A Multibiometric Hand Security System

Maleika Heenaye-Mamode Khan
Department of Computer Science and Engineering, University of Mauritius
Email: m.mamodekhan@uom.ac.mu

***Abstract*—There is practically no wholesome approach in ensuring total security of systems. In this revolutionized and digital world, the increasing need of security to protect individuals and information has led to a rise in developing biometric systems over traditional security systems. Recently, hand vein pattern biometrics has gained increasing interest from both research communities and industries. However, there are many problems like noisy data, intra-class variations, restricted degrees of freedom, non-universality, spoof attacks, and unacceptable error rates that can occur when using unimodal biometric. To overcome the disadvantages of unimodal biometrics of the hand features, a multimodal hand biometric using dorsal hand vein patterns and palmprints, has been deployed. However, another challenge that crops up with multibiometric is the level at which fusion takes place. In this work, fusion was experimented at feature extraction level and at score level. From the experiments conducted, it can be concluded that multimodal biometrics has a better recognition rate compared to unimodal biometrics. Thus, using this multimodal hand biometric deployed, a higher level of security can be achieved.**

***Index Terms*—dorsal hand vein, palmprints, multibiometrics**

I. INTRODUCTION

Biometrics is replacing traditional methods of security. The emergence of biometric systems has addressed the problems encountered by traditional verification method. Hand biometrics which includes dorsal and palmar biometrics are gaining popularity. These new characteristic are being explored and developed at its full swing [1]-[3]. The attractive reasons for choosing dorsal hand vein characteristics as biometric are due to its uniqueness, stability and strong tolerance to forgery [4]. Researchers are exploring dorsal hand vein biometric security system with great enthusiasm with a view to find suitable techniques which can satisfy the criteria of different applications. Likewise, palmprint which contains unique features such as geometry features, line features, point features, texture features and statistical features can be used to differentiate between two individuals [5], [6]. Thus, palmprint recognition biometric system can be developed using different approaches based on structural features, statistical features or a hybrid of these two features [7]. Different researchers are working on these different features in the hope of obtaining the ideal discriminating features to recognize human [8]. Each feature poses different kind of challenges that need to be addressed when developing biometric system. The motivating characteristics that are pushing researchers to explore palmprint biometric compared to some other biometrics like face recognition and iris are: uniqueness of the features, stability of the features and the low cost imaging techniques required to capture the images.

Despite extensive research, it is noticeable that there are scopes for developing techniques and/ or to find out new ones to improve the performance of biometric systems.

II. RELATED WORKS

Unimodal biometric has been deployed for many applications. However, there are many problems like noisy data, intra-class variations, restricted degrees of freedom, non-universality, spoof attacks, and unacceptable error rates that can occur when using unimodal biometric [9], [10]. Some of these limitations can be addressed by deploying multibiometric systems. Multibiometric systems are those that utilize more than one physiological or behavioral characteristics and rely on the evidence presented by multiple sources of biometric information [11]. A biometric system has four important modules namely the sensor module, feature extraction module, matching module and decision module [12]. Sensor module is the one which can capture the raw biometric data. Feature extraction module processes the data to extract a feature set. The matching module is one which employs a classifier to compare the extracted feature with the templates found in the database and the decision module uses the matching score to identify or validate the claimant. Based on the nature of these sources, multibiometric can be classified into five different approaches as follows: multisensory, multialgorithmic, multi-instance, multi-sample and multi-modal. A variety of factors should be considered when designing a multibiometric system. These include the choice and number of biometric traits; the level in the biometric system at which information provided by multiple traits should be integrated; the methodology adopted to integrate the information; and the cost versus matching performance trade-off [12].

Multisensor systems employ multiple sensors to capture a single biometric trait of an individual. According to [13], either 2-D image or 3-D image can be taken. In this type of fusion, the same biometric trait is captured with two or more distinctly different sensors. The processing of the sample can be done with one or more algorithm. However, there are many design issues

Manuscript received December 16, 2015; revised June 20, 2016.

doi: 10.18178/ijsps.4.6.504-509

and trade- offs that need to be considered in an operational environment. Some of the factors are improved performance (identification or verification accuracy, system speed and throughput, robustness and system requirements), acceptability, circumvention, ease of use, operational cost, environmental flexibility, and population flexibility. Additional factors such as reliability, system acquisition cost, life cycle cost and system response are taken into consideration for large scale human identification system.

Another approach is the multi-algorithmic systems which employs multiple feature extraction and /or multiple matching algorithms on the same biometric to improve the performance [11]. In this method, two different feature extractor algorithms or modules are used to extract features from the same data, which are then fused to form a single feature vector. It is better to have algorithms which are based on distinctly different and independent principle. In face recognition, in [14] authors have developed a multi-algorithmic face recognition biometric by combining PCA, ICA and LDA. Raghavendra *et al.* (2010) have used two algorithms namely; Log- Gabor transform and Kernel direct discriminant analysis with a mask of 5x5 for handvein and palmprint biometric [15]. According to the results obtained, the proposed multibiometric performs better compared to unimodal biometric. In a multi-algorithmic approach for palmprint and face, Imran *et al.* (2010) have fused PCA, FLD and ICA [14]. The conclusion drawn by the authors of this particular work is that in multi-algorithmic approach, the combinations of algorithms play a major role rather than the fusion of number of algorithms. Deepika and Kandaswamy (2010) have used two feature extraction modules namely the morphological feature extractor and the statistical feature extractor to develop a multi-algorithmic dorsal hand vein pattern recognition system [3]. The feature vectors obtained from these two feature extraction algorithms are then fused to form a single vector. The fused algorithm provides better results compared to unimodal biometric where the False Acceptance Rate (FAR) is 0.3 % and the False Rejection Rate (FRR) is 0.54%.

Multi-instance is another classification under multi-biometric. The latter is defined as the combination of the biometric information extracted from different sources of the same biometric modality. In [16], authors have used different instances of the index fingers and according to the results obtained, it was found that the verification performance has increased by more than 4%. Multi-instance biometric is also used in iris recognition biometric system.

Multibiometrics has many advantages compared to unimodal biometrics. However, they have not been extensively deployed in hand biometrics. The objective of this work is to deploy multibiometrics using hand features consisting of dorsal hand vein patterns and palmprints. The following section explains the image preprocessing and feature extraction of the dorsal hand vein patterns and palmprints.

III. Image Preprocessing

A. Image Capture of the Hand

Image acquisition is the first crucial phase in a biometric security system. This involves capturing the required feature or behavior that need to be represented in the security system. Different biometrics has different methods of capturing the required features. A setup was devised at the University of Mauritius to build a hand database to carry out this research work. Since veins are found beneath the skin, they can only be captured using infrared light. In the experimental setup of this project, images were obtained with a digital camera with infrared filters using an appropriate setup. Likewise, a palmprint database was also built in this research. However, palmprints could be obtained in visible lights itself.

To build the hand database, a Nikon digital camera D3100, a Hoya R-72 infrared filter, LED lights and diffusing papers have been used. To capture the hand images, the camera and lights were carefully mounted using a closed wooden box with one open side. Both images were captured using the same setup. However, for palmprints image capture, the infrared filter was removed from the camera. After the image capture phase, the hand images are enhanced.

Images were captured from 300 subjects and 10 instances were taken for each. Each instance was captured after a time interval of 3-4 mins. The latter were from different ethnic groups, age ranging from 19 years old to 65 years old and have different skin colour. During image capture, various factors namely the positions of the light, the light intensity, background light, the arrangement of the light positions, the angle of orientation of the hand, the distance between the camera and the hand were considered.

B. Image Extraction

In this preprocessing phase, hand images were first enhanced to improve their quality. Vein patterns were then thinned to obtain a 1-pixel wide skeletal version. The main steps that need to be performed for the preprocessing phase are as follows: Normalization, Histogram Equalisation, Image Thresholding, Image Filtering and Image Thinning. The images were first normalized so that all the pixel intensities were converted to a domain of [0, 255]. The normalized image was then equalized using the adaptive histogram. To eliminate remaining noise and to obtain an enhanced image, different filters were applied on the vein images. The first filter applied, that is, 2-D median filtering performs median filtering of the image in two dimensions. Each output pixel contained the median value in the M-by-N neighborhood around the corresponding pixel in the thresholded vein image. To further enhance the vein images, the Gaussian smoothing was applied. The operator is a 2-D convolution operator that was used to ‘blur’ images and remove detail and noise. Wiener filter was the third filter applied to obtain a better image. The Wiener filter was a stationary linear filter for images degraded by additive noise and blurring. The vein images are enhanced and less blurred. As for the palmprints, the pre-processing steps are as follows: Normalisation, Background estimation and Image enhancement. The next step is to extract and represent the features representing the hand images.

C. Hand Feature Extraction Using Whole Image

After extensive research on feature extraction techniques of biometrics, it was found that one main method of extracting their features is by using their pixel values. One reliable method of representing the data was by using correlation method which counts the number of overlapped pixels between the test images and the sample set. In addition, to test other new techniques that would be applied for the first time on hand features, it was important to have a base case method with which the devised techniques can be compared with. Ultimately, this highlights the importance of representing the hand biometric features using correlation method. The objective is to extract and represent the hand features using correlation method.

The vein representation is constructed by taking a vein image $X_i(x,y)$ to be a 2-dimensional $M \times M$ array of 8-bit intensity values for an individual i, where $i = 1, 2.3, \dots I$. This image is further represented as a vector of dimension M^2 by concatenating the rows. For instance, a vein image for a particular individual of size 256×256 becomes a vector of dimension 65,536. Note that this vein image is for a single individual i. Thus, for a set of I individuals, the dimension of the overall vein matrix space X can be represented as:

$$X = [X_1, X_2, \dots, X_i, \dots X_I]_{M^2 \times I} \tag{1}$$

D. Pixel Representation of Dorsal Hand Vein Patterns and Palmprints

The vein and palmprints features are then represented using pixel method. Pixel-by-pixel method is a simple method used whereby each vein pixel is extracted. In this method, the vein patterns are preprocessed until the thinning phase, whereby the intensity value of each a pixel is obtained. Thus, a matrix of intensity values is obtained for the vein branches. Using this method, the test image is tested against all the images that exist in the database. The number of correlated pixels is computed. A threshold value is set is determined whether a test is a genuine or an imposter.

To apply the pixel representation method, the thinned version of the image was considered for processing. The dorsal hand vein patterns and the palmprints were thinned to 1-pixel wide. The pixel values were extracted from the raw images and were used for the feature representation. The matching was done by using correlation method, also known as pixel-by-pixel matching. This technique counts the number of correlated pixels between the test image and the template.

To conduct experiments, sample sets and test sets were created. Sample sets contained all the templates of the subjects. The test set contained images that were to seek access to the system, that is, images that needed to be authenticated. Since a hand multibiometrics consisting of dorsal hand vein pattern and palmprints were to be built, each subject was associated with a vein pattern and a palmprint. The next section presents the development of the multimodal biometrics using fusion.

IV. Fusion of Hand Features

The key to multimodal biometric system is the fusion of various biometric modality data. The system requires an integration scheme to fuse the information obtained from the individual modalities. It was found that in multimodal biometric system, information fused can be correlated at different levels and these levels correspond to four important components of the biometric systems namely sensor module, feature extraction module, matching module and decision-making module. Thus, fusion can occur at sensor level, feature extraction level, matching score level, or decision level [17], [18].

A. Sample Level

Sample level is where individual biometric process outputs a collection of samples. At this level of fusion, images collected are fused into a single sample. For example, two dorsal hand vein patterns are fused into a single image. Sample fusion is the combination of raw data from the biometric sensor [11].

B. Feature Level

Feature level fusion is where features extracted from different biometric process outputs are fused. Therefore, there can be any number of feature extraction modules and each of these modules output its collection of features. The fusion process then fuses these collections of features into a single feature set or vector.

C. Score Level

In this type of system, each individual's process outputs a match score. The number of match score that will be obtained depends on the number of processes. This type of system sets a threshold value. The fusion process fuse all the individual score obtained into a single score. This is then compared with the threshold set.

D. Decision Level

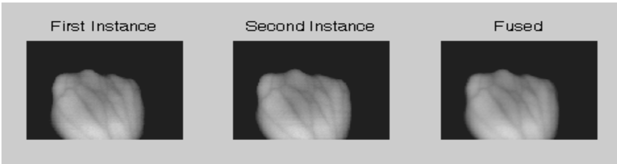
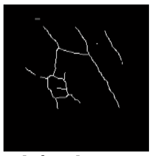
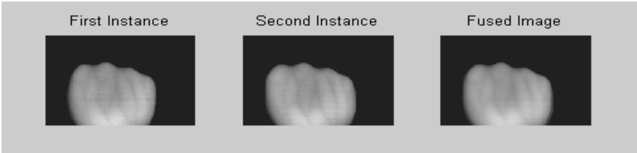
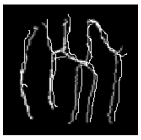
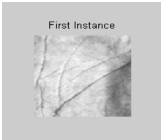
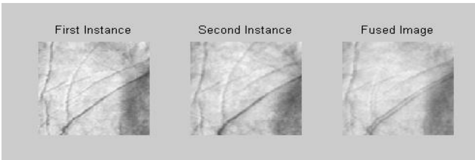
Decision level fusion is where each of the biometric process involved outputs its own result. Each of the processes is independent of each other. The fusion process then fuses them together by a combination algorithm such as AND, OR.

V. Experimental Results of Fusion

A. Results at Sample Level

At the image capture level of dorsal hand vein pattern and palmprints, 10 instances are captured for a subject. Two raw images are fused and their features are then extracted. This experiment is carried out at random at several times combining two different instances. Table I shows the results of fusion and preprocessing of the fused images.

TABLE I. RESULTS OF FUSION AT SAMPLE LEVEL

Fused Image at sample Level	**Preprocessed Image**
 Images captured at two instances have the same alignment	 The branches are properly defined
 Images have slight orientations between images captured.	 There are different additional branches leading to a different pattern.
 In this figure, only one instance has been captured. It is found that there is slight movement between the image capture of the different instances of the same subject. Thus, no two images are the same.	 For one image, the palmprints are extracted without any additional lines.
 In this figure, two instances are fused. It can be seen that there are overlaps of lines between the fused images.	 After preprocessing the fused image, there are many additional lines which make the pattern different.

For the first case of the dorsal hand pattern, there is no movement of the hand between the first and the second instances captured. There are no additional branches after preprocessing the fused image. After carrying out a pixel-by-pixel match, a match is obtained on a 96% of overlapped pixel. For this particular pattern, the hand orientation did not change and thus the same pattern is obtained. However, it is very rare to obtain the same instances all the time during image capture. For the second case of the dorsal hand vein pattern, there is a slight orientation between the instances captured. Thus, the two instances are different. When the images are fused, the patterns become different by having more branches. The match rate is only 20% or below for 10 different experiments carried out. Likewise, when palmprints are fused, additional lines are obtained and this results to additional palm lines.

When the hand vein images are constrained and there was no movement of the hand between the first and the second instances captured. There are no additional branches after preprocessing the fused image. In fact, it is only in very rare cases that the image captured at different instances are the same. Most of the time, there are slight movements between image capture of different instances. Thus, it is very difficult to obtain the appropriate features. It can be seen that from the images fused at feature level, there are unaligned thinned branches for dorsal hand vein patterns. Likewise, palmprints have similar issues. For palmprints, instances are more prone to slight orientations since the hand is not constrained to any type of handle during image capture.

B. *Results at Feature Level*

At this level of fusion, two extracted features of the dorsal hand vein patterns and the palmprints are fused. In this case, the thinned version of the images is considered. The raw features are taken. Table II shows the results obtained after fusing the instances.

The results of Table II are for images that have been aligned. Thus, the aligned image of the first instance is fused with the aligned image of the second instance. The fused image has no big differences in terms of structure and patterns.

The average recognition rate is provided in Table III. The experiments are based on 10 sets of 20 images, that is, 10 pairs of dorsal hand vein patterns and 10 palmprints.

From the experiments carried out, it was found that there are no big differences in the recognition rate of the fused images and individual instances. For the vein patterns, the first instance overlaps the second instance and thus the same features are extracted. It is to be noted that the hands were constrained and there is no big translations. In addition the hand was moved to the image centre of gravity. Therefore, even when two different instances were merged, the same vein pattern was obtained. As for the palmprints, there may be slight differences. This is because palmprints have more lines compared to the dorsal hand veins. Note that this experiment shows the result of 10 sets of 20 images that is 10 pairs of dorsal hand vein patterns and 10 palmprints. It can be concluded that fusing images at feature level does not help in improving the results.

TABLE II. RESULTS OF FUSION AT FEATURE LEVEL

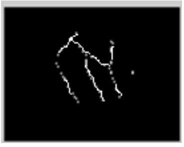
Instance 1	Instance 2	Fused Image at Feature Level
 Features extracted from the first instance	 Features extracted from the second instance	 Fused image
 Features extracted from the first instance	 Features extracted from the second instance	 Fused image

TABLE III. AVERAGE RECOGNITION RATE

Case	Average Recognition Rate (First Instance)	Average Recognition Rate (Second Instance)	Average Recognition Rate (Fused Image)
Dorsal Hand Vein pattern	89%	87.5%	86%
Palm prints	81%	83%	82%

C. *Results at Score Level*

Score level fusion can be divided into broadly two categories namely: classification method for e.g. Support Vector Machine (SVM) and combination method for e.g. sum rule based fusion. In the classification method, the feature vectors generated from the individual matchers are classified as genuine or imposter [19]. In the combination method, the individual scores generated from individual systems are combined to form a single score and a decision is then taken by using a threshold of the multi-biometric system. However, in the combination method, the matching scores are generated from by different modalities and are heterogeneous. Thus, before fusion, the challenging task is to choose a robust score normalization technique to transform the scores into a common domain

Using the combination methods, scores were generated from individual matcher namely dorsal hand vein pattern and palmprints. The scores were normalized using min-max technique. According to literature [20], Min-Max had the disadvantage of being sensitive to outliers. To overcome this problem, the Enhanced Min-Max normalization technique as proposed by He *et al.* (2009) was used to normalize the scores to a common range and scale of values to avoid any exceptional case. Enhanced min-max was derived and is as follows:

$$x' = \frac{x - \min(X)}{\{mean(X^{*}) + std(X^{*})\} - \min(X)} \qquad (2)$$

where X is the raw scores, X is the distribution of the genuine scores. The mean genuine scores distribution added with the standard deviation has been used instead of just the maximum values of the scores. This enhanced min-max technique reduces the effect of high scores at the right-tail of the genuine scores distribution. Table IV shows the results obtained for fusing dorsal hand vein patterns and palmprints at score level.

TABLE IV. PERFORMANCE AT SCORE LEVEL FUSION

Number of Images in the Sample Set	RR using Dorsal Hand Vein Pattern (%)	RR Using Palmprints (%)	RR with fused Vein and Palmprints (%)
100	90.4	92.4	95.3
200	89.2	91.2	96.7
500	91.1	91.8	95.9

From the results, the recognition rate for the fused features yield better results compared to unimodal biometrics. Fusion can achieve up to 96% of recognition rate which is desirable in biometric security systems.

VI. CONCLUSION

Unimodal biometrics encounters many problems like noisy data, intra-class variations, restricted degrees of freedom, non-universality, spoof attacks, and unacceptable error rates. Thus, multimodal biometrics has been investigated upon and deployed. There are different levels of fusion namely: sample level, feature level, score level and decision level. At the sample levels, different instances captured are fused. When there is no movement between the instances, there are no additional branches after preprocessing the fused image. However, even for a slight orientation between the instances captured, the two fused images are not aligned. This leads to additional branches for dorsal hand vein patterns and additional lines for palmprints. At the feature extraction level, the preprocessed images are fused. The preprocessed fused images for both dorsal hand vein patterns and palmprints have additional information. Score level fusion has also been implemented. Two types of score level fusion namely classification method and combination method can be used. Using the combination methods, scores were generated from individual matcher namely dorsal hand vein pattern and palmprints. The scores were normalized using min-max technique. . Fusion can achieve up to 96% of recognition rate.

REFERENCES

[1] J. Cross and C. Smith, "Thermographic imaging of subcutaneous vascular network of the back of the hand for biometric identification," in *Proc. IEEE 29th Annual International Carnahan Conference*, 1995, pp. 20-35.

[2] C. Lin and K. Fan, "Biometric verification using thermal images of palm-dorsa vein patterns," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, no. 2, 2004.

[3] C. Deepika and A. Kandaswamy, "An algorithm for improved accuracy in unimodal biometric systems through fusion of

multiple feature sets," *ICGST-GVIP Journal*, vol. 9, no. 3, June 2009.

[4] L. Wang and G. Leedham, "Near- and- far- infrared imaging for vein pattern biometrics," in *Proc. IEEE International Conference on Video and Signal Based Surveillance*, 2006.

[5] L. Zhu and S. Zhang, "Multimodal biometric identification system based on finger geometry, knuckle print and palmprint," *Pattern Recognition Letters*, vol. 31, no. 12, 2010.

[6] D. Kisku, P. Gupta, and J. Sing, "Feature level fusion of face and palmprint biometrics by isomorphic graph-based improved k-Medoids partitioning," in *Proc. International Conference on Advances in Computer Science and Information Technology*, 2012.

[7] X. Wu, K. Wang, and D. Zhang, "Palmprint recognition using fisher's linear discriminant," in *Proc*. *International Conference on Machine Learning and Cybernetics*, 2003, pp. 3150-3154.

[8] L. Shang, D. Huang, J. Du, and C. Zheng, "Palmprint recognition using FastICA algorithm and radial basis probabilistic neural networks," *Neurocomputing*, vol. 69, pp. 1782-1786, 2006.

[9] M. Hanmandlu, J. Grover, V. Madasu, and S. Vasurkala, "Score level fusion of hand based biometrics using T-norms," in *Proc*. *IEEE International Conference on Technologies for Homeland Security*, December 2010, pp. 70-76.

[10] A. Yuksel, A. Akarun, and B. Sankur, "Biometric identification through hand vein patterns," in *Proc. 18th IEEE International Conference on Signal Processing and Communication Applications*, Diyarbakir, April 2010, pp. 708-711.

[11] M. Imran, A. Rao, and G. Kumar, "Multibiometric systems: A comparative study of multi-algorithmic and multimodal approaches," in *Proc*. *International Conference and Exhibition on Biometrics Technology*, 2010, pp. 207-212.

[12] A. Ross and A. Jain, "Multimodal biometrics: An overview," in *Proc*. *12th European Signal Processing Conference*, September 2004, pp. 1221-1224.

[13] T. Ko, "Multimodal biometric identification for large user population using fingerprint, face and iris recognition," in *Proc. 34th Applied Imagery and Pattern Recognition Workshop*, 2005, pp. 218-223.

[14] J. Lu, K. Plataniotis, and A. Venetsanopoulos, "Face recognition using LDA-based algorithms," *IEEE Transaction on Neural Networks*, vol. 14, no. 1, January 2003.

[15] S. Prabhakar and A. K. Jain, "Decision-Level fusion in fingerprint verification," *Pattern Recognition*, vol. 55, no. 4, pp. 861-874, 2001.

[16] R. Raghavendra, M. Imran, A. Rao, and G. H. Kumar, "Multimodal biometrics: Analysis of hand vein and palmprint combination used for person verification," in *Proc*. *Third International Conference on Emerging Trends in Engineering and Technology*, 2010, pp. 526-530.

[17] N. Woo and H. Kim, "Multiple-Biometric fusion methods using support vector machine and kernel fisher discriminant," in *Proc. 6th International Conference on Recent Advances in Soft Computing*, 2006, pp. 428-433.

[18] S. Horng, Y. Chen, R. Run, R. Chen, J. Lai, and K. Sentosal, "An improved score level fusion in multimodal biometric systems," in *Proc*. *International Conference on Parallel and Distributed Computing, Applications and Technologies*, 2009, pp. 239-246.

[19] A. Jain and A. Ross, "Information fusion in biometrics," *Pattern Recognition Letters*, vol. 24, no. 13, pp. 2115-2125, September 2003.

[20] M. He, *et al*., "Performance evaluation of a score level fusion in multimodal biometric systems," *Pattern Recognition*, vol. 43, no. 5, pp. 1789-1800, 2009.

Maleika Heenaye-Mamode Khan is a senior lecturer at the University of Mauritius. She is currently the Head of Department of Computer Science and Engineering. She has a PhD in Computer Science and Engineering. Her field of interest is biometrics, image processing and computer vision.