



Soft Computing Approach to Multi-Modal Biometric System

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Abstract: The increasing demand for high secure and reliable authentication schemes, led to improvement in unimodal biometric system and hence multimodal biometric system has emerged as a mean of more secure and reliable authentication scheme. This work examines the multimodal fusion of palmprint (principal lines) and fingerprint (minutiae points). After an introduction to theoretical principles, related works in palmprint, fingerprint, and fusion of palmprint and fingerprint are highlighted. The developed system modules include image acquisition, morphological stage, feature extraction stage, fusion stage and classification stage. The database is composed of 600 posed fingerprints, 120 posed palmprints and 6480 fused posed palmprints and fingerprints. The data were trained and tested with a variant of neural network back-propagation algorithm. Three thresholds were employed viz; 0.35, 0.65 and 0.95. The results showed that threshold 0.95 produced average accuracy of 98.3%, threshold 0.65 produced average accuracy of 5%, and threshold 0.35 produced average accuracy 16.4%.

Keywords: Multimodal, Minutiae, Feature level fusion, Gabor filter, Crossing Number, Backpropagation Neural Network

I. INTRODUCTION

Multimodal biometrics has become increasingly important, particularly because single modal biometrics has reached its bottleneck; i.e. non-universality, noise in sensor data and spoofing. Multimodal biometrics gives supplementary information between different modalities that increases recognition performance in term of accuracy and ability to overcome the drawbacks of single biometrics. Bhardwaj explained the advantages of using multimodal biometric system instead of conventional unimodal biometric system [1]. There are two types of biometric techniques: Physiological (face recognition, iris recognition, and finger print recognition). And the other one is Behavioral (signature recognition, gait, voice recognition). In this work we concentrate on the physiological features particularly finger print and palm print recognition. A palm print or finger print refers to an image acquired of the palm region or finger region of the hand. Most of the problems and limitations of biometrics are imposed by unimodal biometric systems, which rely on the evidence of only a single biometric trait. Some of these problems may be overcome by multi biometric systems and an efficient fusion scheme to combine the information presented in multiple biometric traits.

In multimodal biometrics, the classification results obtained from each independent biometric channel is fused to obtain composite classification is known as biometric fusion. The fusion process in biometric provides increased reliability. Multimodal biometric fusion is very promising process to enhance the strengths and reduce the weaknesses of the individual measurements. Four possible levels of fusion methods are used for integrating data from two or more biometric systems. These are sensor level, feature extraction level, matching score level and decision level. Sensor level and feature extraction level are called pre-mapping fusion levels while matching score level and decision level are called post-mapping fusion levels. [2]. Although fusion increases accuracy, it generally increases computation costs and template sizes and reduces user acceptance. [3] The system proposed employed Otsu threshold for image normalization (both finger print and palm print). And the normalized images were subjected to morphological processing using Sobel gradient for palm prints and Histogram equalization-cum-secure alignment for finger prints. Palm print features were extracted with Gabor filter while Crossing Number was used to extract feature for finger prints. Both features are fused with concatenation and Classification is achieved by using a variant of Back-propagation Neural Network.

The structure of human hand is discussed in the next section. Related works are discussed in section III, while section IV describes the structure of the proposed system. Results are discussed in section V and the conclusion is in section VI.

II. Structures of Palm and Fingers

The hand is part of human organ and it's located at the lower part of human arm. The hand is made up of palm and fingers as shown in figure 1.



Figure 1. Human hand showing Palm and Fingers

A. Palmprint- The Palm print is a physiological or is an external characteristic of human being which is found to be unique and distinct from among every individual. The palm has an inner surface which has rich features including Principal lines, wrinkles, minutiae points, singular points and texture. These line structures are stable and remain unchanged throughout the life of an individual. These features can be used for uniquely identifying a person. Palm print identification systems measure and compare ridges, lines and Minutiae found on the palm. [4]. There are three groups of marks which are used in palm print identification namely; *Geometric features*, (such as the width, length and area of the palm); *Line features* (that is principal lines and wrinkles) and; *Point features or minutiae* (which includes ridges, ridge endings, bifurcation and dots). Palm creases and ridges are often superimposed which makes feature extraction difficult. Raut and Humbe proposes a Biometric Palm print lines extraction using image processing morphological operation. [5] proposed work is centered upon collection of minutiae terms based on Region of Interest of the image of the fingerprints. [6] proposed a Genetic Algorithm based Palm Recognition Method for Biometric Authentication Systems which does not require special equipment and can be used in systems where fast detection is needed.

B. Fingerprints- Fingerprints are the patterns formed on the epidermis of the fingertip. Fingerprints are made up of series of ridges and valleys (also called as furrows) on the surface of the fingertip and have core around which pattern like swirls, whorls, loops or arches are curved to ensure that each print is unique [7]. The interleaved pattern of ridges and valleys are the most evident structural characteristic of a fingerprint. The ridges are the single curved segment and valleys are the region between two ridges. The most commonly used fingerprint features are minutiae. Minutiae are the discontinuities in local ridge structure. There are about 150 different types of minutiae [8]. Some of the techniques employed for fingerprint recognition includes; *Minutiae Extraction* (which is used in this work include termination and bifurcation); *Ridge Feature* (involves extracting features based on series of ridges); *Correlation based* (involves adjusting and computing the correlation for each corresponding pixel of fingerprint) and; *Image based* (attempts to do matching which based on the global features of all fingerprint images).

The authors in [9] proposed a system which uses minutiae based matching algorithm for fingerprint identification. There are three main phases in proposed algorithm viz: enhance the input fingerprint image by conversion into thinned binary image; minutiae are extracted by using Crossing Number (CN) Concept and; compares input fingerprint image with fingerprint images enrolled in database. [10] proposed Fingerprint Verification System using Minutiae Extraction Technique. In this system, Segmentation with Morphological operations is used to improve thinning, false minutiae removal and minutia marking, and CN Concept for Minutiae Extraction. Other related works can be found in [11], [12] [13].

III. RELATED WORK

The recent developments in biometrics recognition of a person lead to improvements in reliability and accuracy. A number of studies have been done on multimodal biometrics and these works show that multi- biometric has more advantage than single- biometric. Ross and Jain [14] combined face, fingerprint and hand geometry biometrics with sum, decision tree and linear discriminant-based methods. The authors report that sum rule outperforms others. [15] proposed multimodal biometric system using face and fingerprint and combining ridge based matching for fingerprint and Eigen face. [16] proposed an authentication method for a multimodal biometric system identification using two traits i.e. face and palmprint using matching score at fusion level. [17] proposed two unimodal biometrics, iris and fingerprint, are used as multi-biometrics and the result showed that this biometrics has good result with high accuracy. Decision level is used for fusion and each biometric result is weighted for participate in final decision. [18] proposed a multi-biometric system including face and Palmprint biometrics at feature level fusion. [19] presented a multimodal biometric system using hand images and by integrating two different biometric traits palmprint and finger-knuckle-print (FKP). [20] examined relatively large face and fingerprint data sets over a spectrum of normalization and fusion techniques and the

results of this study shows multimodal biometric systems better perform than uni-modal biometric systems. [21] proposed a new multi-biometric based verification system using hand geometry and finger stripe geometry. Closely related to this work is multimodal system proposed by [3] developed a Multimodal biometric identification system based on palmprint and fingerprint trait. The processed information is combined using an appropriate fusion scheme. Successively, the comparison of data base template and the input data is done with the help of Euclidean-distance matching algorithm. The experimental results demonstrated that the proposed multimodal biometric system achieves a recognition accuracy of 87%.

IV. STRUCTURE OF THE PROPOSED SYSTEM

Biometrics is a technique used to provide unique individual characteristics of a human being. The unimodal biometric has a number of disadvantages, which are discussed in the introduction section, so this paper proposes the multimodal biometrics system by integrating fingerprint and palmprint. The proposed system firstly acquires the fingerprint and palmprint images. Next is the binarization using Otsu thresholding scheme on both biometric traits; the methodologies for these processes viewed as some blocks in Fig 2. Main workflow includes (a) Image Acquisition (b) Binarization (c) Morphological stage (d) Feature Extraction (e) Fusion stage (f) Classification stage.

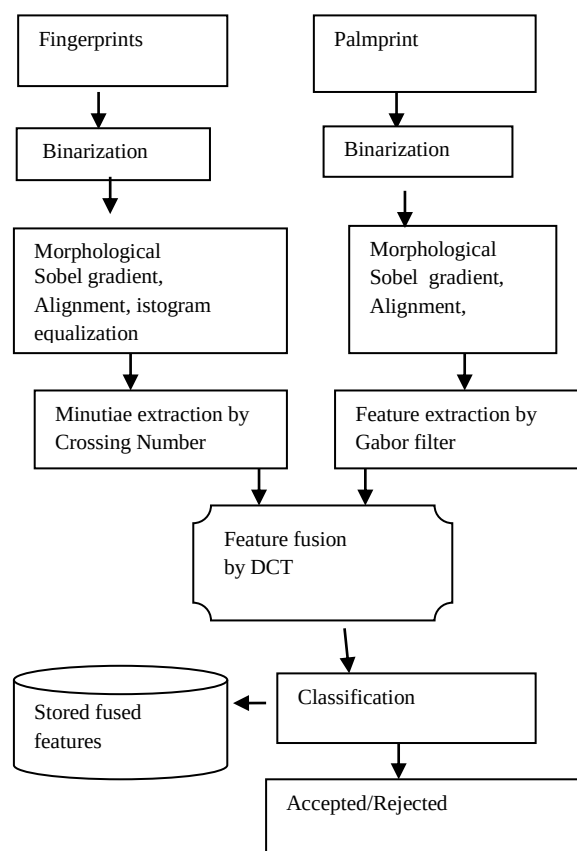


Figure 2. Workflow of the proposed system

A. Image Acquisitions

A multimodal biometric system collects the samples of biometric features. In the proposed system we took the images of fingerprint and palmprint from 200 students using high quality web camera. Fingerprint image size is 320*240 pixels and palm is 128*128 pixels. Samples are shown in figure 5a.

B. Binarization

Binarization is a thresholding problem and targets the segmentation of the input image, which precedes image analysis supporting the extraction of higher-level image information, such as object contours or features. The binarization step is used to obtain a rough palmprint/fingerprint area from the palm/finger image. The algorithm applies the Otsu thresholding scheme to binarize the input palm/finger image to determine the palm/finger print area. The Otsu thresholding scheme searches an optimal threshold to divide a gray scale image's pixels into two classes. The optimal threshold is evaluated by the discriminated criterion which maximizes the separability between target and background classes. Samples of outputs are shown in figure 5b.

C. Morphological processing

1. Palm print: The morphological opening operation is combined with the morphological erosion and the dilation operations. Where erosion operation is applied to “shrink” or “thinning” the objects called *Palm contour*

detection, the algorithm applies the Sobel gradient (edge detection method) mask on the shrink region of the noise-removal palm print image to acquire the palm contour. Palm alignment is for aligning palm poses to a standard pose to reduce the disturbing of nonlinear factors such as rotation, translation and distortion in sampling process. The palm alignment is to find suitable key points from the palm to normalize the position of the palmprint image. Thus, reference line construction is employed from [25]. Samples of outputs are shown in figure 5c.

2. Fingerprint print: Fingerprint thinning is usually implemented via morphological operations such as erosion and dilation to reduce the width of ridges to a single pixel while preserving the extent and connectivity of the original shape. In order to extract similar features from two different impressions from the same finger, they should be appropriately aligned before feature extraction. In this work, we use the secure alignment technique which does not require storage of minutiae. [27]. Also, it is necessary to adjust the global contrast of finger print images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast without affecting the global contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. Samples of outputs are shown in figure 5c.

D. Features Extraction: Feature extraction involves extraction of palm region of interest (principal lines) and finger minutiae extraction (ridges).

1. Palm print ROI Extraction

Gabor transformation can capture prominent visual properties. Gabor filter can be used to extract the rich line features of palmprint. Palmprint is more reliable biometric feature as it covers larger area than the fingerprint. The rich line features remain unaltered throughout the person's life. In this paper Gabor filter approach can be used which transforms palmprint images into specific transformation domains to find useful image representations in compressed subspace. It computes a set of basis vector from a set of palmprint images, and the images are projected into the compressed subspace to obtain a set of coefficients called as Gabor code. [3]. Samples of outputs are shown in figure 5d.

2. Fingerprint Minutiae Extraction

The most commonly employed method of minutiae extraction is the Crossing Number (CN) concept. This method involves the use of the skeleton image where the ridge flow pattern is eight-connected. The minutiae are extracted by scanning the local neighbourhood of each ridge pixel in the image using a 3×3 window. The CN value is then computed, which is defined as half the sum of the differences between pairs of adjacent pixels in the eight-neighbourhood. The CN for a ridge pixel P is given by:

$$CN = \frac{1}{2} \sum_{i=1}^8 |P_i - P_{i-1}|, \quad P_9 = P_1 \quad 1$$

where P_i is the pixel value in the neighbourhood of P. For a pixel P, its eight neighbouring pixels are scanned in an anti-clockwise direction. [22]. Samples of outputs are shown in figure 5d.

E. Fusion Stage

In this stage, the feature sets extracted from multiple data source can be fused to create a new feature set to represent the individual. Augmenting the two feature vectors, x' and y' , results in a new feature vector, $Z' = \{x'_1, x'_2, \dots, x'_s, y'_1, y'_2, \dots, y'_t\}$ $Z' \in R_{s+t}$. The curse-of-dimensionality' dictates that the augmented vector needs not necessarily improved matching performance. Further, some of the feature values may be 'noisy' compared to the others. The feature selection process entails choosing a minimal feature set of size r , $r < (s + t)$, that improves classification performance on a training set of feature vectors. The sequential forward floating selection technique is employed to perform feature selection on the feature values of Z' . This results in a new feature vector $Z = \{Z_1, Z_2, \dots, Z_r\}$. [24]. The following figure (see figure 4) shows intermediate fusion of palm prints features (X'), intermediate fusion of finger prints features and the final fusion matrix of both modalities based on morphological operations.



Figure 4: Fusion of Palmprint and Fingerprint

It may result in a new high-dimension feature vector. In order to reduce the high dimensionality of the feature vectors, we used the DCT (Discrete Cosine Transform). The discrete cosine transform (DCT) is defined as: [23].

In this work, procedures for feature level fusion is accomplished by a simple concatenation of feature sets obtain from multiple modalities. Sample of output is shown in figure 5.

F. Classification Stage

Classification can be the first step in identification tasks as it reduces database entries requiring searching. A biometric identification system's task is finding a biometric object in a database matching a query biometric object. Firstly the neural network has been trained before test the matching operation. To test or recognize the fingerprint first take any image from the data set and fed that image to the trained network then it gives the result by showing whether it matches to the right person or wrong. In this work, the classification is done in which the imposter is classify as Accepted/Rejected.

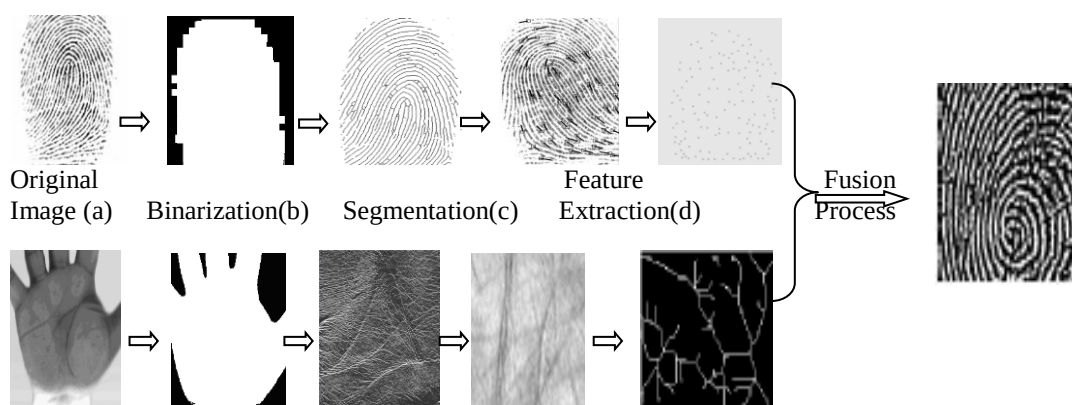


Figure 5. Samples of Palmprint and Fingerprint (b) Outputs of Binarization of fingerprint and palmprint (c) Results of morphological process of palmprint and fingerprint; (d) Feature extraction outputs of palmprint and fingerprint.

V. RESULTS

We collected palmprint and fingerprint from twenty students (they are of the relatively the same age) for both male and female in three different poses. The poses are central, left and right poses. The left and right palms were captured in three different poses making $2 \times 3 \times 20 = 120$. The fingerprints were collected for both left and right hands in three different poses making $2 \times 15 \times 20 = 600$. By fusion 120 palmprints with 600 fingerprints (one palmprint with three fingerprints of the same hand), we have 6,480 fused palmprints and fingerprints.

For the classification experiments the neural network was employed. A feed forward single-layer perceptron trained with the Levenberg-Marquardt back propagation algorithm included in the Neural Network toolbox of MATLAB 7.0, was used in this work [26]. The network architecture used in this work which gives a relatively optimum results was composed of 25 input nodes, a hidden layer of 30 nodes, and 20 output nodes. All neurons used a sigmoid as an activation function. Convergence of the Levenberg-Marquardt algorithm is very fast. In this example the network was trained with a large number of epochs (500 epochs) and learning rate of 0.5.

For training and testing phases, the different poses fingerprints, palmprints and their fused features were introduced into DCT and then to the classifier for matching. Six imposters were designed for training and testing. The imposters are (i) 50 posed fingerprints from first five persons for both left and right hands, (ii) five pairs of posed palmprints from next five persons, (iii) fusion of each of each right hand and left hand posed fingerprint, fp_1 , fused with five posed palmprints, pp_1 , (that is one posed right hand fingerprint fused with all posed right palmprint of the different hands and vice versa) making 250; (iv) another posed of each right hand fingerprints, fp_2 , fused with normal poses of five right hand palmprints of different persons, pp_2 , (same for left hands) making 250; (v) fusion of normal posed fingerprints (left and right hands) from another five selected persons, nf_1 , with normal poses of palmprints (left and right hands) of the same five persons, np_1 , making 250; and (vi) fusion of normal posed fingerprints (left and right hands) from new (that is not in database) two persons, nf_2 , with normal poses of palmprints (left and right hands) of the same two persons, np_2 , making 40.

Three thresholds (0.35, 0.65 and 0.95) were set basically to classify palmprint, fingerprint of fused features for acceptability or not. The thresholds were set such that the computed accepted biometrics values are not less than the thresholds. The results of the classification are shown in table 1. Performance metric employed is accuracy such that the imposter recognised by the classifier in the database is classified as acceptable based on certain thresholds.

From table 1, it can be seen that threshold 0.95 produced 100% accuracy for fingerprints and palmprints poses while it gives 97.2% for imposter_5. Its average accuracy is 98.3%.

Table 1: Results of Classification of Assumed Imposters

Impostor No.	Biometric features	Classifications with Thresholds		
		0.35	0.65	0.95
1	Fingerprints	-	-	50
2	Palmprints	-	-	50
3	Fp1+ pp1	46	7	-
4	Fp2+ pp2	33	8	-
5	Nf1+ np1	-	27	243
6	Nf2+np2	7	2	-

These results depict that fingerprints, palmprints poses and imposter_5 were correctly matched in the database while imposter_3, imposter_4 and imposter_6 were not fully matched in the database. Threshold 0.65 produced average accuracy of 5% for fingerprints, imposter_3, imposter_4, imposter_5 and imposter_6 shows that there are averagely represented image prints of the imposters. While threshold 0.35 produced average accuracy 16.4% for imposter_3, imposter_4 and imposter_6 which showed that the images are partially represented in the database.

VI. Conclusion

Biometric systems are widely used to overcome the traditional methods of authentication. But the unimodal biometric system fails in case of biometric data for particular trait. We proposed a multimodal biometric system which has fusion stage in addition to other stages in the biometric system. This work examines the multimodal fusion of palmprint (principal lines) and fingerprint (minutiae points). Individual biometric feature extraction was done differently using different algorithms. The individual score of two traits (palmprint and fingerprint) after been extracted using Gabor filtering are combined at feature level in fusion stage to develop a multimodal biometric system. A feed forward single-layer perceptron trained with the Levenberg-Marquardt back propagation algorithm was used for classification and three thresholds were tested on six different designed imposters.

However, this work can be further subjected to experimentations for improvement by using (i) the same feature extraction algorithm at segmentation level; (ii) different feature extraction algorithms at fusion level; and (iii) employ different algorithm like genetic algorithm, swarm optimization, ant algorithm etc, for classification of fused multimodal biometric.

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