A Multimodal Biometric System Based on Palmprint and Finger Knuckle Print Recognition Methods

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Abstract: *Biometric authentication is an effective method for automatically recognizing a person's identity. In our previous paper, we have considered palm print for human authentication. Recently, it has been found that the Finger Knuckle Print (FKP), which refers to the inherent skin patterns of the outer surface around the phalangeal joint of one's finger, has high capability to discriminate different individuals, making it an emerging biometric identifier. In this paper, the local convex direction map of the FKP image is extracted. Then, the local features of the enhanced FKP are extracted using the Scale Invariant Feature Transform (SIFT), the Speeded Up Robust Features (SURF) and frequency feature. SIFT are formed by means of local patterns around key-points from scale space decomposed image. Feature vectors through SURF are formed by means of local patterns around key-points which are detected using scaled up filter. The frequency range of pixel levels in each image is employed by using Empirical Mode Decomposition (EMD). For the authentication of FKP image, we used shortest distance between the query image and the database, to evaluate their similarity. Here, we use PolyU FKP database images to examine the performance of the proposed system. The proposed biometric system is implemented in MATLAB and compared with the previous palm print human authentication system. For the same person, the matching score of the two methods are fused for the multimodal biometric recognition. The experimental results demonstrated the efficiency and effectiveness of this new biometric characteristic.*

Keywords: *FKP, convex direction map, SIFT, SURF.*

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1. Introduction

A biometric system is essentially a pattern recognition system which recognizes a user by determining the authenticity of a specific anatomical or behavioral characteristic possessed by the user. Several important issues must be considered in designing a practical biometric system [1, 12]. First, a user must be enrolled in the system so that his biometric template or reference can be captured. This template is securely stored in a central database or a smart card issued to the user. The template is used for matching when an individual needs to be identified. Depending on the context, a biometric system can operate either in verification (authentication) or an identification mode. Biometrics is considered as a currently ongoing scientific research topic with many applications, regarding safety and convenience [1]. Recognizing the identity of a person with high confidence is a critical issue in various applications, such as e-banking, access control, passenger clearance, etc., the need for reliable user authentication techniques has significantly increased in the wake of heightened concerns about security and rapid advancement in networking, communication and mobility [2].

Most of the biometric systems deployed in real world applications are unimodal which rely on the evidence of single source of information for authentication (e.g., fingerprint, face, voice, palmprint, Finger Knuckle Print (FKP) etc.,). These systems are vulnerable to variety of problems such as noisy data, intra-class variations, inter-class similarities, non-universality and spoofing. It leads to considerably high False Acceptance Rate (FAR) and False Rejection Rate (FRR), limited discrimination capability, upper bound in performance and lack of permanence. Some of the limitations imposed by unimodal biometric systems can be overcome by including multiple sources of information for establishing identity. These systems allow the integration of two or more types of biometric systems known as multimodal biometric systems.

These systems are more reliable due to the presence of multiple, independent biometrics. Biometric systems are being deployed to enhance security and reduce financial fraud. In some applications, more than one biometric trait is used to attain higher security and to handle failure to enroll situations for some users. Such systems are called multimodal biometric systems [13].

Biometric authentication is the study of methods for recognizing humans based on one or more physical or behavioral traits [3]. Palmprint is a unique biometric characteristic and palmprint recognition has been attracting much attention in the past decade [6] because of its attributes such as high accuracy, high speed, high user friendliness and low cost, etc., however, there is much room to improve the palmprint systems, e.g., in the aspects of both accuracy and its vulnerability to spoof attacks [19]. Some of the problems that affect unimodal biometric systems can be alleviated by using multimodal biometric systems. Hand-based person identification provides a reliable, low-cost and user-friendly viable solution for a range of access control applications. In fact, in contrast to other modalities like face and iris, the human hand contains a wide variety of modalities, which are fingerprint, hand geometry, palm print and FKP. First, data acquisition is relatively easy and economical via commercial low-resolution cameras. Second, hand-based access systems are very suitable for indoor and outdoor usage and can work well in extreme weather and illumination conditions. Third, hand features of adults are more stable over time and they are not susceptible to major changes. Finally, human hand-based biometric information is very reliable and it can be successfully used for recognizing people among several populations [13].

In our previous work [17], we have recognized the person using palm print. Palm print recognition is one of the most promising biometrics, has received considerable recent biometric research interest. Among various palm print recognition techniques, coding based methods have been very successful due to their simplicity, high precision, small size of feature and rapidness for both feature extraction and matching. Palmprint identification has emerged as one of the popular and promising biometric modalities for forensic and commercial applications. Recent research on palm print recognition indicates that the orientation information of palm lines is one of the most promising features palm lines generally are considered as typical multistage features, where the principal lines could be analyzed at a lower resolution and the wrinkles should be extracted at a higher resolution.

The inner surface of the palm normally contains three flexion creases, secondary creases and ridges. The flexion creases are also called principal lines and the secondary creases are called wrinkles. The flexion and the major secondary creases are formed between the third and fifth months of pregnancy and superficial lines appear after the birth. Although, the three major flexions are genetically dependent, most of other creases are not. Even identical twins have different palm prints [10]. These non-genetically deterministic and complex patterns are very useful in personal identification. Human beings were interested in palm lines for fortune telling long time ago. Scientists know that palm lines are associated with some genetic diseases including down syndrome, aarskog syndrome, cohen syndrome and fetal alcohol syndrome.

In palmprint recognition [20], the features used for matching are the principal lines and wrinkles. Actually, the outer surfaces of finger joints have even more obvious line features than the palm surface, while they have much smaller area than the palm surface. This motivates us to propose a new biometric technique which is the FKP, which refers to the image of the outer surface of the finger phalangeal joint [14, 24]. Palm print recognition is one kind of biometric technology. A simple palm print biometric system has a sensor module, for acquiring the palm print, a feature extraction module for palmprint representation and a matching module for decision making. A FKP-based biometric recognition is more recent biometric technology and it has attracted an increasing amount of attention. The image-pattern formation of a finger-knuckle contains information that is capable of identifying the identity of an individual. The FKP biometric recognizes a person based on the knuckle lines and the textures in the outer finger surface [11]. 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.

2. Literature Survey

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

Kakadiaris *et al*. [9] presented 3D face recognition in the presence of facial expressions: An annotated deformable model approach. In that paper, they presented the computational tools and a hardware prototype for 3D face recognition. Full automation was provided through the use of advanced multistage alignment algorithms, resilience to facial expressions by employing a deformable model framework and invariance to 3D capture devices through suitable preprocessing steps. In addition, scalability in both time and space was achieved by converting 3D facial scanned into compact metadata.

Yan and Bowyer [22] have proposed biometric recognition using 3D ear shape. In that work, the preprocessing of ear images has had manual steps and algorithms had not necessarily handled problems caused by hair and earrings. They presented a complete system for ear biometrics, including automated segmentation of the ear in a profile view image and 3D shape matching for recognition. In their system, they achieved a rank-one recognition rate of 97.8 percent for an identification scenario and an equal error rate of 1.2 percent for a verification scenario on a database of 415 subjects and 1,386 total probes.

A coding scheme for indexing multimodal biometric databases was proposed by Gyaourova and Ross [4]. In biometric identification systems, the identity associated with the input data was determined by comparing it against every entry in the database. That exhaustive matching process increased the response time of the system and potentially, the rate of erroneous identification. A method that narrows the list of potential identities will allow the input data to be matched against a smaller number of identities. They described a method for indexing large-scale multimodal biometric databases based on the generation of an index code for each enrolled identity. In that proposed method, the input biometric data was first matched against a small set of reference images. The set of ensuing match scores was used as an index code. The index codes of multiple modalities were then integrated using three different fusion techniques in order to further improve the indexing performance. Experiments on a chimeric face and finger print bimodal database indicated a 76% reduction in the search space at 100% hit rate.

Nageshkumar *et al.* [15] proposed a new and efficient secure multimodal biometric fusion using palmprint and face image. Biometrics based personal identification was regarded as an effective method for automatically recognizing, with a high confidence a person's identity. In that paper, they have proposed the authentication method for a multimodal biometric system identification using two traits i.e., face and palmprint. The proposed system was designed for application where the training data contains a face and palmprint. Integrating the palmprint and face features increased robustness of the person authentication. The final decision was made by fusion at matching score level architecture in which features vectors was created independently for query measures and was then compared to the enrolment template, which was stored during database preparation.

Zhang *et al*. [25] proposed a new biometric identifier, named FKP, for personal identity authentication. First a specific data acquisition device was constructed to capture the FKP images and then an efficient FKP recognition algorithm was presented to process the acquired data. The local convex direction map of the FKP image was extracted based on which a coordinate system was defined to align the images and a Region Of Interest (ROI) was cropped for feature extraction. A competitive coding scheme, which used 2D Gabor filters to extract the image local orientation information, was employed to extract and represent the FKP features. When matching, the angular distance was used to measure the similarity between two competitive code maps. An FKP database was established to examine the performance of the proposed system and the experimental results demonstrated the efficiency and effectiveness of that biometric characteristic.

Zhanga *et al*. [27] presented a new biometric authentication system using FKP imaging. For matching two FKPs, a feature extraction scheme which combines orientation and magnitude information extracted by Gabor filtering. An FKP database, which consists of 7,920 images from 660 different fingers, has been established to verify the efficacy of the proposed system and promising results were obtained.

Compared with the other existing finger-back surface based biometric systems, the proposed FKP system achieved much higher recognition rate and it works in real time. It provided a practical solution to finger-back surface based biometric systems and has great potentials for commercial applications.

Meraoumia *et al*. [13] proposed a new approach of FKP and palm print for an efficient multi-biometric system of person recognition. Biometric system had been actively emerging in various industries for the past few years and that was continuing to roll to provide higher security features for access control system. Addressing that problem they proposed an efficient matching algorithm based on Phase-Correlation Function (PCF) and using the two biometric modalities the palm print and the FKP. The two modalities were combined and the fusion was applied at the matching-score level. The experimental results showed that the designed system achieved an excellent recognition rate and provided more security than unimodal biometric-based system.

Zhang *et al*. [26] proposed a novel approach based on Local-Global Information Combination (LGIC) based FKP recognition method. That was based on the fact that both local and global features were crucial for the image recognition and perception and they have played different and complementary roles in such a process. In the LGIC, the local orientation was extracted by the gabor filters based competitive coding scheme was taken as the local feature. From the perspective of time-frequency analysis, when the scale of the gabor transform goes to infinity, it degenerates to the fourier transform. Thus, the fourier transform was naturally taken as the global feature in their work. LGIC exploits both local and global features for FKP verification, where the global features were also used to refine the alignment of FKP images in matching. Extensive experimental results conducted on their FKP database indicate that, their scheme could achieve much better performance in terms of EER and the decidability index than the other state-of-the-art competitors.

Hanmandlu and Grover [5] proposed a feature level fusion of FKP's. To overcome the curse of dimensionality, feature selection using the triangular norms was proposed. An unknown parameter in t-norms was learnt using reinforced hybrid evolutionary technique. Feature level fusion was performed by combining the significant features of all FKP's. Results showed an improvement in the accuracy when the features were selected by a divergence function derived from the new entropy function using t-norms on two pairs of training features taken at a time.

Yang *et al*. [23] presented a novel finger vein recognition method based on a Personalized Best Bit Map (PBBM). That method was rooted in a local binary pattern based method and then inclined to use the best bits only for matching. They first presented the concept of PBBM and the generated algorithm. Then, they proposed the finger vein recognition framework, which consisted of preprocessing, feature extraction and matching. Finally, they have designed extensive experiments to evaluate the effectiveness of their proposal. Experimental results gave that PBBM achieves not only better performance, but also high robustness and reliability. In addition, PBBM could be used as a general framework for binary pattern based recognition.

3. FKP Recognition

The biometric systems based on palm print and FKP which provides rich personal information for automatic recognition of individuals based on the principal lines, wrinkles and ridges in the finger and palm. Here, we present a new biometric identifier known as FKP, for personal identity. Normally, to extract the features, Gabor filter coding is used. The Gabor filter can simultaneously capture spatial and frequency uncertainty information [8]. By the use of Gabor filter it is possible to evaluate three basic features like magnitude, phase and orientation. Among this, orientation feature is the most robust and distinctive feature. Gabor filter in combination with a competitive code scheme is used, so that it allows the extraction of orientation information concerning the finger knuckle image stressing its efficiency. Specifically, the orientation information extracted by the Gabor filters is coded as the local feature. By increasing the scale of gabor filters to infinite, actually we can get the fourier transform of the image and hence the fourier transform coefficients of the image can be taken as the global features. Such kinds of local and global features are naturally linked via the frame work of time-frequency analysis [26].

In our proposed work, we are using FKP for recognition, since it have so many advantages in the field of biometrics over finger print images. It is seen that the skin pattern on the finger-knuckle is highly rich in texture due to skin folds and creases and hence, can be considered as a biometric identifier [21]. Further, advantages of using FKP include easily accessible, invariant to emotions and other behavioral aspects such as tiredness, stable features [26] and acceptability in the society [11]. Actually, the outer surfaces of finger joints have even more obvious line features than the palm surface, while they have much smaller area than the palm surface. Since, the finger knuckle will be slightly bent when being imaged, the inherent skin patterns can be clearly captured and hence the unique FKP features can be better exploited.

4. Multimodal Biometric Recognition

In our proposed work, we are considering palm print and FKP for recognition purpose. In our previous work [17], we have discussed about palm print recognition and in our current work we proposed recognition using FKP and fused the matching score with the previous work to make the decision for multi modal biometric recognition. Figure 1 shows the basic flow diagram of the proposed method.

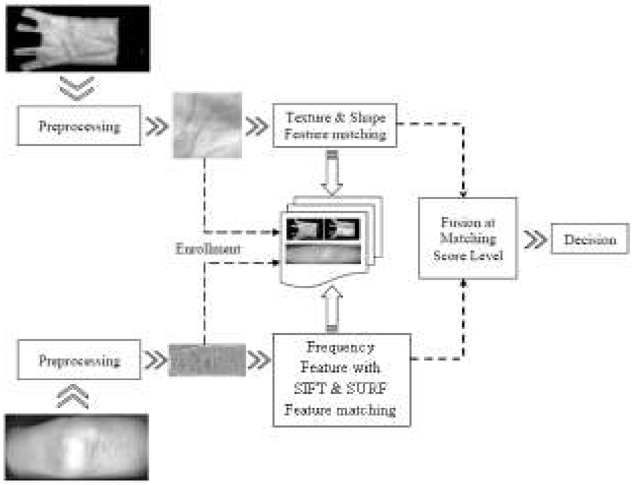


Figure 1. Flow diagram of proposed system.

4.1. FKP Recognition using Extensive Feature Set

Here, we present a robust FKP based recognition system which is designed by fusing SIFT and SURF features at matching score level. The FKP image is subjected for non-uniform brightness correction and contrast enhancement. Scale Invariant Feature Transform (SIFT) and SURF features are extracted from the enhanced FKP images. During recognition, corresponding feature vectors of query and enrolled FKPs are matched using nearest-neighborhood-ratio method to obtain the respective matching scores and these SIFT and SURF matching scores are fused using weighted sum rule. The block diagram of the proposed FKP based system for recognition as shown in Figure 2.

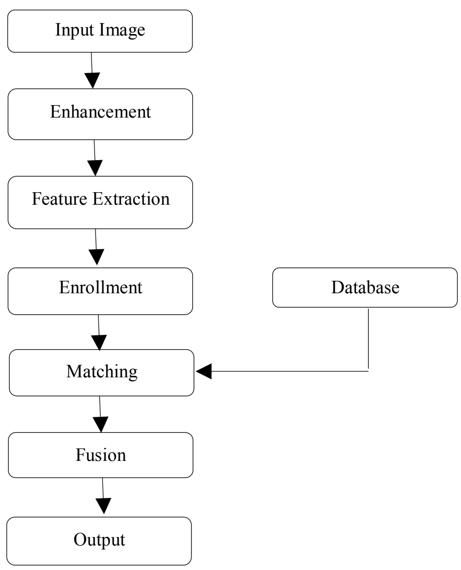


Figure 2. Proposed flow diagram of knuckle print recognition.

4.1.1. Enhancement

The finger-knuckle surface represents a relatively curvature surface and results in non-uniform reflections. FKP has low contrast and non-uniform brightness. To obtain the well distributed texture image following operations are applied on FKP. Each FKP image is divided into sub-blocks of 11×11 pixels. Mean of each block is calculated which estimates the reflection of the block. The estimated coarse reflection is expanded to the original size of the FKP image using bi-cubic interpolation. For the coarse estimate of reflection, if the block size is very small, the estimate is almost same as the extracted FKP and if the block size is high, the estimate becomes improper. Based on the experiments, block size of 11×11 pixels has been chosen for computing the coarse estimate of reflection. The estimated reflection is subtracted from the original image to obtain a uniform brightness of the image. Histogram equalization is performed on blocks of 11×11 pixels to improve the contrast in the texture of FKP and then subjected to filtering operation to smooth the boundaries between blocks.

4.1.2. Feature Extraction

Features are extracted from all FKP images. Here, we will extract SIFT, SURF and frequency feature from the images. SIFT and SURF is used to extract the local features of FKP. Both SIFT and SURF has been designed for extracting highly distinctive invariant features from images. Further, extracted feature vectors are found to be distinct, robust to scale, robust to rotation and partially invariant to illumination. Thus, features can be matched correctly with high probability against features from a large database of FKPs. The frequency feature can be extracted by using Empirical Mode Decomposition (EMD).

4.1.2.1. Scale Invariant Feature Transform

Feature vectors through SIFT are formed by means of local patterns around key-points from scale space decomposed image. Following are the major steps to generate SIFT features of a given image:

- *Scale-Space Extrema Detection*: The first step of computation searches over all scales and image locations. It is implemented efficiently by using a Difference-of-Gaussian function to identify potential interest points that are invariant to scale.
- *Key-Point Localization*: At each candidate location, a detailed model is fitted to determine location and scale. Key-points are selected based on measures of their stability.
- *Orientation Assignment*: Consistent orientation is assigned to the key-point following local image properties to make the key-point descriptor rotation invariant.
- *Key-Point Descriptor*: Feature vector of 128 values is computed from the local image region around the key-point.

4.1.2.2. Robust Features

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. 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 3×3×3 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.

4.1.2.3. Frequency Feature Extraction using EMD

In this phase, normalized FKP image is partitioned into multiple small blocks and the pixel values in each block are formed into 1D vector. Subsequently, 1D vector is applied to linear scaling and EMD [18], which provides the feature vector. Huang *et al*. [7] recently introduced a technique that decomposes a signal into a sum of components, each with slowly varying amplitude and phase. Once, a signal has represented in such a form, using the hilbert transform one may analyze the properties of each component. Every component of the EMD is called an Intrinsic Mode Function (IMF). The two criteria will satisfy the IMFs, so that they will resemble a generalized Fourier decomposition.

In the whole dataset, the number of extrema and the number of zero-crossings must either equal or differ almost by one and:

1. At any point, the mean value of envelope defined by the local maxima and the envelope defined by the local minima is zero.
2. More particularly, a real valued input signal is represented by $X(k)$ and then the application of EMD generates a set of M $IMFs$ $\{IMF_j(k)\}_{j=1}^{M}$, such that:

$$X(k) = \sum_{j=0}^{M} IMF_j + res(k) \tag{1}$$

Where, the residual $res(k)$ is a monotonic function and it represents the trend within the original signal. The following algorithm gives the method that is used for the extraction of IMF from the signal $x'(k)$.

1. The set of $IMFs$ is initially defined as $M=\emptyset$ (empty set).

2. Find the locations of all extrema of $x'(k)$.

   a. $x'(k) = X - \sum_{i \in I} IMF_i$.
   b. Compute k^{th} IMF (sifting).
      1. Interpolate (using cubic spline interpolation) between all the minima (respectively for maxima) to obtain the signal envelope passing through the minima $e_{min}(k)$ (respectively for $e_{max}(k)$).
      2. Compute the local mean of these envelopes $m(k)=(e_{min}(k)+e_{max}(k))/2$.
      3. Subtract $x'(k)$ from the mean $m(k)$ to obtain the oscillating signal $s(k)=x'(k)-m(k)$.
      4. If the resulting signal $s(k)$ obeys the stopping criterion, $IMF(k)=s(k)$ becomes IMF.
      5. Otherwise, set $x'(k)=s(k)$ and repeat the process from steps 1 to 5.
   c. $x'(k)$ is added to set M.

The normalized squared difference between two successive sifting iterates $s_{pre}(t)$ and $s_{cur}(t)$, that is:

$$SD = \sum_{t=0}^{T} \left[\frac{\left| \left(s_{pre}(t) - s_{cur}(t) \right) \right|^2}{s_{pre}(t)} \right] \tag{2}$$

Where, T represents the total number of samples in the original series and the empirical value of SD is using a set with in the range (0.2-0.3). Upon obtaining an IMF, the same procedure is applied to the residual signal $res(k)=x'(k)-IMF(k)$ to extract the next IMF. The process is continued until all the $IMFs$ are extracted and no other oscillations are carried in the remaining signal, illustrated by an insufficient number of extrema. From the element with high frequency the $IMFs$ are successively obtained. Hence, the residual signal $res(k)$ has the lowest frequency.

EMD is applied to each block on the FKP image 1D vector FB_V^N in order to, obtain the Feature of Block (FB). The EMD produces the intrinsic mode functions for all the blocks along with residual vectors. After the iteration ends, the values are taken from the Feature vector FB. The feature vector Fv^b (residual) of the block is represented as $Fv^b = \left(Fv_1^b, Fv_2^b, L, Fv_i^b, L, Fv_m^b \right)$ where, Fv^b represents the residual of the EMD results of FB_V^N.

Now, we concatenate the feature vector of each block and store the concatenated vector $\left(Fv^b = \left(Fv_1^b, Fv_2^b, L, Fv_i^b, L, Fv_m^b, C_v \right) \right)$ in the database for further processing.

In our work, Euclidean distance is used to generate the similarity between two feature vectors:

$$F_p = ED(Fv_r^b, Fv_t^b) = \sqrt{\sum_{i=1}^{m} (Fv_{r_i}^b - Fv_{t_i}^b)^2} \tag{3}$$

4.1.3. Matching and Fusion

The feature template of the FKP is represented by local feature vectors extracted using SIFT, SURF and frequency feature. During recognition, the feature set of the query FKP image is matched with the corresponding features of all the knuckle-prints in the database. The matching scores between corresponding feature vectors are computed using nearest-neighbor-ratio method as follow:

Let Q, E and F be vector arrays of key-points of the query and the enrolled FKP respectively obtained using either SIFT, SURF and frequency feature:

$$Q = \{q_1, q_2, q_3, \ldots q_m\} \tag{4}$$

$$E = \{e_1, e_2, e_3, \ldots e_n\} \tag{5}$$

$$F = \{f_1, f_2, f_3, \cdots, f_p\} \tag{6}$$

Where, q_i, e_j and f_k are the feature vectors of key-point i in Q and that of key-point j in E and k in F respectively. If $\|q_i-e_j\|$ and $\|e_j- f_k\|$ are the Euclidean distance between q_i and its first nearest-neighbour e_j and that between e_j and its nearest-neighbor of f_k respectively, then:

$$q_i = \begin{cases} \dfrac{\|q_i - e_j\|}{\|e_j - f_k\|} < T & \text{Matched with } e_j \\ \text{Otherwise} & \text{Unmatched} \end{cases} \tag{7}$$

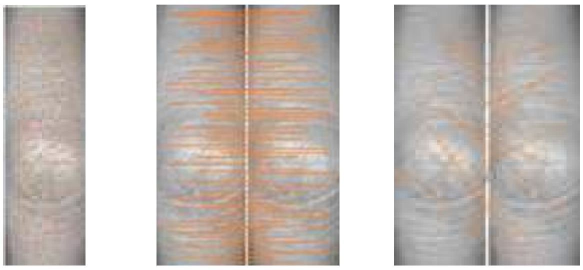
Where, T is a predefined threshold.

The matched key-points q_i, e_j and f_k are removed from Q, E and F respectively. The matching process is continued until there are no more matching points in Q, E and F. Total number of matching pairs M is considered as the matching score. More, the number of matching pairs between two images, greater is the similarity between them. Matching between FKP images of same user is called genuine matching while that of different users is known as imposter matching. An example of genuine matching and imposter matching using SIFT is shown in Figure 3. Similarly, Figure 4 shows an example of genuine matching and imposter matching using SURF.

Let M_T, M_S and M_F be SIFT, SURF and frequency feature matching scores respectively between the query and an enrolled FKP. These matching scores are fused by weighted sum rule to obtain the final matching score S as:

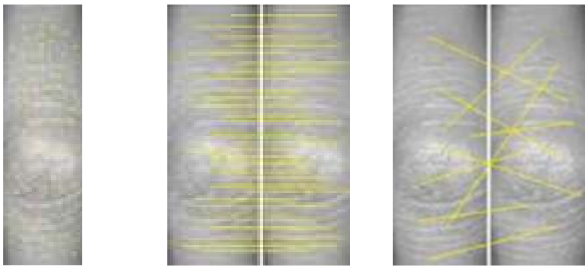
$$S = W_T * M_T + W_S * M_S + W_F * M_F \tag{8}$$

Where, W_T, W_S and W_F are weights assigned to SIFT matching score M_T, SURF matching score M_S and frequency feature matching score M_S respectively, with $W_T+W_S+W_F=1$. Here, $W_T=C_T/(C_T+C_S+C_F)$, $W_S=C_S/(C_T+C_S+C_F)$ and $W_F=C_F/(C_T+C_S+C_F)$ are considered where, C_T, C_S and C_F are the Correct Recognition Rate (CRR) of the system for SIFT alone and SURF alone. Here, means, the ratio of the number of the samples being correctly classified to the total number of the test samples.



a) SIFT key-points detected. b) Genuine matching of SIFT key-points. c) Imposter matching of SIFT key-points.

Figure 3. SIFT key points identification.



a) SURF key-points detected. b) Genuine matching ofSURFkey-points. c) Imposter matching of SURF key-points.

Figure 4. SURF key points identification.

4.2. Fusion

The likelihood ratio based score fusion framework proposed in the presented multimodal biometric human recognition system was developed specifically for the verification scenario where the goal is to decide whether an input sample belongs to the genuine or impostor class. In verification, the biometric query is compared only to the template of the claimed identity, resulting in a single match score for each matcher. However, in an identification system, the biometric query is compared with all the templates in the database resulting in N match scores for each matcher, where, N is the number of persons enrolled in the database. Scores generated from individual biometric traits are combined at matching score level using sum rule. M_{Spalm} and MS_{fkp} are the matching scores generated by palmprint and FKP respectively. Since, the matching scores output by the two traits are heterogeneous because they are not on the same numerical range. The normalization of the three scores is done.

$$N_{palm} = \frac{MS_{palm} - min_{palm}}{max_{palm} - min_{palm}} \tag{9}$$

$$N_{fkp} = \frac{MS_{fkp} - min_{fkp}}{max_{fkp} - min_{fkp}} \tag{10}$$

Min-max normalization transforms all the scores into a common range [0, 1]. N_{palm} and N_{fkp} are the normalized matching scores of palmprint and FKP respectively. Prior to combining the normalized scores, it is necessary that all the two normalized scores are transformed as either similarity or dissimilarity measure. In the proposed system, the normalized scores of FKP and palm print are converted to similarity measure by subtracting them from as given below:

$$N'_{palm} = 1 - N_{palm} \tag{11}$$

$$N'_{fkp} = 1 - N_{fkp} \tag{12}$$

Finally, the two normalized similarity scores N'_{palm} and N'_{fkp} are fused using weighted sum rule to generate final matching score as follows:

$$MS_{final} = X * N'_{palm} + Y * N'_{fkp} \tag{13}$$

Here, X and Y are the weightage assigned for palm print and FKP images.

5. Results and Discussion

In this section, we can discuss about the performance of our proposed approach with existing method. Our proposed approach is implemented in Matlab (7.10) and FKP recognition was performed using the set of FKP images in PolyU Database [16].

5.1. PolyU Database

PolyU Database is the publicly available largest FKP database from the Hong Kong Polytechnic University. This database contains 7920 FKP images obtained from 165 subjects. Images are acquired in two sessions. At each session, 6 images of 4 fingers (distinct index and middle fingers of both hands) are collected. Subjects comprise of 125 males and 40 females. The age distribution of users is as follows: 143 subjects are having age lying between 20 and 30 while remaining is between 30 and 50. The images collected in first session are considered for training and those images collected in the second session are used for query. Figure 5 shows some of the sample FKP images in PolyU database.

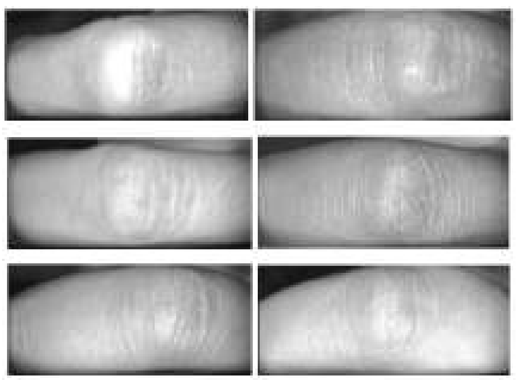
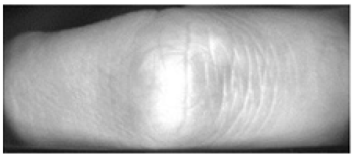


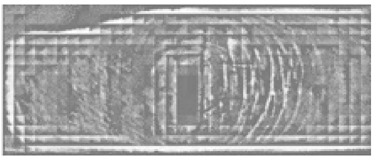
Figure 5. Sample FKP images in PolyU database.

5.2. Experimentation

This section describes the experimental result of our proposed method. Initially, the query image is preprocessed to make the image ready for recognition. Each FKP image is divided into sub-blocks of 11×11 pixels. Then, the mean values of the intensity of all the blocks are subtracted from the intensity value of each block to make the whole image in same brightness. Then the image is subjected for normalization process. Figure 6 shows the sample output of the query image after normalization process.



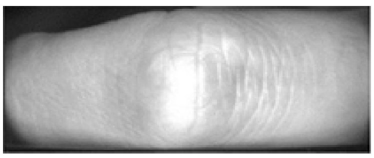
a) Query image.



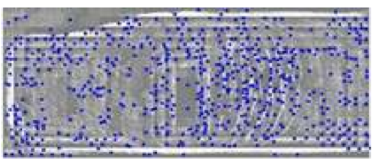
b) Normalized image.

Figure 6. Normalization process.

Then, the normalized image is subjected to feature extraction process. In our approach, SIFT and SURF features are extracted for the recognition process. SURF is a robust image detector and descriptor, that can be used in computer vision tasks like object recognition or 3D reconstruction. SIFT is an algorithm in computer vision to detect and describe local features in images. For any object in an image, interesting points on the object can be extracted to provide a "feature description" of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects. Figures 7 and 8 show the sample output for SIFT and SURF feature extraction. Figure 9 represents the EMD feature extraction process for FKP images. EMD plot represents the frequency range of pixel levels in each image. The frequency feature is extracted by using EMD method and Figure 9 represented its corresponding histogram plot.

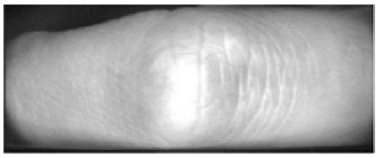


a) Query image.

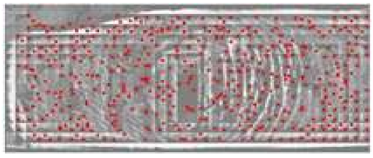


b) SIFT features.

Figure 7. SIFT feature extraction.

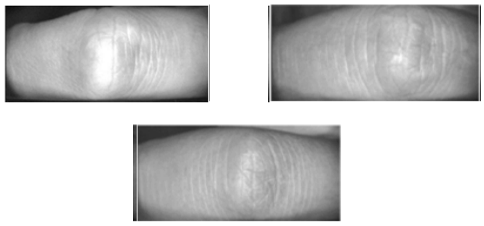


a) Query image.

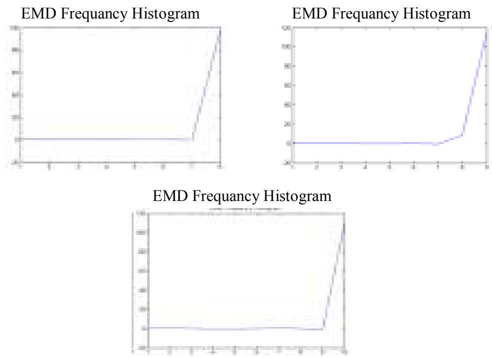


b) SURF features.

Figure 8. SURF feature extraction.



a) Sample images from the database.



b) EMD plot for the corresponding images.

Figure 9. Sample output obtained from the frequency feature extraction process.

After extracting the features of the FKP images, the matching algorithm is applied for the recognition. In our proposed work, we have used shortest distance to match the FKP query images with the database images. By considering all the features of the query image is matched using the shortest distance. Matching between FKP images of same user is called genuine matching while that of different users is known as imposter matching.

5.3. Comparative Analysis

In this section, we present the evaluation results Local-Global Information Combination (LGIC) based FKP recognition [26] and our proposed technique. In order to determine the accuracy of an FKP recognition system, we have to measure the error rates. There are two types of error rates namely, FAR and FRR. FAR is the percentage of incorrect acceptances i.e., the measure of the likelihood that the biometric security system will incorrectly accept an access attempt by an unauthorized user. FRR is the percentage of incorrect rejections-i.e., the measure of the likelihood that the biometric security system will incorrectly reject an access attempt by an authorized user. The following equation is used to calculate the accuracy measurement of the overall approach:

$$Accuracy = 100 - \left[\frac{FAR + FRR}{2} \right] \tag{14}$$

For comparison of LGIC based technique and our proposed technique, we have to estimate the error rates of each technique separately using the PolyU Database. The percentage of FAR, FRR, accuracy rate and the computational time for the LGIC based technique and for our proposed technique are shown in the Table 1.

The Table 1 clearly shows that the recognition performance of the proposed technique is more efficient compared to that of the LGIC based technique. Figures 10 and 11 clearly shows that the overall percentage of accuracy for the proposed technique is higher compared to that of the LGIC based technique since the percentage of FAR and FRR is less in the proposed technique.

Table 1. Comparison result of our proposed technique with LGIC based technique.

PolyU FKP Image Database				
Techniques	**FRR (%)**	**FAR (%)**	**Accuracy (%)**	**Time (ms)**
LGIC based Technique	0.96	0.0011	99.519	80.926
Proposed Technique	0.83	0.761	99.541	76.431

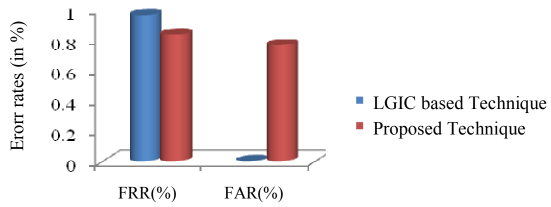


Figure 10. Comparison of FAR and FRR of our proposed technique with LGIC based technique.

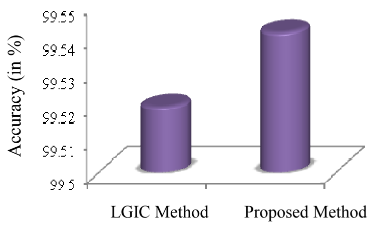


Figure 11. Comparison of accuracy of our proposed technique with LGIC based technique.

From the above graph, we can clearly observe that, the proposed method for the FKP recognition is very effective as compared with LGIC based technique in terms of accuracy. Since, the system can be effective, if it has less FAR and FRR and high accuracy. Still, runtime is an important factor for designing a biometric system to be practical as SIFT, SURF are time-consuming processes. So, the better accuracy alone was not enough for the efficiency of the proposed system. So, we can consider the computational time also. The speed or computational time is less when compared to the existing method [26] which is described in Table 1. Our proposed system satisfies this condition. Thus, our system is effective as compared with LGIC based technique. Figure 12 depicts the corresponding FAR and FRR curves depend upon the variation in threshold value.

Figure 13 gives the variation in accuracy of the proposed method when the threshold value changes. From the figure we can analyze that, from the accuracy of the proposed work becomes maximum.

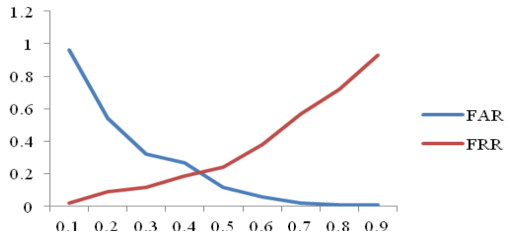


Figure 12. Variation of FAR and FRR depend upon threshold value.

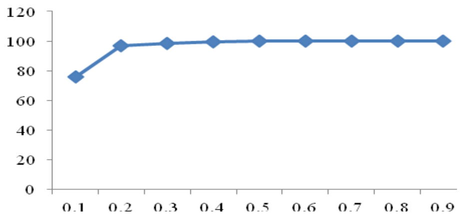


Figure 13. Variation in accuracy due to threshold.

5.3.1. Comparison of Palm Print, Knuckle Print and Multimodal Biometrics

In this section, the accuracy of the palm print recognition, knuckle print recognition and multimodal biometric recognition are compared. In our previous work [17], we have done the biometric recognition using palm print and in this paper, we have done the recognition using FKP and then the matching scores are fused to find the matching score of multimodal biometric. All the methods are compared to find the better method for biometric recognition using PolyU image database. Table 2 shows the accuracy values of all the biometric recognition methods.

From Table 2 and Figure 14, we can find that the multimodal biometric is the efficient system. Since, the overall accuracy of the multimodal biometric recognition is higher than palm print recognition and FKP recognition.

Table 2. Accuracy comparison of recognition types.

Recognition Type	Accuracy (%)
Palm Print Recognition	99.20
FKP Recognition	99.541
Multimodal Biometric Recognition	99.61

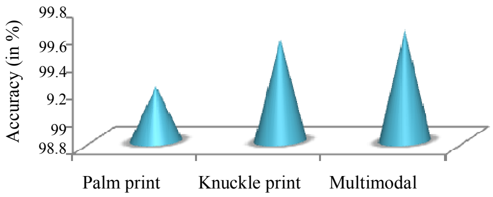


Figure 14. Comparison of accuracy of recognition types.

6. Conclusions

In this paper, an efficient multimodal biometric recognition method is proposed. In our previous work, we have done a biometric recognition using palm print. In this paper, we have proposed biometric recognition using FKP and combined both works to form multimodal biometrics. Here, local information of the FKP is extracted using extensive feature sets and they are fused at matching score level. During recognition, the corresponding features of enrolled and query FKPs are matched using nearest-neighborhood-ratio method and the derived features matching scores are fused using weighted sum rule to obtain fused matching score. The proposed system has been evaluated using publicly available PolyU database. The accuracy of multimodal biometric recognition is high as compared with palm print recognition and FKP recognition. Thus, the proposed multimodal biometric recognition is efficient.

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