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SCORE LEVEL FUSION OF MULTIPLE FEATURES FOR EFFICIENT PERSONAL RECOGNITION

Esther Rani P.[1] and Shanmugalakshmi R.[2]
[1]Department of Electronics and Communication Engineering, VSB Engineering College, Karur
[2] Department of Computer Science Engineering, Government College of Technology, Coimbatore, India
E-Mail: esther.ece28@gmail.com

ABSTRACT

Hand based biometric systems are widely used in many applications owing to their reliability and high user acceptance. In this work, a multimodal biometric system for personal identification using score level fusion of palmprint and finger knuckle print is proposed. Features are extracted from palmprint using Gabor filter and Principal Component Analysis. Euclidean distance is used for matching and the minimum scores generated by the matchers are combined using sum rule. Also from finger knuckle print Speeded up Robust Features and Bidirectional Empirical Mode decomposition is used to extract features and scores are combined using sum rule after score normalization using min-max technique. Finally score level fusion using different rules is applied on the palmprint and finger knuckle print matching scores. The multimodal system is implemented using MATLAB and it is found that it provides low value of false acceptance rate, false rejection rate and equal error rate and high genuine acceptance rate in comparison to unimodal system using either palmprint or finger knuckle print.

Keywords: palmprint, finger knuckle print, score level fusion, speeded up robust features, bidirectional empirical mode decomposition, euclidean distance.

1. INTRODUCTION

In this e-connected world, it is possible for human beings to get access to any resources sitting at one corner of the world. This requires reliable personal identification to permit only registered users to get access to protected resources, building entry, e-banking and so on. Hence in most applications the traditional methods used are being replaced by biometric systems as these biometric characteristics are more reliable and cannot be easily forged. Biometric characteristics include Fingerprint, face, hand/finger geometry, iris, retina, signature, gait, palmprint, voice pattern, ear, hand vein, odor or the DNA information of an individual (Wayman *et al*., 2005). Biometric systems that make use of a single biometric characteristic are known as Unimodal biometric systems. Such systems are easy to implement and are also less expensive but suffer from factors like noisy data, intra-class variations, Inter-class similarities, Non-universality, Interoperability issues and spoof attacks (Ross *et al*., 2006).The solution to these problems is to make use of two or more biometric characteristics, in which case the system is called as multimodal system.In the proposed work two biometric characteristics such as palmprint and finger knuckle print are used for feature extraction.

Palmprint represents the skin patterns of the inner surface of the palm and consists of lines, points and texture. It contains three flexion creases called the principal lines and the secondary creases called wrinkles (Kong *et al.,* 2006].Palmprint based recognition systems have received considerable research interest because of its attributes such as high accuracy, high speed, high user friendliness and low cost. However, there is much room to improve the palmprint recognition systems, e.g. in the aspects of both accuracy and its vulnerability to spoof attacks (Guo *et al.,* 2010). Among various palm print recognition techniques, coding based methods have been very successful because of its simplicity, high precision, small size of feature and rapidness for both feature extraction and matching (Yue *et al*., 2008). Palmprints have several advantages over other hand-based biometrics, such as fingerprint and hand geometry. Compared to fingertips, palms are larger in size and therefore are more robust to injuries and dirt. Also, low-resolution imaging can be employed in the palmprint recognition based on creases and palm lines, making it possible to perform real time preprocessing and feature extraction (Chen *et al.,* 2010). Although palmprint recognition has achieved a great success, it has some intrinsic weaknesses. For example, some people may have similar palm lines, especially principal lines and also create fake palmprints. These problems can be addressed by using multi-biometric systems, such as fusing facial trait and palmprint trait or fusing iris and palmprint traits (Zhang *et al.,* 2010).

Recently it has been found that image patterns of skin folds and creases, the outer finger knuckle surface is highly unique and this can serve as distinctive biometric identifier (Kumar and Ravikanth, 2009). It has got more advantages when compared to finger prints. First it is not easily damaged since only the inner surface of the hand is used widely in holding of objects. Secondly it is not associated with any criminal activities and hence it has higher user acceptance. Third it cannot be forged easily

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since people do not leave the traces of the knuckle surface on the objects touched/ handled. Also the Finger Knuckle Print (FKP) is rich in texture and has a potential as a biometric identifier. The FKP biometric system recognizes a person based on the knuckle lines and the textures in the outer finger surface (Kumar and Zhou, 2009). These line structures and finger textures are stable and remain unchanged throughout the life of an individual. An important issue in FKP identification is to extract FKP features that can discriminate an individual from the other. Certain approaches for FKP identification using line-based and texture-based methods is proposed in the literatures. This paper describes the prototype of a biometric recognition system based on a fusion of palm print and FKP.

In this paper, an efficient multimodal biometric recognition system is proposed based on multiple feature extracted from palmprint and finger knuckle print. Texture feature is extracted from palmprint using 2D Gabor filter and also Principal Component Analysis (PCA) is used to extract the global features. Speeded up Robust Features (SURF) and Bidirectional Empirical Mode decomposition (BEMD) is used to extract features from the finger knuckle print. The scores generated from different matchers are combined using score level fusion to make the final decision as to whether to accept or reject the user. The rest of the paper is structured as follows: section 2 describes some of the recent related works. Section 3 described about an efficient palm recognition system and section 4 describes a FKP based recognition system with necessary diagrams and section 5 describes the multimodal biometric system. Section 6 tells about the matching and fusion techniques used Experimental results and analysis of the proposed methodology is discussed in Section 7. Finally, comparison of the proposed work with existing is presented in section 8 and concluding remarks are provided in Section 9.

2. EXISTING WORK

A handful of researches have been presented in the literature for the human authentication using multimodal biometrics. A brief review of some of the recent works based on multimodal biometrics is presented here.

Wang and Sun (2008) in their work have proposed a multimodal biometric system based on face and palmprint. Feature fusion of palmprint and face based on Kernel Fisher Discriminant Analysis (KFDA) is carried out. KFDA method of feature extraction is carried out in two phases. Firstfeatures are extracted using Kernel PCA (KPCA) and then apply Linear Discriminant Analysis (LDA) The discriminant vectors existing in null space and range space of within-class scatter matrix were calculated respectively by dual space analysis. The feature fusion is implemented by kernel fusion The ORL face database and the PolyU palmprint database was used to test the performance of the proposed system. Equal Error Rate (EER) was found to be 1.2% for the unimodal system using palmprint, 3.5% for face based system and 0.2% for the multimodal system using feature fusion of face and palmprint. Thus the multimodal system is shown to perform better than the unimodal system.

Subbarayuduand Prasad (2008) in their work have used iris and palmprint to implement a multimodal system. The iris image is first preprocessed and then Gabor filtering is used with four different orientations. The filtered images are then divided into blocks of size 16×16. For each of these blocks the standard deviation of the pixels is computed and they are concatenated to form the feature vector. Correlation coefficient is used to calculate the similarity between two iris images. Next 2D Log Gabor filtering is used to extract the real and imaginary parts of the palmprint image which are represented as feature vectors. Hamming distance is used compute the distance between the two palmprint images. Fusion of iris and palmprint features is done using sum rule of the scores generated from the two different matchers. The multimodal system is shown to outperform the unimodal system in terms of accuracy.

Wang *et al* (2007) presented a multimodal personal identification system using palmprint and palm vein images. A color camera and a monochrome JAI CV-M501R ½" CCD IR was used to capture palmprint and palm vein image. An IR light source is used to irradiate the palm as the NIR camera is not capable of detecting the IR radiations emitted by the human body. The two cameras are mounted on a fixture and when the user puts his hand under the camera with the fingers spread out, a color palmprint image and a vein image are captured simultaneously. A modified multiscale edge representation of the palmprint and palm vein images is fused to enhance the image contrast and intersection points. After fusion, the images are normalized and Locality Preserving Projections (LPP) is used to extract features of the fused images and it is called as the Laplacian palm features. The experimental results are compared with Eigen palm, Fisher palm and it is found that this method provides very low error rates.

In their work, shen *et al.* (2010) aims to improve the performance of the personal identification system, when only a single sample of palmprint and finger knuckle print is registered as template. The images are convolved with Gabor wavelets with different frequency and orientation. The phase values are obtained and each value is coded into two bits .The code thus generated is called as the fusion code and is stored as a template. Hamming distance is used for matching and the final decision is made by fusing the two distances using weighted sum rule. For each of the 165 users, 12 images of palmprint and FKP was captured and only one set of mages was used during the training phase and remaining 11 during the testing phase. An identification accuracy of 85.34% for

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palmprint and 44.68% for FKP and 89.2% for the fusion scheme was achieved.

Goh *et al* (2010) proposed an innovative contact-less palm print and knuckle print recognition system.The palm print and knuckle print features are extracted using Wavelet Gabor Competitive Code and Ridget Transform methods. Several decision-level fusion rules are used to consolidate the scores output by the palmprint and knuckle print. They include the AND- and OR-voting rules, sum rule, as well as weighted sum rule. The fusion of these features yields promising result of EER=2.99% for FKP,2.16% for palmprint and 1.25% using weighted sum rule fusion for verification .

Meraoumia *et al*. (2011) has used 1D Log Gabor filter to extract the features from palmprint and FKP. Each of these characteristics is represented by the real and imaginary parts of the Gabor filter response. They are then coded into two bits and stored as feature vectors. Hamming distance is used for matching .The scores from the individual matchers are normalized using Min-max normalization technique and then combined using min rule. The performance is compared in terms of EER% and is found to be 0.402% for palmprint, 5.407 for FKP and 0.066% for the fusion of palmprint and finger knuckle print.

3. PALMPRINT RECOGNITION

In our previous work (Rani and Shanmugalakshmi, 2014), a biometric system based on palmprint was proposed. The block diagram is shown in Figure-1.The images from the PolyU database are used for testing the performance.

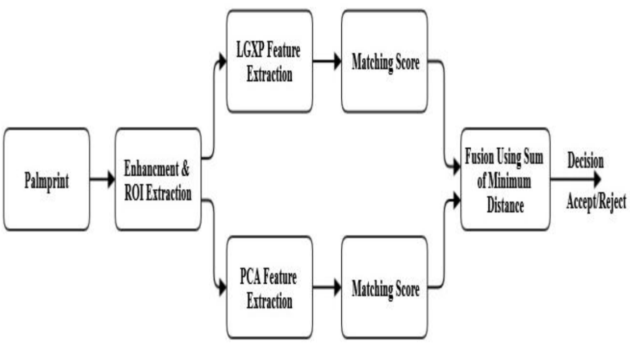

Figure-1. Block diagram of the palmprint recognition system.

Each palmprint image is first filtered using median filter. Then a Region of interest (ROI) of size 120×120 is extracted from the palmprint image for feature extraction. 2D Gabor filtering with six different orientations is convolved with the extracted ROI. For each of the filtered image the phase values are computed, quantized and then coded to obtain the Multiple Orientation LGXP (MOLGXP) features. Next PCA feature is extracted and the minimum matching score from the individual matchers of MOLGXP and PCA are fused using sum rule. Euclidean distance is used for matching between the test image and the database image. The Error trade off characteristics for palmprint recognition system is shown in Figure-2.In the Figure-2 the LGXP represents the feature vector extracted from the palmprint with a single orientation. It is observed that the fusion scheme provides better performance in comparison to LGXP and MOLGXP methods.

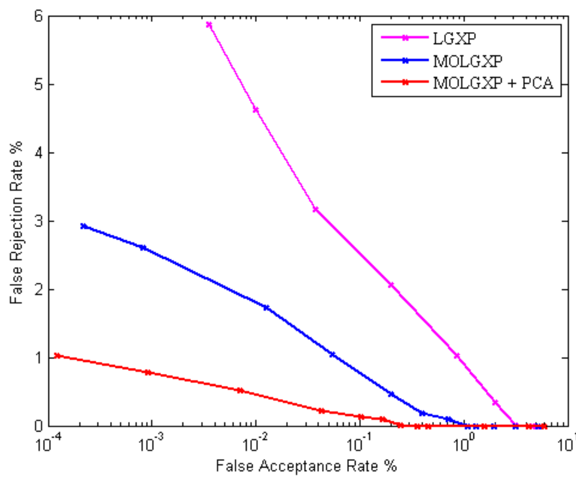

Figure-2. Error trade off curves for palmprint recognition systems.

4. FKP RECOGNITION

The finger knuckle surface is a highly curved surface and results in non uniform reflections during acquisition. After the preprocessing stage, it is found that resulting FKP is a low contrast image and also with non uniform brightness. Hence to improve the quality of the image it is next subjected to enhancement process. The extracted FKP image is divided into subimages of size 12×12 pixels. The mean gray level of all the subimages is then determined. This represents the reflection of the subimage and this computed value is expanded into the original size of the extracted FKP using bicubic interpolation. The resulting reflection is subtracted from the original image to obtain uniform brightness image which is subjected to histogram equalization to improve the contrast and to smoothen the boundaries between the subimages. The block diagram of the FKP recognition system is shown in Figure-3.

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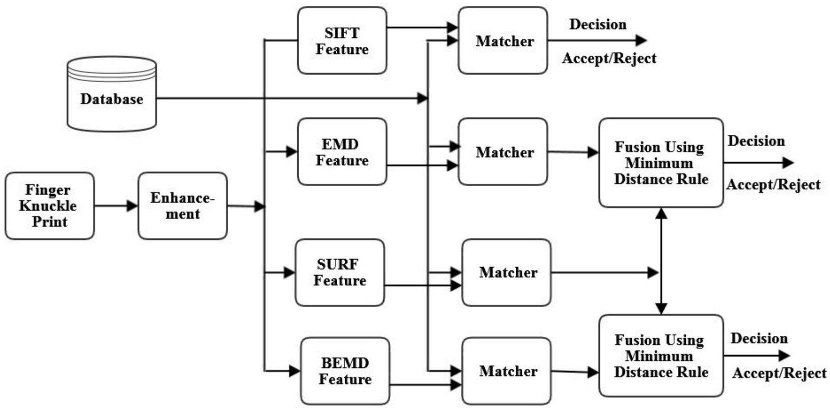
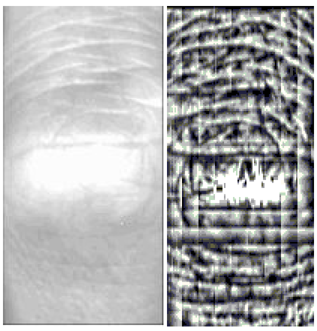


Figure-3. Block diagram of the FKP recognition system.

4.1 Feature extraction

Feature extraction is the most important step in a biometric system. The features must be unique to each individual, and more distinct they are, the better the performance of the biometric system. Hence in the proposed FKP recognition, Speeded up Robust Features (SURF) and Bidirectional Empirical Mode decomposition (BEMD) algorithms are used to extract the features. One of the important steps in a biometric system is preprocessing. The entire image captured during the data acquisition process is not used for feature extraction but a desired portion is cropped from the original image first. Such a cropped image called as the Region of interest (ROI) is available in the PolyU database and the same is used in this work. Figure-4(a) shows the extracted ROI and Figure-4(b) the enhanced ROI.



(a) (b)

Figure-4.(a) Extracted ROI (b) Enhanced ROI.

4.1.1 Speeded Up Robust Features (SURF)

SIFT(Lowe 2004) and SURF (Bay *et al.*, 2008) are two promising technique that are used to detect interest points called as keypoints in images. They also provide means to represent the keypoints in terms of keypoint descriptors. These descriptors presents a method for detecting distinctive invariant features from images that can be used to perform reliable matching. They are computationally fast and could be used to distinctively identify individuals. In comparing with the existing keypoint detectors, SURF is more robust because Hessian based detectors are more stable and repeatable than their Harris-based counterparts. Further, due to descriptor's low dimensionality, any matching algorithm is bound to perform faster. SURF has two significant advantages over SIFT. Firstly, SURF uses sign of Laplacian to have sharp distinction between background and foreground features. Secondly, SURF uses only 64 dimensions compared to SIFT using 128 dimensional vectors. This reduces feature computation time and allows quick matching with increased robustness simultaneously (Valgrenand Lilienthal, 2007). Feature vectors through SURF are formed by means of local patterns around key-points which are detected using scaled up filter. Following are the major steps to determine the SURF feature vectors of a given image.

Key-point detector: At this step, SURF key-points are detected using Hessian matrix approximation. Let *P(x, y)* represent a point in the image *I* and then the Hessian matrix *H (P, σ)* at scale σ is defined as

$$H(P,\sigma) = \begin{bmatrix} L_{xx}(P,\sigma) L_{xy}(P,\sigma) \\ L_{yx}(P,\sigma) L_{yy}(P,\sigma) \end{bmatrix} \quad (1)$$

The second order Gaussian derivatives for Hessian matrix are approximated using box filters. Key-points are localized in scale and image space by applying non-maximum suppression in a 3 x 3 x 3 neighborhood.

Key-point descriptor: This stage describes the key-points. It fixes a reproducible dominant orientation based on information from a circular region around the interest point. Feature vector of 64 values is computed from the oriented square local image region around key-point.

4.1.2 Feature extraction using BEMD

The joint space-spatial frequency representations have received special attention in the fields of image processing, vision, and pattern recognition (Chang *et al*., 2009). Huang *et al*. (1998) developed Empirical Mode Decomposition (EMD) for processing non linear and non stationary data. It decomposes the signal into a sum of oscillatory functions called the intrinsic mode function (IMF). An IMF is a function that satisfies two conditions: (1) in the whole data set, the number of extrema and number of zero crossings must either be equal or differ at most by one; and (2) at any point, the mean value of the envelope defined by local maxima and the envelope defined by local minima is zero. These two conditions are necessary to allow the calculation of a meaningful instantaneous frequency. The EMD decomposes a signal $X(t)$) into a set of IMF's by method called the sifting process. The EMD algorithm can also be used for the decomposition of images or 2D data which is known as Bidimensional EMD (BEMD), Image EMD (IEMD), 2D EMD, etc (Bhuiyan*et al*., 2009).

The 2D-EMD also called as Bidimensional EMD (BEMD) for an image $X(m,n)$operates as follows:

a) The local maxima and minima of the signal $X(m,n)$are determined.

b) Interpolate using cubic spline interpolation among the local maxima and local minima to get the upper envelope $X_{up}(m,n)$ and the lower envelope$X_{lo}(m,n)$.

c) The mean of the upper and lower envelope is computed using the relation

$$s(m,n) = \frac{X_{up}(m,n)+X_{lo}(m,n)}{2} b \quad (2)$$

d) Then subtract $s(m,n)$from $X(m,n)$to get the signal $X_1(m,n)$ where

$$X_1(m,n) = X(m,n) - s(m,n) \quad (3)$$

e) Next check if $X_1(m,n)$ obeys the criteria for an IMF, otherwise replace $X(m,n)$ by $X_1(m,n)$ and repeat the above steps to get the IMF.

The first IMF is given by$C_1(m,n) = X_1(m,n)$.To compute the next IMF,$C_1(m,n)$ is subtracted from the original signal $X(m,n)$ to get the residue$r(m,n) = X(m,n) - C_1(m,n)$.The sifting process is then continued until the final residue is a constant value or it is a function that contains only one maxima or minima from which no more IMF's can be obtained. Once the decomposition process is complete the original image can be reconstructed from

$$X(m,n) = \sum_{i=1}^{k} C_i(m,n) + r_k(m,n) \quad (4)$$

Where $C_i(m,n)$ denotes the intrinsic mode functions and $r_k(m,n)$ the residue. In BEMD both the IMF's and the residue are two dimensional signals (images). The texture feature of each IMF is then represented using fractal dimensions. There are different methods for computing the fractal dimensions and in this proposed work differential box-counting method is used which is a widely used technique. In this work the Finger Knuckle Print image is decomposed into three IMFs and a residue using BEMD. The ROI is first resized to 128×64 size image and then divided into 32 non over lapping regions of size 16×16 and the fractal dimensions are computed for all sub-images and concatenated to form the feature vector.

5. MULTIMODAL RECOGNITION

The Figure-5 shows the block diagram of the multimodal biometric system based on palmprint and finger knuckle print. Features are extracted from the palmprint and finger knuckle print using the techniques mentioned above. The scores generated from the matchers are combined to make a decision to accept or reject the user. The scores generated from different matchers may lie in different ranges; hence they must first be transformed to occupy a common range. This process is known as score normalization. In this work the scores from different matchers are normalized using Min-max normalization. Next simple fusion rules such as i) Min rule ii) Max rule iii) Sum rule and Weighted sum rule are used the generate the combined score.

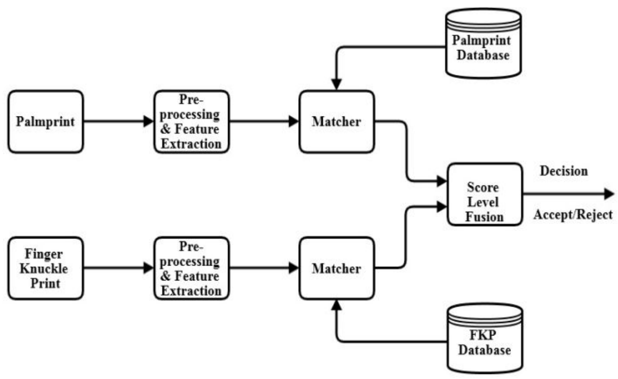


Figure-5. Block diagram of the multimodal recognition system.

6. MATCHING AND FUSION

For the FKP images the features are computed using SURF and EMD and stored in the database. During the recognition phase, the features are computed for the given test image and compared with the templates stored in the database. For SURF feature matching, the test image is compared with the master template in the database using nearest neighbor ratio. Let S and T represent the vector array of the keypoint descriptor for the images in the database and the test image as given below

$$S = (s_1, s_2, s_3 \dots \dots s_m) \quad (5)$$

$$T = (t_1, t_2, t_2 \dots \dots t_n) \quad (6)$$

Where s_i and t_j are the descriptor for the keypoint in the database and the test image. The nearest neighbor ratio is computed using the relation

$$R = \frac{\|s_i - t_j\|}{\|s_i - t_k\|} \quad (7)$$

$\|s_i - t_j\|$and$\|s_i - t_k\|$ represent the Euclidean distance between s_i and its first nearest neighbor t_j and that between s_i and its second nearest neighbort_k. A match is said to be found for s_i with t_j if the following condition is satisfied.

$$s_i = \begin{cases} matchedif R < threshold \\ notmatchedif R > threshold \end{cases} \quad (8)$$

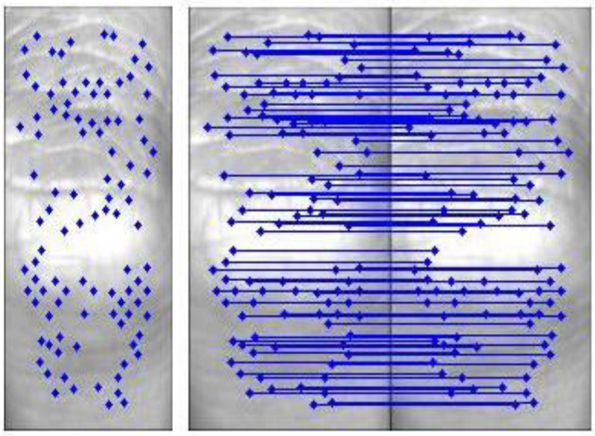
Once a match is found for a keypoint in S and T, then the matched keypoint is removed and the process is repeated till no more matches is found. The total number of matches thus found gives the matching score. Similarly Euclidean distance is used for EMD feature matching. The scores generated from the matchers lie in different range. Hence score normalization is necessary before fusing the scores. In this work Min-max normalization is used which transform the sores to a range [0, 1] (Jain et al. 2005). Let s represent the matching score from a set S of the matching scores from a particular matcher and let the normalized score be represented as n and is given by

$$n = \frac{s - \min(S)}{\max(S) - \min(S)} \quad (9)$$

where$\max(S)$ and $\min(S)$ are the maximum and minimum scores from the given set S.

7. EXPERMENTAL RESULTS

The performance of the SURF, EMD and their fusion are evaluated on the publicly available PolyU FKP database(http://www4.comp.polyu.edu.hk/biometrics/FKP.htm.). The database contains a total of 7920 FKP images collected from 165 individuals in two different sessions. In each session 6 images from left index finger, left middle finger, right index finger and right middle finger are collected from each user. Thus each user provided 6*4=48 images. The average time difference between first and second session was 25 days. In the experiments conducted four images collected in the first session was used as training set and rest of the images as testing set. The figure 6 shows the output obtained for SURF feature extraction. Figure-6(a) shows the SURF keypoints and Figure-6(b) SURF keypoint matching. The output for BEMD feature extraction is shown in Figure-7. In this work the Finger Knuckle Print image is decomposed into three IMFs and a residue using BEMD. The ROI is first resized to 128×64 size image and then divided into 32 non over lapping regions of size 16×16 and the fractal dimensions are computed for all sub-images and concatenated to form the feature vector.



(a) (b)

Figure-6.(a) Detected SURF keypoints (b) SURF keypoint matching.

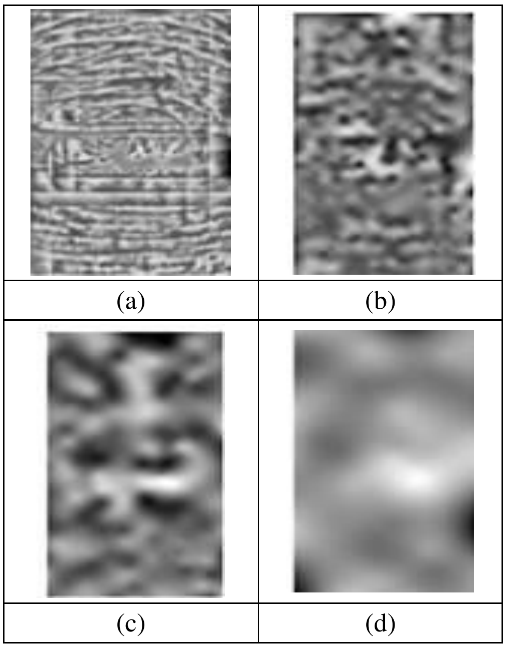


Figure-7.(a) First IMF (b) Second IMF (c) Third IMF components and (d) Residue.

The experimental results obtained for SURF, BEMD and fusion of SURF and BEMD using sum of minimum scores is shown in Table-1 below. The SIFT and one 1D EMD features were also computed and the results obtained is also shown in the table below. It is observed

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that the error rates are more for SIFT when compared with SURF and EMD features. Hence in the proposed work only fusion of SURF and EMD and SURF and BEMD feature is considered.

Table-1. Error rates and genuine acceptance rate comparison for FKPbased recognition system.

Biometric trait	Method	FRR%	FAR%	EER %	GAR%
Finger knuckle print	**SIFT**	**5.92**	**0.514**	**1.88**	**94.08**
	SURF	4.35	0.0059	0.30	95.65
	EMD	3.98	0.0027	0.27	96.02
	BEMD	2.84	0.0016	0.23	97.16
	SURF + EMD	1.96	0.0013	0.18	98.04
	SURF + BEMD	1.54	0.001	0.17	98.46

The Figure-8 below shows the Error Trade off Curves for the FKP recognition system. From the graph it is observed that the variation of false acceptance rate against false rejection rate is less for the system in which SURF and EMD scores are fused using score level fusion.

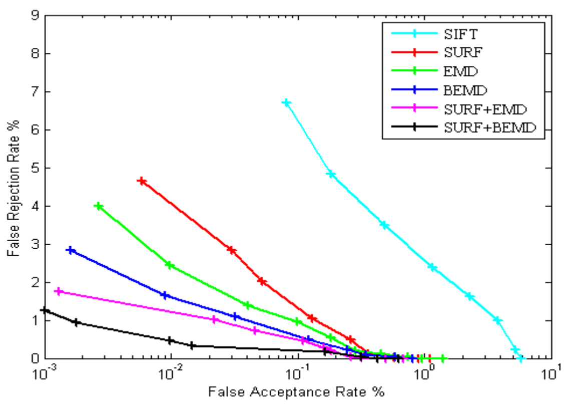

Figure-8. Error Trade off Curves for FKP Recognition system.

The Table-2 shows the results obtained for the multimodal recognition system using palmprint and finger knuckle print. As shown in the block diagram the features are extracted for a given test image and matching scores are obtained. The matching scores from the matchers are combined using simple fusion rules such as i) Min Rule ii) Max Rule iii) Sum Rule and Weighted Sum Rule (Michael et al. 2003).The weights are calculated based on the EER of the individual matchers as given in equation below.

$$w_m = \frac{\frac{1}{\sum_{m=1}^{M}\frac{1}{e_m}}}{e_m} \tag{10}$$

where w_m is the weight associated with matcher m and e_m is the EER of matcher m.In this experiment the weight assigned to matcher of palmprint recognition is $w_1 = 0.567$ and that of finger knuckle print matcher is $w_2 = 0.434$ The error trade off curves is shown in Figure-9.

Table-2. Error rates and Genuine Acceptance rate comparison for themultimodal system using different fusion rules.

Rule	FRR%	FAR%	EER%	GAR%
Min rule	0.48	4.86×10^{-4}	0.0242	99.52
Max rule	0.37	3.47×10^{-4}	0.00885	99.63
Sum rule	0.21	2.77×10^{-4}	0.00662	99.79
Weighted sum rule	0.12	6.94×10^{-5}	0.00554	99.88

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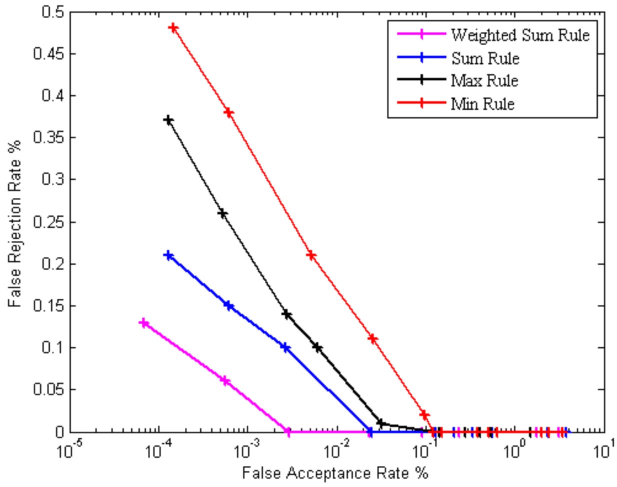

Figure-9. Error Trade off Curves for Multimodal system using different score level fusion rules.

8. COMPARATIVE ANALYSIS

In this section the results obtained for the proposed method is compared with the existing method. The results are compared with the method proposed by Meraoumia *et al* (2011).In their work the real and imaginary parts of 1D Log Gabor filter response of palmprint and finger knuckle print are stored as feature vectors. Min rule is used to combine the scores using score level fusion. Computing the false acceptance rate (FAR) and false rejection rate (FRR) is the common way to measure the biometric recognition accuracy. FAR is the percentage of incorrect acceptances i.e., percentage of distance measures of different people's images that fall below the threshold. FRR is the percentage of incorrect rejections - i.e., percentage of distance measures of same people's images that exceed the threshold. Genuine acceptance rate (GAR) gives the recognition rate and is given by GAR=1-FRR. The Table-3 below shows the results for existing and proposed technique in terms of EER and the graphical representation is shown in Figure-10.

Table-3. Error rates and recognition rate of existing and proposed multimodal recognition systems.

Technique	EER%
Existing Technique(Log Gabor Filter-real and imaginary- Min rule)	0.066
Proposed Technique-1(MOLGXP+PCA+SURF+EMD-Min rule)	0.0352
Proposed Technique-2(MOLGXP+PCA+SURF+BEMD- Min rule)	0.0242
Proposed Technique-1(MOLGXP+PCA+SURF+EMD-Weighted Sum rule)	0.00647
Proposed Technique-2(MOLGXP+PCA+SURF+BEMD- Weighted Sum rule)	0.00554

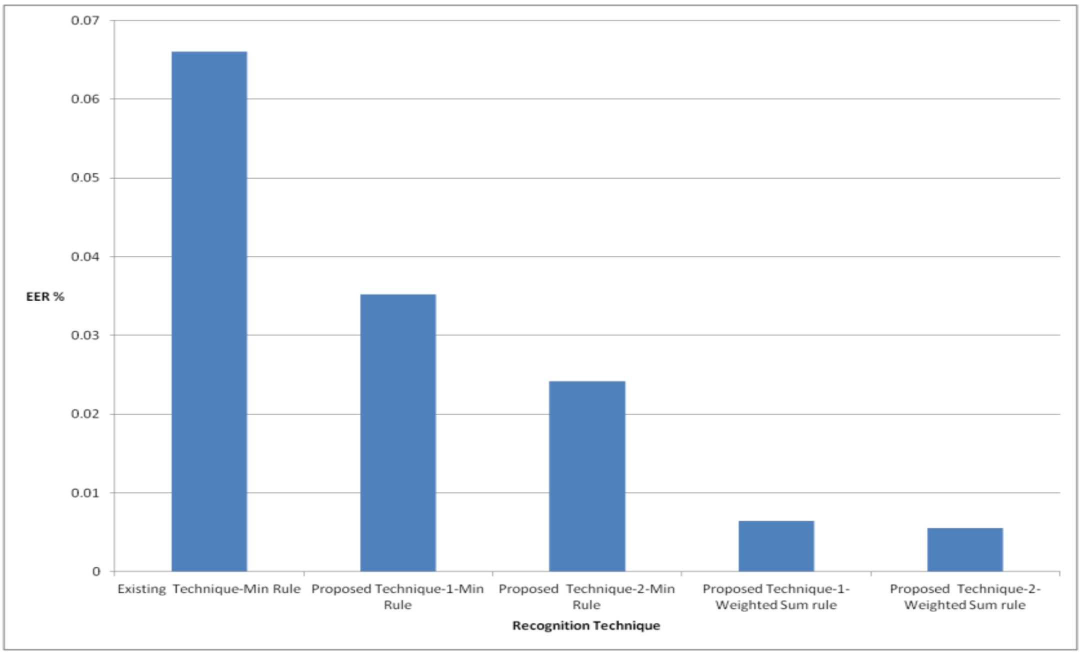

Figure-10. Comparison of EER for existing and proposed technique.

9. CONCLUSIONS

In this work, a multimodal recognition system based on palmprint and finger knuckle print is proposed. Multiple features are extracted from both palmprint and finger knuckle print and the score generated by the matchers are combined using score level. Different experiments have been conducted using different rules for combining the scores and it is found that the multimodal system using weighted sum rule provides better performance. The proposed system has low value of equal error rate and high recognition rate.

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