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Multimodal Biometric System using Score Level Fusion of Palmprint and Finger Knuckle Print

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***Abstract**:* Biometric based recognition systems are now effectively used in industries, educational institutions and banks for reliable personal identification. Among various biometric characteristics hand based biometrics has received greater attention among researchers because of its stability, feature richness, reliability and high user acceptability. In this paper, the finger knuckle print which refers to the inherent skin patterns that are formed at the joints in the finger back surface is used to extract the features. Speeded Up Robust features (SURF) and Empirical mode decomposition (EMD) are used to extract features from finger knuckle print. Score level fusion is used to combine the matching scores using the sum rule.The performance of the proposed algorithm is evaluated on the PolyU database. The proposed system is combined with the previous work using palmprint for personal identification. A multimodal system is thus developed based on score level fusion of palmprint and finger knuckle print. It provides a low value of false acceptance rate, false rejection rate and a high genuine acceptance rate in comparison to the unimodal system using palmprint or finger knuckle print.

***Keywords**:* Finger knuckle print, score level fusion, Speeded up Robust Features, Empirical mode decomposition, Euclidean distance.

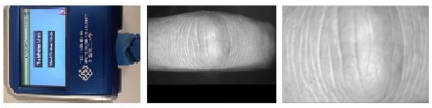
I. INTRODUCTION

Biometrics is the art of identifying a person based on the physical or behavioral characteristics possessed by the person [1]. Different physical or behavioral characteristics like fingerprint, face, iris, palmprint, hand geometry, voice, gait, signature etc., have been widely used in biometric systems. Among these traits hand based biometrics such as palmprint, fingerprint and hand geometry are very popular because of their high user acceptance. 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 [2]. 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 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.

II. EXISTING WORK

Woodard and Flynn [3] are the first scholars who made use of the finger knuckle surface in their work. They set up a 3D finger back surface database with the Minolta 900/910 sensor. This sensor captures both a 640x 480 range image and a registered 640x480 24 bit color intensity image nearly simultaneously. They used the 3D range image of the hand to calculate the curvature and shape based index surface representation of the index, middle and ring fingers. Normalized correlation coefficient was used for similarity comparison. The disadvantage in their system is that the size and cost of the sensor used in data acquisition is large and costly and the time consuming data acquisition limits its use in practical applications. Next Kumar and Ravikanth [2] developed a system for acquiring the finger back surface images. This imaging system uses a digital camera focused against a white background under uniform illumination. The back area of the whole hand was captured and then preprocessing steps was used to extract the finger back surface. Appearance based techniques like PCA, LDA and ICA was used for feature extraction and matching. Next Zhang and his team [4] in their work development a system for FKP acquisition. The figure 1(a) shows the FKP recognition system, Figure 1(b) shows the captured image and figure 1(c) the extracted ROI (Region of Interest) which is now publicly available in the PolyU database. Gabor filtering is used from which the orientation information is extracted and represented as Competitive Code. Angular distance is used for matching and an EER of 1.09% was achieved. Next the author [5] developed an Improved Competitive and Magnitude code by extracting the orientation and magnitude information using Gabor filters.These features are used to set up a code map based on the competitive code. Angular distance and magnitude distance is computed for the code maps during matching. The two distances are fused and the minimum of the resulting distance is considered to be the final distance for matching and an EER of 1.475% was achieved. Next he developed the Riesz Compcode [6] which integrates the advantages of Riesz transform and Compcode. Normalized Hamming distance is employed for matching and EER1.912**%.** Le-quing [7] proposed a robust FKP feature presentation and matching method based on Speeded-Up Robust Features (SURF). In matching the distance of the closest neighbor that of the second closest neighbor is compared and all matches in which the distance ratio is less than 0.6 is retained. Thus the initial tentative correspondence between two key point set of training image and template are got. Then RANdom SAmple Consensus (RANSAC) is employed to establish a geometric constraint for removing the false matching. The amount of final matched point pairs is referred to decide the consistency of the palm images. This method is invariant to rotation, scale and view point changes which proves its robustcity. The method provides an accuracy of 90.63% for verification and 96.91% for identification.

Zhang in his work [8] proposed Local Global Information Combination (LGIC) technique where the competitive coding scheme was used to represent local information and Fourier coefficients was taken as global feature. For matching two competitive code maps, angular distance based on normalized Hamming distance is used. Band Limited Phase Only Correlation (BLPOC) is used to measure the similarity between Fourier transforms of the images. The final distances were fused and an EER of 0.402% is achieved. The author in his work [9])used a bank of Gabor filters to extract the orientation information with five different scales and eight different orientations and a combination of PCA and LDA was used for dimensionality reduction.. Euclidean distance is used for matching and the proposed algorithm was tested on all four fingers and it is found that right middle finger provides better performance with a recognition rate of 75.25%.Feature level information fusion was carried out for different finger combinations and a maximum recognition rate of 98.79% was obtained for all four fingers. Meraoumia and his team [10] have designed a biometric recognition system based on the fusion of FKP and palmprint modalities. This scheme uses 1D Log Gabor filter response for feature extraction and Hamming distance for feature matching. The real and imaginary parts of the filter response is encoded and stored as feature vector. Analysis is done for separate fingers and the right index finger is shown to have better performance. The two modalities are combined and fusion at matching score level is applied using the min rule. Zhang [11] in his work presents a novel approach by fusing two kinds of biometrics i.e. palmprint and middle inner surface of the finger Discriminant features are obtained by combining the statistical information and structural information of each modality which are extracted using locality preserving Projections (LPP) based on wavelet transform.. The two types of features are fused at score level for the final hand based single sample bio metric recognition. A recognition efficiency of 99.56% is obtained.



(a) (b) (c)

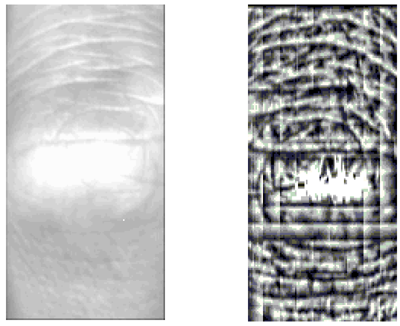
Figure 1(a) FKP recognition system (b) Captured image (c) Extracted ROI

III. FINGER KNUCKLE PRINT BASED 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 sub images.

A. Feature Extraction

Feature extraction is an important step in biometric system and more distinct the features, then identification can be accomplished accurately. Two types of feature can be extracted from the images –the global and local features. Global features are fast and easy to implement but they not efficient in handling rotation and scale variations but local features are more robust to illumination and rotation changes. In the proposed work local features using SURF and EMD is extracted. 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 2(a) shows the extracted ROI and figure 2(b) the enhanced ROI.



(a) (b)

Figure 2 (a) Extracted ROI (b) Enhanced ROI

A.1 Speeded Up Robust Features (SURF)

SURF [12] is a scale invariant and rotation invariant keypoint detector and descriptor like SIFT [13]. 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 use sonly 64 dimensions compared to SIFT using 128 dimensional vectors. This reduces feature computation time and allows quick matching with increased robustness simultaneously [14]. 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 $H(P, \sigma)$ at scale σ is defined as

(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.

A.1.1 Feature Extraction using EMD

N.E Huang [15] 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). This method is used in a number of applications [16, 17, and 18]. 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) into a set of IMF's by method called the sifting process. The sifting process is explained as follows

1) The local maxima and minima of the signal are determined.

2) Interpolate using cubic spline interpolation among the local maxima and local minima to get the upper envelope $X_{up}(t)$ and the lower envelope $X_{lo}(t)$.
3) The mean of the upper and lower envelope is computed using the relation

$$m(t) = \frac{X_{up}(t)+X_{lo}(t)}{2} \quad (2)$$

Then subtract m(t) from $X(t)$)to get the signal $X_1(t)$ where

$$X_1(t) = X(t) - m(t) \quad (3)$$

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

The first IMF is given by $C_1(t) = X_1(t)$.To compute the next IMF $C_1(t)$ is subtracted from the original signal $X(t)$ to get the residue $r(t) = X(t) - C_1(t)$.The sifting process is then continued until the final residue is a function that satisfies the condition, of extrema is less than three. Once the the total number decomposition process is complete the original signal can be reconstructed from

$$X(t) = \sum_{i=1}^{n} C_i(t) + r_n(t) \quad (4)$$

where n is the total number of IMF's and $r_n(t)$ represents the final residue. In this work, six IMF's are computed including the residue. The figure below shows the extracted IMF and the residue. The first IMF contains the highest frequency component and the highest IMF the lowest frequency component. In this work only the residue is used to represent the feature vector.

IV. MULTIMODAL RECOGNITION

In our previous work [19] a biometric system for personal identification based on palmprint is developed. Features are extracted using Gabor filter called Multiple Orientation Local Gabor XOR (MOLGXP) feature and Principal Component Analysis (PCA) and the performance is evaluated on the PolyU database [20]. In this paper a unimodal system based on finger knuckle print is developed. Next a multimodal system using palmprint and FKP is developed. The block diagram of the multimodal system is shown in figure 3 below.

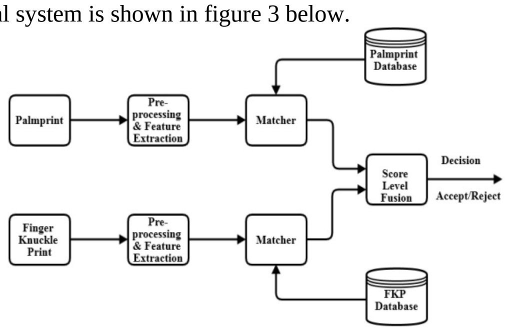


Figure 3 Block diagram of the multimodal recognition system

V. 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 teat 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 neighbor t_k. A match is said to be found for s_i with t_j if the following condition is satisfied.

$$s_i = \begin{cases} matched & if\ R < threshold \\ not\ matched & if\ R > threshold \end{cases} \quad (8)$$

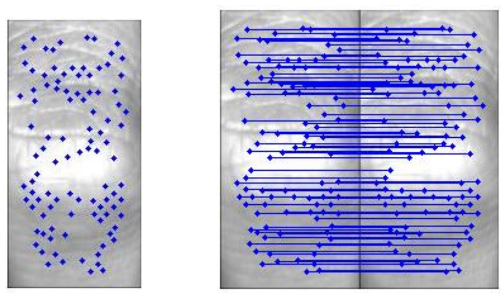
Once a match is found for a keypoint in S and T, then the matched keypoint is removed and the process is repeated till no more matches is found. The total number of matches thus found gives the matching score. Similarly Euclidean distance is used for EMD feature matching. The scores generated from the 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] [20]. 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*.

VI. EXPERIMENTAL RESULTS

The performance of the SURF, EMD and their fusion are evaluated on the publicly available PolyU FKP database [22].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 shows the output obtained for SURF feature extraction. Figure 4(a) shows the SURF keypoints and figure 4(b) SURF keypoint matching. The output for EMD feature extraction is shown in figure. To extract the EMD feature the FKP image is first resized to 60×60 then EMD algorithm is applied. For each of the extracted ROI five IMF's and the residue are obtained. Each of these IMF's contains 3600 feature components. The Figure 5 shows the five IMF components and residue obtained after the application of the EMD algorithm on the original FKP signal. For each of these signals only the first 900 components are shown. In this work only the 3600 components corresponding to the residue are stored in the database as the feature vector for each ROI.



(a) **(b)**

Figure 4 (a) Detected SURF keypoints (b) SURF keypoint matching

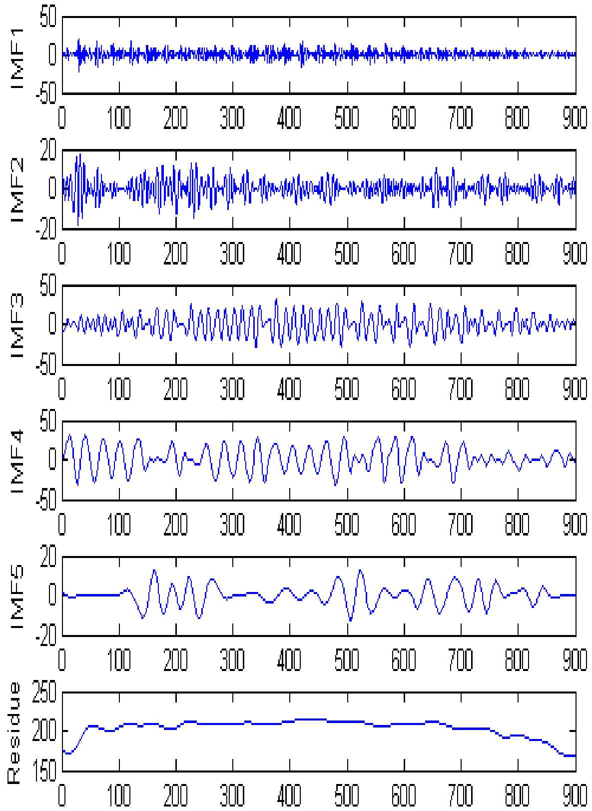


Figure 5 Five IMF components and the residue

The experimental results obtained for SURF, EMD and fusion of SURF and EMD using sum of minimum scores is shown in table I below. The SIFT features were also computed and the results obtained for SIFT feature matching is also shown in the table below. It is observed that the error rates are more for SIFT when compared with SURF and EMD feature. Hence in the proposed work only fusion of SURF and EMD feature is considered.

Table I Error rates and Genuine Acceptance rate comparison for FKP based recognition system

Method	**FRR%**	**FAR%**	**EER %**	**GAR%**
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
SURF+ EMD	1.96	0.0013	0.18	98.04

The Figure 6 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.

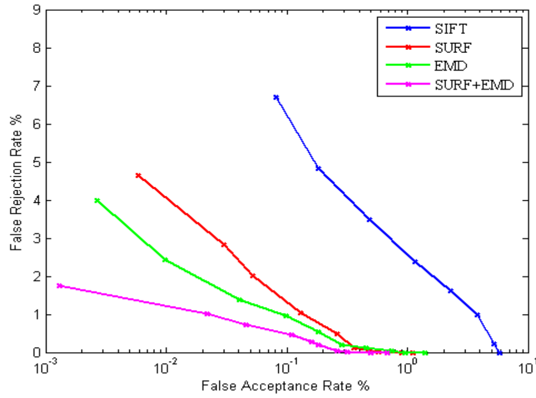


Figure 6 Error Trade off Curves for FKP Recognition system

The Table II 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 the following rules i) Min Rule ii) Max Rule iii) Sum Rule and Weighted Sum Rule [23]. The weights are calculated based on the EER of the individual matchers as given in equation below.

$$w_m = \frac{1}{\frac{\sum_{m=1}^{M}\frac{1}{e_m}}{e_m}} \qquad (10)$$

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 $w_1 = 0.58$ and that of finger knuckle print matcher is $w_2 = 0.42$.The error trade off curves is shown in figure 7.

Table II Error rates and Genuine Acceptance rate comparison for the multimodal system using different fusion rules

Rule	FRR%	FAR%	EER%	GAR%
Min Rule	0.58	6.25×10^{-4}	0.0352	99.42
Max Rule	0.44	5.55×10^{-4}	0.00987	99.56
Sum Rule	0.32	3.47×10^{-4}	0.00744	99.68
Weighted Sum Rule	0.17	1.38×10^{-4}	0.00647	99.83

VII. 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 Abdallah 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

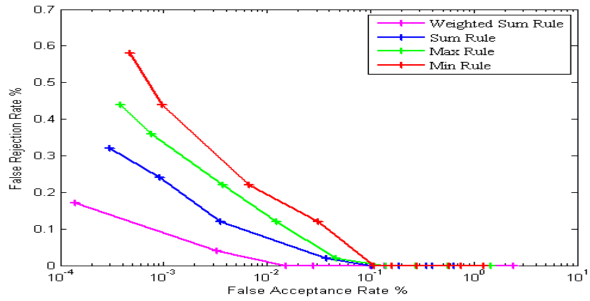


Figure 7 Error Trade off Curves for multimodal Recognition system

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 III below shows the results for existing and proposed technique in terms of EER.

Table III Error rates and Recognition rater of Existing and ProposedMultimodal Recognition systems

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

VIII. CONCLUSION

In this work, first a finger knuckle print recognition system is proposed where SURF and EMD features are extracted and score level fusion using sum rule is used before matching. Next a multimodal system is developed by combining palmprint and finger knuckle print. Different experiments have been conducted 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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