingerprint that our proposed matching algorithm can use, especially if the image is corrupted or distorted. The proposed feature extraction method is applied to extract only one type of minutiae that is a ridge ending with its ridge point. Therefore, the method will be executed twice: first using ($I_{Thinned1}$) to extract a ridge ending and then using ($I_{Thinned2}$) to extract also a ridge ending, but its coordinates correspond to ridge bifurcation coordinates in ($I_{Thinned1}$).

1. Exclusion of Ridge Pixels on the Border: Ridge pixels on the border can cause a large number of spurious minutiae of ridge ending type. To remove these pixels, the second mask (I_{mask2}) produced in the segmentation step will be applied to eliminate every pixel that exists outside the mask. To do that, each ridge pixel (P) in the thinned image will be scanned by checking its coordinates with the mask as follows:

$$P(x,y) = \begin{cases} Keep\ it, & I_{mask2}(x,y) = 1. \\ Delete, & otherwise. \end{cases} \qquad (1)$$

2. Ridge Ending Extraction: Ridge ending will be extracted by scanning the eight-neighbourhood pixels around P, then by calculating the summation (N) of these eight pixels. The pixel P is considered to be a ridge ending (M) if $N = 1$. Figure 7 illustrates the notion derived from crossing number method [16].
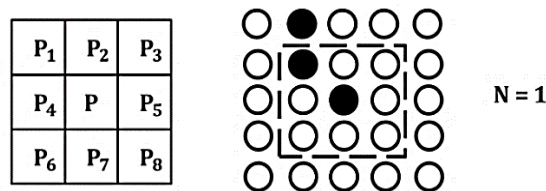

Figure 7. Extraction of ridge ending point.

3. Ridge Point Extraction: An extra feature was extracted to get more accurate information about minutiae and ridge line shape, defined as ridge point (R). Figure 8 illustrates the concept [20] with a sample.

(a) The concept [20].

(b) An example of a fingerprint feature.

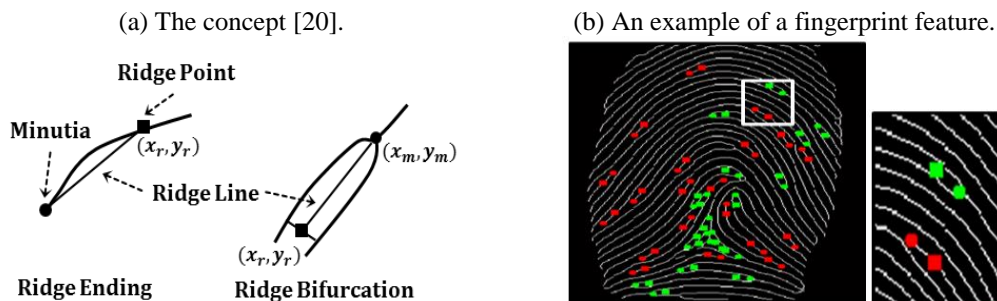Figure 8. Illustration of minutiae and ridge points.
Ridge ending (red), bifurcation (green), minutiae point (●) and ridge point (■).

4. In our system, extracting the ridge point R according to minutiae type is derived from the algorithm mentioned in [19], which is also used to validate the minutiae. This algorithm depends on the ridge shape, which means that if there is any deformation in the ridge shape,

the minutiae will be ignored and deleted. Therefore, our focus was only on ridge ending point M, since it has only one branch which reduces the presence of ridge distortions.

The proposed ridge point extraction method is summarized as follows:

a. Create an initial image (L) with size ($W \times W$) and fill it with pixels from $I_{Thinned}$ which is centered by M and located in its ($W \times W$) neighbourhood.

b. Label each connected region in L.

c. Count the number (C) of similar pixel values on the border, which is equal to the value of the center pixel M.

d. In case ($C=1$), M is a true ridge ending and the pixel on the border is the ridge point (R). Otherwise, delete it as shown in Figure 9.
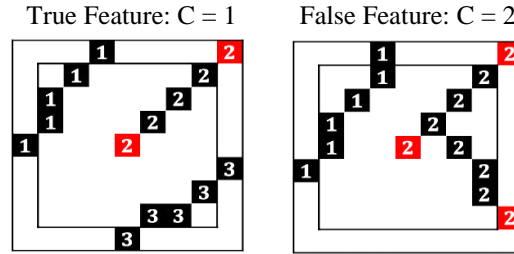

Figure 9. An example of ridge point extraction.

All true feature points extracted will be saved in a set called feature point set (FPS) in the following arrangement:

$$FPS = \begin{cases} (M_x^1, M_y^1, M_\theta^1, R_x^1, R_y^1, R_\theta^1), \\ (M_x^2, M_y^2, M_\theta^2, R_x^2, R_y^2, R_\theta^2), \\ \dots\dots\dots \\ (M_x^n, M_y^n, M_\theta^n, R_x^n, R_y^n, R_\theta^n) \end{cases}. \tag{2}$$

Here, n is the number of minutiae in the set, M represents minutiae point, R is ridge point and (x, y, θ) are the point components; the coordinates and the orientation, respectively.

Figure 10 displays an example of feature set FPS for ($I_{Thinned1}$) which consists of minutiae (ending and bifurcation) and their ridge points. FPS is a union between FPS_1 in ($I_{Thinned1}$) and FPS_2 in ($I_{Thinned2}$) of the same fingerprint.
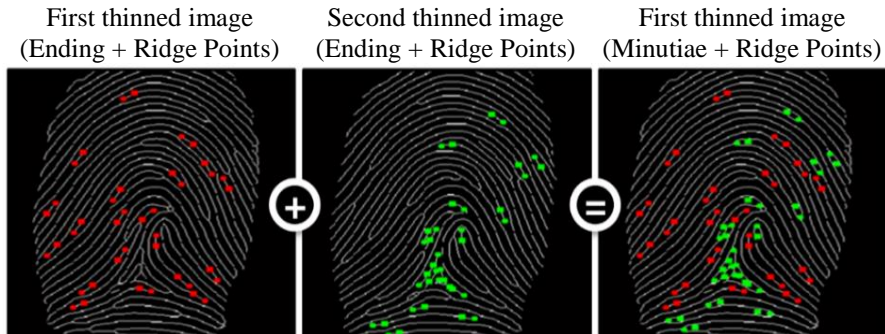

First thinned image (Ending + Ridge Points) ⊕ Second thinned image (Ending + Ridge Points) = First thinned image (Minutiae + Ridge Points)

Figure 10. An example of feature extraction in the fingerprint system.

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3.1.3 Feature Matching

This step is used to determine whether two biometric traits are matched by comparing their extracted features and calculating the similarity score. Minutiae-based matching algorithms [21, 22, 41, 42] are commonly used in fingerprint systems. They basically depend on extracted minutiae information; the minutia coordinates (x, y) and the ridge orientation direction θ.

In our system, a weighted feature matching algorithm was proposed and derived from the classic minutiae-based matching algorithm. It has a simple changing with two features: minutiae and ridge points. These will be stored in a feature point set (FPS) as stated in the previous subsection. This suggested FPS allows the combination between the two classical matching algorithms; minutiae-based and ridge-based algorithms. In this way, more information about extracted minutiae can be gathered in the partial fingerprint. The steps of the proposed matching algorithm are as follows.

1. Registration: Registration is a process applied on two (FPS); template feature point set (FPS^T) and input feature point set (FPS^I). The goal is to align and register them with respect to each other using an affine transform [43]. The steps to estimate the appropriate transformation parameters for accepted registration are as follows:

    a. Make a list of reference points (RP) in the origin using each minutia in FPS.

    b. Transform the original coordinate system of each point in (FP) whether it is minutia point M or ridge point R in FPS to a new one and update its field values with:

$$\begin{pmatrix} new\_FP_x \\ new\_FP_y \\ new\_FP_\theta \end{pmatrix} = \begin{pmatrix} cos(RP_\theta) & -sin(RP_\theta) & 0 \\ sin(RP_\theta) & cos(RP_\theta) & 0 \\ 0 & 0 & 1 \end{pmatrix} \times \begin{pmatrix} FP_x - RP_x \\ FP_y - RP_y \\ FP_\theta - RP_\theta \end{pmatrix}. \qquad (3)$$

    c. Finally, pair the features to calculate the maximum number of matching pairs.

    Since the system does not know whether the two fingerprints are belonging to the same person, it performs the registration process using all RP in order to find best transformation. Figure 11 shows a registration of two different samples for the same fingerprint.

Figure 11. Registration of two samples for the same fingerprint.

2. Feature Pairing: After the registration process, two features are considered to be paired or matched if their point coordinates (x, y) and orientation (θ) are close enough to each other [43, 44]. In our proposed algorithm, we just check the match of point coordinates without the orientation, since the direction minutiae will be specified by the ridge point. Moreover, the possibility of the existence of matching pair candidates is eliminated by using two tolerance boxes; one for each feature point. Figure 12 illustrates the idea.

Any pairing feature inside the tolerance box is supposed to take the similarity value 1, while in case of un-matched feature, it will be 0. However, the matching pairs in our system were classified

according to their component level and took a similarity value in the range [0, 1]. To find the feature similarity value, we do the following:

a. Compute the Euclidean distance ($Dist_1$) between minutiae pairs (M^T, M^I) and ($Dist_1$) between ridge point pairs (R^T, R^I) using the general equation between two points (p, q):

$$Dist(p,q) = \sqrt{(p_x - q_x)^2 + (p_y - q_y)^2}\,. \qquad (4)$$

b. Calculate the difference angles between (M^T, M^I) to get (Ang_1) and between (R^T, R^I) to get (Ang_2) using the general equation:

$$Ang(p,q) = |p_\theta - q_\theta|. \qquad (5)$$

c. Associate a level value for each $Dist$ and Ang according to a threshold:

$$Level_{Dist} = \begin{cases} 2, & Dist \le Th_1. \\ 1, & otherwise. \end{cases} \qquad (6)$$

$$Level_{Ang} = \begin{cases} 2, & Ang \le Th_2. \\ 1, & otherwise. \end{cases} \qquad (7)$$

d. Calculate a feature pair similarity using Table 2. The table shows that the components ($Dist_1$, Ang_1, $Dist_2$ and Ang_2) have different weights (CW) from high (4) to low (1). The algorithm depends on the minutiae points; therefore, it will have the higher weight. Furthermore, the coordinates will be with higher weight, because the orientation value depends on the location of the point. The steps to create the table are as follows:

   i. Find feature pair priority (Pr) through multiplying each component level by its weight, then sum the results.

$$Pr = \sum_{i=1}^{4} (CL_i \times CW_i). \qquad (8)$$

   ii. Arrange Pr in ascending manner to get Feature Weight (FW).

   iii. Obtain feature pair similarity (FS) by normalizing FW to be in the range [0, 1].

$$FS_i = \frac{FW_i}{16}, \qquad i = 1, 2, \dots, 16. \qquad (9)$$

   iv. In case multiple points exist inside tolerance boxes, higher FS will be chosen. In addition, if multiple points exist with same highest FS, maximum FW will be taken with minimum minutiae pair distance ($Dist_1$).

In this way, we can decide whether the matching feature has been affected during the registration process or not. Therefore, a weight and different similarity value were given to the matching feature according to its quality: high value for high quality and low value for low quality.

Finally, we compute the matching similarity score of the two fingerprints (FP_{Score}) within the range [0, 1] by the next traditional equation.

$$FP_{Score} = \left(\sum_{i=1}^{m} FS_i\right) \Big/ min(n^T, n^I). \qquad (10)$$

Here, m is the number of matching features, while n^T and n^I are the numbers of features in the template and input fingerprints, respectively.

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(a) Classic minutiae matching algorithm [43].

Paired minutiae | Unpaired minutiae (Outside the box) | Unpaired minutiae (Unmatched angle) | Unpaired minutiae (No pairing possible)

(b) The proposed feature point matching algorithm

Paired feature (Both points) | Unpaired feature (Ridge point) | Unpaired feature (Minutia) | Unpaired feature (Both points)
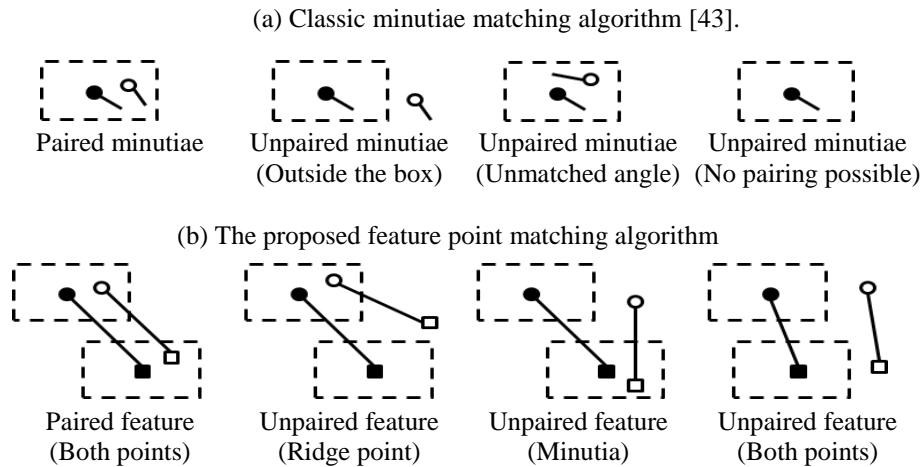
Figure 12. Possibilities of feature matching in the fingerprint system.
Minutiae point (●) and ridge point (■).

Table 2. Feature point weight table in the fingerprint system.
(Two feature levels with four point components; 24 = 16 possibilities)

	Minutia		Ridge Point		Pr	FW	FS
	Dist$_1$	Ang$_1$	Dist$_2$	Ang$_2$			
CW	4	3	2	1			
CL	1	1	1	1	10	1	0.063
	1	1	1	2	11	2	0.125
	1	1	2	1	12	3	0.188
	1	1	2	2	13	4	0.250
	1	2	1	1	13	5	0.313
	1	2	1	2	14	6	0.375
	1	2	2	1	15	8	0.500
	1	2	2	2	16	10	0.625
	2	1	1	1	14	7	0.438
	2	1	1	2	15	9	0.563
	2	1	2	1	16	11	0.688
	2	1	2	2	17	12	0.750
	2	2	1	1	17	13	0.813
	2	2	1	2	18	14	0.875
	2	2	2	1	19	15	0.938
	2	2	2	2	20	16	1.000

CW: Component weight, CL: Component level,
Pr: Feature pair priority, FW: Feature Weight, FS: Feature pair similarity.

3.2 The Second Modality: Hand Geometry System

In this subsection, the proposed hand geometry system will be described in detail with all methods and algorithms that were applied. The proposed system could work on any image, whether it contains pegs or not, but the hand image must be separate fingers as shown in Figure 4. The system passes through the following steps:

3.2.1 Pre-processing

The goal of pre-processing is to clean up any noise from the image and to make it appropriate and easy for the next step of extracting features as shown in Figure 13.
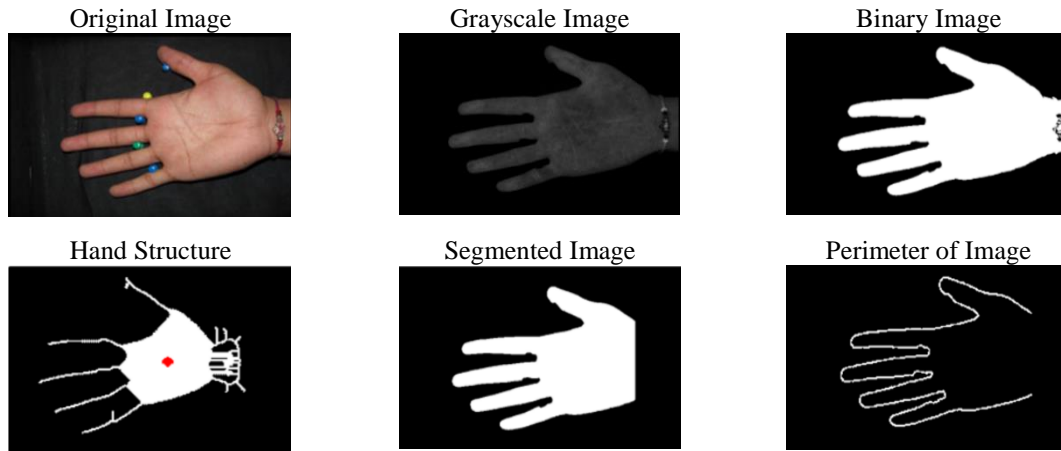
Figure 13. An example of pre-processing
steps in the hand geometry system.

3. <u>Convert to Grayscale Image:</u> In our system, color images were used and they contain color pins to fix the suitable position of the hand. These pins are distorting hand borders and must be discarded. As is known, the color images are composed of three channels: red, green, and blue. An arithmetic operation is performed with these different channels to transform the color image into grayscale image. In our case, green channel (I_{Green}) of the image is subtracted from the red one (I_{Red}) using equation (11). In this way the pins are removed from the image and give a clear grayscale image I_{Gray}) of the hand.

$$I_{Gray} = I_{Red} - I_{Green}. \tag{11}$$

4. <u>Binarization:</u> This process is used to generate the binary image (I_{Binary}), which means making the image with only two colors; black and white. To do that, first an appropriate global threshold value (th_1) must be determined by applying Otsu method on the grayscale image. Then, each pixel in the grayscale image is compared with (th_1) as shown in the next equation.

$$I_{Binary}(x,y) = \begin{cases} 0, & I_{Gray}(x,y) < th_1. \\ 1, & otherwise. \end{cases} \tag{12}$$

5. <u>Segmentation:</u> As shown in Figure 13, the hand image shows a part of the arm. Hence, it was necessary to apply segmentation process to remove the arm part regardless of its length. The main idea is to determine the centroid point (C) of the hand. In literature [27], the binary image is used to locate C. In our system, we decided to thin the binary image and get the hand structure to do that. In this way, the extracted centroid point is more accurate. The following steps will be implemented:

a. Removing noise from the binary image by applying 2-D median filter. This filter is used to replace each pixel (P) in I_{Binary} by the median of all pixel values inside a window with size ($W \times W$). The window is a copy of I_{Binary}, so that its center pixel will be corresponding to P.

b. Performing morphological operations for:

i. Removing all small objects from the binary image using erosion operation.

ii. Thinning the binary image to get hand structure ($I_{Thinned}$) using thin operation.

c. Determining the centroid point (C) of the thinned image:

i. Count the total number of white pixels (n) in $I_{Thinned}$.

ii. Find the (x, y) coordinates of all white pixels.

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iii. Locate the centroid point using:

$$C = I_{Thinned}(mean_x, mean_y).$$

(13)

$$mean_x = \frac{1}{n} \sum_{i=0}^{n} x_i.$$

(14)

$$mean_y = \frac{1}{n} \sum_{i=0}^{n} y_i.$$

(15)

d. Determining the hand length (L) according to hand acquisition; in our case, it will be in the x-direction. Therefore, a suitable threshold value (th_2) will be added to the x value of the centroid point (C).

$$L = C_x + th_2.$$

(16)

e. Finally, Remove arm part and estimate the segmented image ($I_{Segment}$) from the binary image.

$$I_{Segment}(x, y) = \begin{cases} I_{Binary}(x, y), & x < L. \\ 0, & otherwise. \end{cases}$$

(17)

6. <u>Hand Perimeter:</u> A morphological operation was applied on the segmented image to create the perimeter image with hand boundary that is exactly one pixel thick [45]. The method works by executing erode operation on $I_{Segment}$, then subtracting the resulting image from $I_{Segment}$ to get the perimeter image ($I_{Perimeter}$).

3.2.2 Feature Extraction

From previous studies, we found that the number of extracted features differs from a system to another. In general, those features are often represented in distances of hand width, finger width and finger length at different points along the finger [37]. The features in hand geometry depend on the landmark points of the hand, which are denoted by peaks and valleys between adjacent fingers. As well, additional points could be extracted from basic landmark points, represented in the finger middle points.

In our system, chain code algorithm [46] was applied to extract basic hand points from the perimeter image ($I_{Perimeter}$) as Figure 14 displays. Then, the extracted hand points were used to estimate five distance features of hand width (blue lines, a) and five distance features of finger length (yellow lines, b), while using ten distance features of finger width (red lines, c) and (green lines, d). The basic equations that we need to extract the distance features are as follows:

a. The Euclidean distance ($Dist$) between (p, q) by equation (4).

b. The center point (C) coordinates of a line exist between (p, q):

$$C_x = (p_x + q_x) / 2.$$

(18)

$$C_y = (p_y + q_y) / 2.$$

(19)

All twenty distance features extracted will be saved in a set known as the feature distance set (FDS):

$$FDS = \begin{cases} a_1, a_2, a_3, a_4, a_5, \\ b_1, b_2, b_3, b_4, b_5, \\ c_1, c_2, c_3, c_4, c_5, \\ d_1, d_2, d_3, d_4, d_5 \end{cases} = \{Dist_1, Dist_2, \dots, Dist_{20}\}.$$
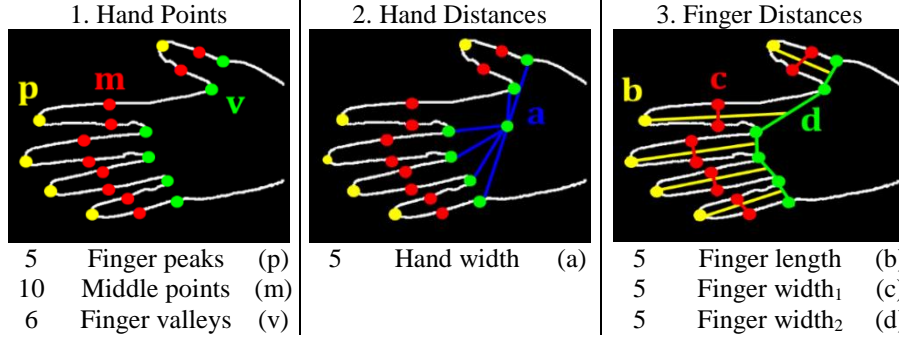
(20)

Figure 14. Feature extraction in hand geometry system.

3.2.3 Feature Matching

Feature matching determines the matching score of similarity between two hands; template feature distance set (FDS^T) and input feature distance set (FDS^I). In a hand geometry system, there is no need to align the hands, since the algorithm directly compares between distances. The classic method [28] for feature matching is based on a distance measure. This is done through computing the summation of absolute difference (*diff_d*) between each distance feature in FDS^T and its corresponding feature in FDS^I:

$$diff\_d = \sum_{i=1}^{m} \left| Dist_i^T - Dist_i^I \right|. \tag{21}$$

Here, *m* is the number of features in the *FDS*.

The perfect feature match can be obtained if the value of *diff_d* is equal to zero. *diff_d* increases whenever it is heading towards mismatches. Therefore, a certain threshold value is determined to decide the outcome of matching. In our system, a simple change in the classic method [47] was proposed to get better results. The steps of the proposed feature matching are:

1. Classifying the features and taking the mean of the absolute difference for each of them:

   - Hand distance (a):

$$diff\_d_1 = \frac{1}{6} \sum_{i=1}^{6} |a_i^T - a_i^I|. \tag{22}$$

   - Finger distances (b, c and d):

$$diff\_d_{i+1} = \frac{1}{3} \left| \left(b_i^T + c_i^T + d_i^T \right) - \left(b_i^I + c_i^I + d_i^I \right) \right|, \qquad i = 1, 2 \ldots 5. \tag{23}$$

2. Determining an appropriate limit for feature pairing by applying two thresholds; *th1* and *th2*, which are also used to give a weight for the feature pair called the feature level.

$$Level_{diff\_d} = \begin{cases} 2, & diff\_d \leq Th_1. \\ 1, & Th_1 < diff\_d \leq Th_2. \\ 0, & otherwise. \end{cases} \tag{24}$$

3. Computing the matching similarity score of the two hands geometry (HG_{Score}) in the range [0, 1] by obtaining distance feature pair similarity (*DS*) using the next two equations.

$$DS = \frac{Level_{diff\_d}}{2}. \tag{25}$$

$$HG_{Score} = \frac{1}{m} \sum_{i=1}^{m} DS_i. \tag{26}$$

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Here, m is the total number of DS of the hand and fingers, which is equal to 6.
The goal of feature classification is to control the selected threshold values for each feature, which makes the classification more accurate. The mean of the features was taken in order to minimize the effect of any error which can occur when calculating distances.

3.3 Proposed Multi-modal Biometric System

Data fusion in multi-biometric systems is commonly applied to improve recognition performance. In our work, score level fusion was proposed to implement the proposed multi-biometric system based on two models; fingerprint and hand geometry, as shown in Figure 4.

3.3.1 Score Level Fusion

To calculate the final score of the proposed multi-modal system, the score resulting from each single mode will be fused using rules like minimum (min), maximum (max), sum, … etc. [48]. The weighted sum rule was the adopted rule for fusion in our system. The expression of weighted sum rule to compute matching similarity score (F_{Score}) of the multi-modal system is:

$$F_{Score} = \frac{1}{m} \sum_{i=1}^{n} w_i . Score_i = \frac{1}{m} (w_1 . FP_{Score} + w_2 . HG_{Score}). \tag{27}$$

$$F_{Score} = \frac{1}{m} (w_1 . FP_{Score} + w_2 . HG_{Score}). \tag{28}$$

Here, m is the value used to normalize the score within the range [0, 1], n is the number of single systems which will be fused, w and $Score$ are the weight and matching score of each single system, respectively.

The value of m depends on the weight given to each module. In the traditional sum rule, the weight of all models will be equal, thus m will be equal to n. On the other hand, to estimate the weights in weighted sum rule, the classic method is used by obtaining the EER for each module and giving small weight to higher EER [31]. This method uses exhaustive search for all samples in the database and depends on the quality of stored samples. This leads to instability in the values assigned for each weight.

We suggested to assign weights according to the degree of distinctiveness factor of the biometric trait as illustrated in Table 1. According to the table, the degree of the fingerprint is high and hand geometry is medium. Thus, we proposed to assign a weight value of $w_1=2$ for fingerprint and $w_2=1$ for hand geometry; which led to assign m with 3 in order to normalize the score between [0, 1]. In this way, we overcame the system dependability on the EER.

3.3.2 Decision Making

Decision making is the final step in the proposed system, which is used to make the final decision. It checks whether the input and template samples belong to the same person by comparing the similarity score estimated from fusion module using a suitable threshold value (Th) as:

$$Decision = \begin{cases} Identified, & F_{Score} \geq Th. \\ Unidentified, & otherwise. \end{cases} \tag{29}$$

4. EXPERIMENTAL RESULTS

4.1 Performance Evaluation

To build a robust biometric system, the effectiveness of the system and its level of error rates

must be measured. Receiver Operating Characteristic (ROC) curve is a common approach to evaluate system performance and calculate error rates [49]. ROC can be used to calculate Error Equal Rate (EER) which describes the point at which genuine and imposter error rates are equal. It shows the correlation between: False Match Rate (FMR) which is known as False Acceptance Rate (FAR) and False Non Match Rate (FNMR) also called False Rejection Rate (FRR) [50].

Our proposed system was designed and programmed using MATLAB language. The experiments were performed using several databases to measure the system performance. Each database contains 800 samples; 100 different persons and 8 samples for each one. Therefore, according to the database, the total number of impostor tests will be: ($100 \times 99 \times 0.5$) = 4950, while the total number of genuine tests performed is: ($8 \times 7 \times 0.5$) $\times$ 100 = 2800 [50]. The EER was calculated through finding FMR and FNMR on different thresholds. In addition, the time cost of two stages was calculated; enrollment stage which consist of pre-processing and feature extraction and matching stage. It takes the average of (4950+2800) = 7750 comparisons.

4.2 Results of Fingerprint System

The system was tested using five public databases known as Fingerprint Verification Competition (FVC) [50, 51]. The results of the proposed fingerprint identification system of the five databases are presented in Table 3. The minimum EER is 2.83% at Th of 0.23 for FVC2002-DB1. The maximum EER is 11.76% at Th of 0.22 for FVC2004-DB2. This is due to the deformation of some images in this database. The performance of the proposed system provides reliable results compared with previous studies with an average EER of 8.86% and Th of 0.22. Table 4 presents time cost of the proposed system. The minimum time cost of the enrollment step is 2.82 sec for FVC2004-DB1, while that of the matching step is 0.79 sec for FVC2002-DB1.

Table 3. Comparison between previous studies and the proposed fingerprint identification system on FVC databases.

EER%	Study [18]	Study [44]	Study [22]	Study [21]	Study [9]	Proposed	
						EER	Th
FVC2002-DB1	4.86	N/A	11.26	N/A	2.88	2.83	0.23
FVC2004-DB1	19.49	12.0	N/A	22.81	11.31	11.16	0.20
FVC2004-DB2	20.76	8.2	9.29	18.54	12.57	11.76	0.22
FVC2004-DB3	13.95	5.0	N/A	9.0	9.23	8.93	0.21
FVC2004-DB4	14.48	7.0	N/A	17.72	9.97	9.64	0.22
Average	14.71	8.05	10.28	17.02	9.19	8.86	0.22

Table 4. Time cost of the proposed fingerprint identification system on FVC databases.

Time in seconds	FVC2002-DB1	FVC2004-DB1	FVC2004-DB2	FVC2004-DB3	FVC2004-DB4	Average
Enrollment	4.60	2.82	4.51	5.70	3.96	4.32
Matching	0.79	2.58	3.62	13.23	1.08	4.26

4.3 Results of Hand Geometry System

The COEP palm print database was adopted to test the proposed hand geometry system. The database is a subsidiary of the College of Engineering, Pune-411005 (Autonomous Institute of Government of Maharashtra). It consists of a total of 1344 images pertaining to 168 persons with 8 different images of a single person. The images were captured using a digital camera with a quality resolution of 1600×1200 pixels [52].

In our system, only 100 persons were selected from the hand geometry database, since the fingerprint database contains 100 persons. We renamed the hand geometry files to correspond to the fingerprint images. In this way, we can claim that the fingerprint and hand geometry belong

to the same person and we can use them in the proposed multi-modal system. The results of the proposed hand geometry system are displayed in Table 5 and compared against those of previous studies. We note that the results are mixed, because there are many variables in each study, including the size of the database, the number of samples, the algorithm used … and so on. In general, the proposed system gives good and reliable results with EER of 8.89% at Th of 0.33. The time cost of the proposed system in the enrollment stage is 3.31 sec; while it takes about 2.5693e-004 sec in the matching stage.

Table 5. Comparison between previous studies and the proposed hand geometry identification system.

EER: FMR=FNMR	Study [28]	Study [29]	Study [53]	Study [30]	Proposed
Database Size	50	108	120	140	100
Samples	10	5	N/A	N/A	8
FMR%	1.24	2.4	11.4	15.0	8.89
FNMR%			10.4		at Th = 0.33

4.4 Results of Multi-modal Biometric System

The proposed multi-modal biometric system depends on the single system databases. Since the fingerprint system used five databases and the hand geometry system used only one, the multi-modal system was tested five times by repeating the hand geometry database for each fingerprint database as shown in Table 6.

Table 6. Experimental results of multi-modal biometric system based on fingerprint and hand geometry at score level fusion using different rules.

EER%	Min	Max	Sum Rule	Proposed Weighted Sum Rule	
				EER	Th
FVC2002-DB1 with Coep	5.94	3.13	2.85	2.02	0.32
FVC2004-DB1 with Coep	9.25	5.15	5.23	3.74	0.25
FVC2004-DB2 with Coep	9.11	5.31	5.18	3.95	0.26
FVC2004-DB3 with Coep	7.49	5.29	5.14	3.59	0.25
FVC2004-DB4 with Coep	8.77	4.69	4.19	3.06	0.28
The Average	8.11	4.71	4.52	3.27	0.27

In order to illustrate the effect of the suggested rule on the EER results of the multi-modal system, different score level fusion rules were applied. Table 6 shows that the results were worst when the system used min rule with average EER of 8.11%, while the system gives best results when using the proposed weighted sum rule. It achieves an average EER of 3.27%.

Furthermore, Table 7 displays some results from previous studies to compare with the proposed multi-modal system. We found that the results are close and the EER values are low in all studies, despite the different characteristics used in each study and the different sizes of the databases used. The minimum EER is 1.8% in [32] and the maximum EER is 5% in [54]. This indicates that the multimodal biometric system generally gives good results.

Finally, Figure 15 presents the three proposed biometric systems; fingerprint, hand geometry and multi-modal systems. The results illustrate that using the multi-modal system will improve the overall accuracy of the system and give more reliable results compared to the single systems. The experimental results showed that the average EER of the multi-modal system was 3.27%, while the fingerprint system and hand geometry system achieved an average EER of 8.86% and 8.89%, respectively.

"A Weighted Score Matching Algorithm for a Multi-modal Biometric System Based on Fingerprint and Hand Geometry", Ezdihar N. Bifari and Lamiaa A. Elrefaei.

Table 7. Comparison between previous studies and the proposed multi-modal system.

EER: FMR=FNMR	Study [32]	Study [33]	Study [34]	Study [54]	Proposed
Traits used	Hand geometry Palmprint	Fingerprint Iris	Fingerprint Signature	Face Speech Signature	Fingerprint Hand geometry
Database Size	230	N/A	110	30	100
Samples	5	N/A	N/A	24	8
FMR%	1.8	2	3.80	~ 5%	2.02 ~ 3.95
FNMR%			3.55		= 3.27

5. CONCLUSION

In this work, we present a multi-modal biometric system framework that utilizes two biometric models; fingerprint and hand geometry model. These models are fused at the score level using weighted sum rule. Several algorithms and techniques were applied at each step in the system to improve recognition rates. The main contribution in the biometric field was through the implementation of the proposed matching algorithm which is based on the weighted feature for all three systems: fingerprint, hand geometry and multi-modal systems.

In addition to the matching algorithm, we enhanced the fingerprint by modifying Gabor filter algorithm and extracted extra points called ridge points beside the minutiae, in order to increase the information from each sample. In the hand geometry system, twenty distance features were extracted by chain code algorithm which were reduced to six features by classifying them into hand features and finger features. Finally, the multi-modal biometric system was experimentally tested using FVC and COEP databases that are not previously fused together according to the literature review. We tested the system using different traditional fusion rules, like min, max and sum rules, in addition to the proposed weighted sum rule to see which rule offers the best results.

In our experiments, it was observed that the use of the proposed matching algorithm with other proposed techniques resulted in improving the performance of each system. Especially, fingerprint module used five public FVC databases which have been created for international competition and contain a large number of low quality fingerprint samples. On the other hand, the COEP database of hand geometry included acceptable samples. Nevertheless, the EER in the hand geometry system is considered high compared to that in the fingerprint system.

Furthermore, the use of multiple biometrics and fusing them at the score level led to increase the performance compared to separate individual biometric systems. The experimental results showed that the average EER of the multi-modal system between fingerprint and hand geometry was 3.27%, while the fingerprint system achieved an average EER of 8.86% for all five FVC databases and the hand geometry system achieved an EER of 8.89% for COEP database. These results showed a significant improvement in the multi-modal biometric system by nearly 5.61%.

For future investigation, researchers can try to enhance the performance of multi-modal biometric systems by introducing the idea of matching algorithm based on weighted features with other enhanced techniques. Also, they can apply it including other biometric traits to create a multi-modal system with more than two models.

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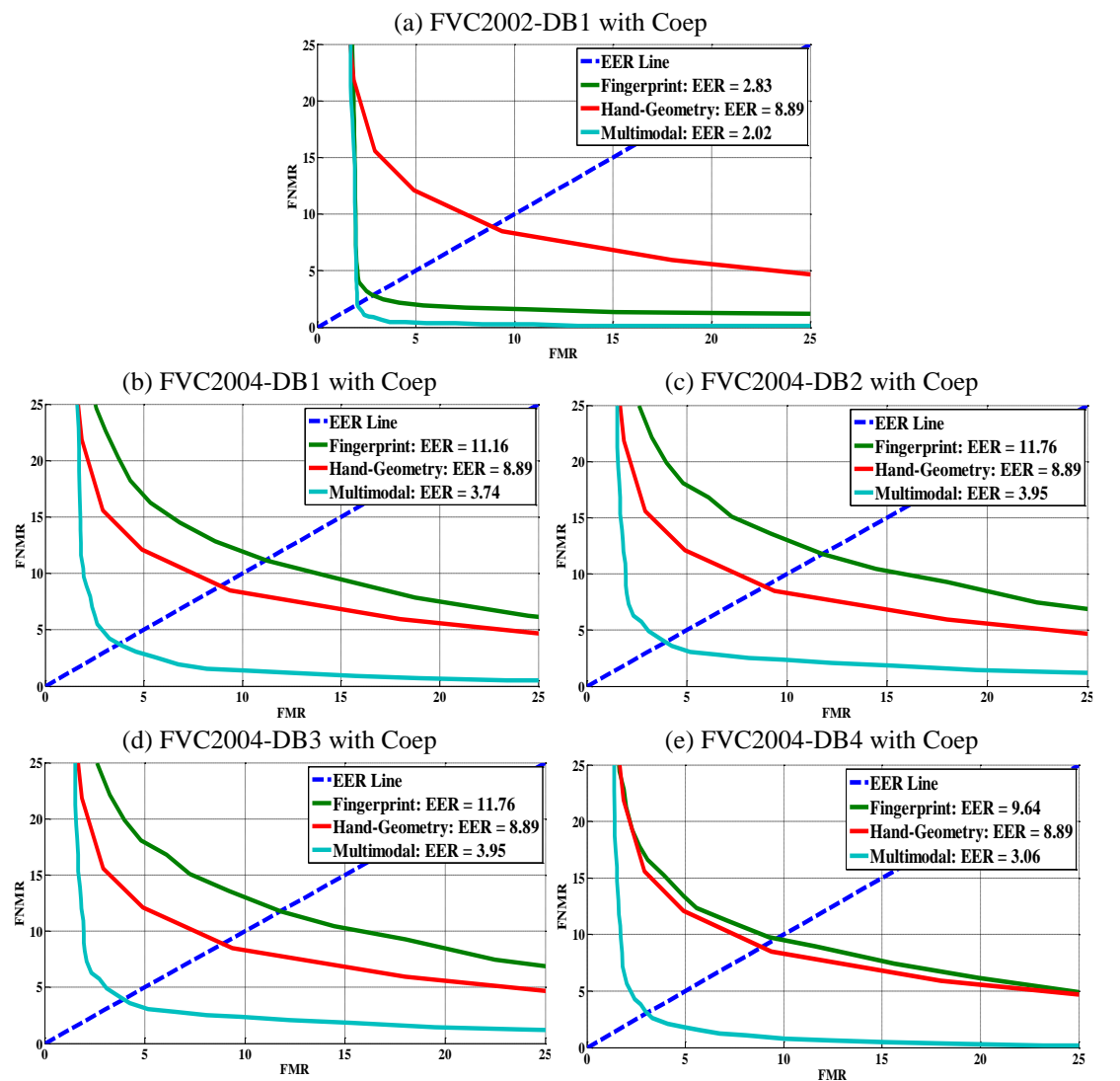Philosophy, Department of Computer Science, University Of Calgary, Calgary, Alberta, 2012.

Figure 15. ROC curves of the comparison between the proposed systems:
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ملخص البحث:

في هذه الورقة، اقترحنا تصـــميم نظام بيومتري متعدد النماذج (Multi-modal Biometric System) باستخدام لغة MATLAB يدمج بين صفتين بيومتريتين: بصمة الإصبع وهندسة اليد. النظام المقترح ســـوف يُدمج في مرحلة درجة المطابقة (Matching Score Level) من خلال تطبيق قاعدة الجمع الموزون (Weighted Sum Rule) المعدّلة. تم اختبار نظام البصمة باستخدام خمس قواعد بيانات معروفة بـ (FVC) واختبار نظام هندسة اليد باستخدام قاعدة البيانات المعروفة بــــــ (COEP). وبالتالي، لاختبار النظام البيومتري متعدد النماذج قمنا بدمج كل قاعدة من قواعد بيانات البصـــمة مع قاعدة بيانات اليد. وقد أظهرت النتائج التجريبية تحسـناً كبيراً في النظام البيومتري متعدد النماذج مع متوسـط (EER) يسـاوي 3.27%، في حين بلغ متوسـط (EER) 8.86% و 8.89% لنظام البصمة ونظام هندسة اليد، على التوالي.