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Personal recognition using finger knuckle shape oriented features and texture analysis

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Hybrid rule

Abstract Finger knuckle print is considered as one of the emerging hand biometric traits due to its potentiality toward the identification of individuals. This paper contributes a new method for personal recognition using finger knuckle print based on two approaches namely, geometric and texture analyses. In the first approach, the shape oriented features of the finger knuckle print are extracted by means of angular geometric analysis and then integrated to achieve better precision rate. Whereas, the knuckle texture feature analysis is carried out by means of multi-resolution transform known as Curvelet transform. This Curvelet transform has the ability to approximate curved singularities with minimum number of Curvelet coefficients. Since, finger knuckle patterns mainly consist of lines and curves, Curvelet transform is highly suitable for its representation. Further, the Curvelet transform decomposes the finger knuckle image into Curvelet sub-bands which are termed as 'Curvelet knuckle'. Finally, principle component analysis is applied on each Curvelet knuckle for extracting its feature vector through the covariance matrix derived from their Curvelet coefficients. Extensive experiments were conducted using PolyU database and IIT finger knuckle database. The experimental results confirm that, our proposed method shows a high recognition rate of 98.72% with lower false acceptance rate of 0.06%.

1. Introduction

Hand based biometrics has drawn considerable attention of researchers due to (i) its low cost in acquiring data, (ii) its reliability in identifying individuals and (iii) its degree of acceptance by the user (Hand-based Biometrics, 2003). Most commonly used hand biometric traits are finger print, palm print, hand geometry, hand vein patterns, finger knuckle print and palm side finger knuckle print (Bolle et al., 2000). Among these biometric traits, finger print is known to be the first modality used for personal identification. Apart from its most beneficiary features, finger print also possesses certain

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drawbacks such as, it has greater vulnerability toward intrusion of acquired finger print image and its feature like minutiae, singular points, delta points etc., are highly distractible by wounds and injuries created on the finger surfaces (Ribaric and Fratric, 2005). On the other hand, palm print recognition system captures a large area for identification, which contains only limited number of features like principal lines, wrinkles, etc., (Sun et al., 2005). In case of finger geometry and hand geometry, the features extracted are not distinctive enough to identify the individuals, when the number of users grows exponentially (Kumar et al., 2003; Malassiotis et al., 2006). In hand vein system, the vein structures present in the dorsum and the palm area of the hand are captured by means of high resolution devices, which are found to be more expensive (Kumar and Venkataprathyusha, 2008).

Finger knuckle print is one of the emerging hand based biometric traits. Basically, finger knuckle surface is defined as the skin pattern that is present in the finger back region of the hand. Each finger back region of the hand has three phalangeal joints. The joint that connects the finger with the hand surface is called as Metacarpophalangeal joint, the joint that is formed in the middle surface of the finger is called as Proximal Inter Phalangeal (PIP) joint and the joint that is present in the tip surface of the finger back region is known as distal joint. The presence of these joints in the finger dorsum surface forms the flexion shrinks on the outer region of the skin which creates the dermal patterns consisting of lines, wrinkles, contours etc. The pattern generated by the PIP joint on the finger back region is referred as finger knuckle print (Zhang et al., 2009a). Unlike finger print, finger knuckle print patterns are very difficult to scrap because it concentrates on the inner surface of the finger regions which are captured in a contactless manner. Moreover, the area of the captured finger knuckle print is very small when compared to the area captured for palm print recognition and further it also possess highly unique features which are well suited for a potential biometric system (Loris and Alessandra, 2009).

Woodard and Flynn were first to introduce FKP as a biometric trait in the year of 2005 by capturing it in a 3D sensor (Woodard and Flynn, 2005). Other researchers have also contributed many effective methods for representing the features of FKP images for effectively classifying them. However, finger knuckle print biometric recognition requires high degree of exploration for establishing its suitability in large scale real time applications. In this paper, we recommend a novel approach which simultaneously extracts shape oriented features and texture feature information from finger knuckle print. In the literature the geometrical analysis performed on any hand based biometric trait including FKP yields only magnitude based feature information. In contrast, this paper incorporates angular geometric analysis method, which results in both magnitude and orientation based shape feature information of FKP. For effective representation of texture features of FKP images, the multi-resolution analysis is required since it could handle distorted FKP images due to scaling, rotation and transformation variant properties. A multi-resolution transform known as Curvelet transform which effectively represents the curved singularities than the wavelets is highly suitable for representing finger knuckle print texture feature since the texture pattern of FKP images are lines, curves and contours (Mandal et al., 2009). Hence, we incorporate Curvelet transform along with principle component analysis to represent the texture features of the captured finger knuckle images. The extracted shape oriented and texture feature information is integrated to yield better accuracy results and makes it highly suitable for large scale personal authentication system.

Rest of the paper is organized as follows. Section 2 details about the feature extraction methodologies for various hand biometric traits available in the literature. Section 3 presents the proposed system model of the finger knuckle personal recognition system. Section 4 illustrates the methods used for preprocessing and ROI extraction from the acquired finger knuckle print image. Sections 5 and 6 present the feature extraction methodology based on geometric analysis and texture analysis respectively. Section 7 presents the fusion process and various rules implemented for generating the final score. Section 8 presents the experimental analysis carried out to evaluate the performance of the proposed system along with its results' discussion. Section 9 concludes the paper with possible recommendations.

2. Related work

In the literature, researchers have proposed various methods for feature extraction on hand based biometric traits. These techniques can be broadly categorized into geometrical analysis and textural analysis. The geometrical analysis methods extract shape oriented features from the biometric trait whereas textural analysis methods extract feature information by analyzing the spatial variations present in the captured image (Kumar and Zhang, 2006; Kumar and Zhou, 2009). Generally, the texture analysis methods for feature extraction are categorized as three types, viz., (i) model based texture analysis method, (ii) transform based texture analysis method and (iii) statistical texture analysis method. The model based texture analysis methods quantify the characteristics of image texture using fractal and stochastic models, while the transform based texture analysis methods represent the image in a spatial coordinate system with interpretations in the characteristics of texture. Whereas, in statistical texture analysis methods image texture patterns are represented using the parameters that are related to the distribution and relationship among the gray level pixels of the image (Aoyama et al., 2013). Some of the geometric analysis methods and transform based texture analysis methods that are incorporated to extract feature information from the hand based biometric traits are discussed below.

Kumar et al. contributed nearly three geometrical approaches for personal authentication using hand biometric traits. In their first work, (Kumar and Ravikanth, 2009) the finger knuckle features are extracted using knuckle texture analysis and finger geometrical analysis. Finger length, finger width etc., are some of the geometrical features extracted from the finger knuckle surface by means of geometric analysis. The authors also used three appearance based methods such as principal component analysis, independent component analysis and linear discriminant analysis for generating matching scores from the knuckle images. In their second work, (Kumar and Venkataprathyusha, 2009) the authors introduced a new modality known as hand vein structure for personal authentication. In this system dorsum surface of the hand is captured using infra-red imaging system. The captured image is subjected to histogram equalization for enhancement and the structure of the vein is studied using key point triangulation method. The authors also incorporated the simultaneous extraction of knuckle shape information to achieve better performance. Further, they also explored the analysis of finger knuckle surface by incorporating the quality feature of the trait which is highly dependent on the capturing device (Kumar and Zhang, 2010). This is achieved by means of quality dependent fusion in which the quantification of quality of the data acquired from the captured image is taken for the estimation of matching scores. In this work, the entire hand image is acquired and feature extraction is carried out by means of palm print textural analysis, hand geometry analysis and finger knuckle print paternal analysis methods.

In addition to these geometric based approaches, Usha and Ezhilarasan (2013a,b) have also contributed two novel geometric analysis based approaches for finger knuckle print recognition which extracts the feature information by examining the subset of the captured feature to achieve better performance. The pattern of hybrid convex curves were identified from the captured finger knuckle print and geometrical methods such as (i) tangents and secants method (Usha and Ezhilarasan, 2013a) and (ii) triangulation methods (Usha and Ezhilarasan, 2013b) were employed. These methods also yield the angular geometric information from the biometric trait which is found to be highly potential toward the identification of individuals. Experiments were conducted using PolyU finger knuckle print database and results show high accuracy rate with low computational complexity.

In addition to this, Zhang et al. (2009b) investigated a novel method viz., band limited phase only correlation method (BPLOC) for matching finger knuckle prints based on texture analysis. This method does the matching process by means of analyzing peak values obtained from the POC method. Further in 2010, (Zhang et al., 2010a) the authors introduced a method which hierarchically codes the finger knuckle print features using monogenic code. This code is generated by applying monogenic signal to each of the pixel of finger knuckle image and binarization of the signal is performed to produce the output. Furthermore, Zhang et al. (2010b) recommend an efficient recognition algorithm for finger knuckle biometrics based on Gabor filters. This method extracts both magnitude and orientation information from captured FKP images. Next, Shen et al. (2010) proposed a biometric system which incorporates the feature sets of both palm print and finger knuckle print. Features of palm print and finger knuckle print are extracted by means of 2D Gabor filters for both palm print and finger knuckle print. The 2D Gabor filters produce information magnitude and phase information of the subjected FKP image which are used to form feature vector for matching. Hamming distance metric is used to identify the similarities and differences between the reference and input images of palm print and finger knuckle print.

Furthermore, Michael et al. (2010) proposed a bimodal verification system using palm print and finger knuckle print. In this system, the entire hand image is captured by the image acquisition device. From the captured hand image, the normalized palm and knuckle regions are extracted by means of competitive hand valley detection algorithm. Feature information from the ROI of the palm print are extracted by means of directional coding techniques and represented in the form of bit strings. The feature information from the ROI of knuckle image is obtained by subjecting it to Ridgelet transform. Choras and Kozik (2010) in their work used Probabilistic Hough Transform (PHT) to code line features of the finger knuckle print. In this work, speeded up robust features are derived by means of SURF algorithm for performance improvement. Euclidean metric is used to find the similarity matching.

Yet, Meraoumia et al. (2011) have shown the implementation of Fourier transform functions for deriving the feature information from the finger knuckle region and palm region. Matching process is done by identifying the linear phase shift in frequency using phase correlation algorithm. The identified phase shift are taken from inverse Fourier transform to define the cross correlation between phase components. Wankou et al. (2011) characterizes finger knuckle print using Gabor filters, linear discriminant analysis and principle component analysis. In this work, recognition of finger knuckle is done by using textural representation techniques which were mostly used for face recognition. The advantage of Gabor filter and orthogonal linear discriminate analysis used in face recognition is exploited in this technique. Jing et al. (2011) proposed a new model based texture analysis methods known as complex locality preserving projection approach for discriminating the finger knuckle surface images. This approach extracts the low dimensional features by preserving the manifold of input data set and also derives the orthogonal based functions to overcome the redundant information.

Additionally, Zhang et al. (2011) proposed a biometric system which incorporates a novel approach for feature extraction and representation based on texture analysis of finger knuckle print. In this work, the authors suggested a new method for feature recognition based on Riesz transform which encodes the FKP features as 6 bit code termed as Riesz-CompCode. Further, Zhang et al. (2012) contributed a novel feature extraction mechanism based on phase congruency model. The phase congruency model extracts local orientation, local phase information and magnitude information of FKP images. Hegde et al. (2011) characterize the finger knuckle print using Random transform. The preprocessed FKP image is subjected to Random transform and as a result of this transformation, Eigen values are computed. The authors in their further work implemented a real time personal authentication using finger knuckle print in which features of the finger knuckle surface were extracted using Radon transform (Hegde et al., 2013). The authors provided two levels of security using Eigen values obtained from the Eigen region of the knuckle surface and the peak points derived from the Radon graphs.

Yet, another method for personal recognition using model based texture analysis was proposed by Madasu et al. (2012). In this work, the authors used Sobel and other divergence operations for representing the feature information based on line feature of finger knuckle print. Zhang and Li (2012) presented an efficient approach to encode the local features of palm print and finger knuckle print images based on Riesz transform. In this work, both palm print and FKP features are coded using two coding schemes viz, Rcode1 and Rcode2 by subjecting them to first and second order Riesz transform respectively. Li et al. (2012), contributed Adaptive Steerable Orientation Coding (ASOC) for finger knuckle print recognition. The authors have incorporated multilevel histogram thresholding method for extraction orientation information.

Zahra Shariatmadar and Karim Faez (2013), proposed a new finger knuckle print recognition scheme for both personal identification and verification. The authors have incorporated a new coding scheme in which the ROI of the captured image is divided into several blocks and subjected to bank of Gabor filters from which binary patterns are generated and represented in the form of histograms. Bio hashing method is incorporated to perform matching process between the obtained fixed length feature vectors of registered and input image.

Pengfei Yu et al. (2014) investigated a feature extraction method which codes FKP features in terms of local binary patterns which are formed as histograms of finger knuckle image blocks and represented together to form feature vector. Gao et al. (2013) recommend a reconstruction approach for FKP images which possess scaling, rational and transformation variant properties. This method does the process of reconstruction on query images using template samples based on dictionary learning method. The authors in their further work, Gao et al. (2014) incorporated a texture feature analysis mechanism which extracts multiple orientation coding and texture feature information from the captured FKP image. Finally, Kumar (2014) in his recent work has investigated minor finger knuckle patterns for personal recognition and also proved that, integrating minor feature patterns with FKP features yields better result in terms of accuracy.

The detailed investigation of existing geometrical and texture analysis methods elucidates some of the following limitations. They are,

- The existing geometric analysis based feature extraction methods for hand biometric traits extract feature information like finger length, finger width, palm width, perimeter and area of the region, which has lower power of discrimination. This method for computing angle oriented feature information from biometric traits is not yet explored in the literature.
- The existing transform based textural feature representation methods like Gabor filters, Fourier transform, Wavelet transform etc., fail to handle higher dimensional singularities since they lack good selecting orientation and scaling parameters. The effect of scale and orientation normalized Curvelet spectral analysis on feature extraction process has not been explored to the best of our knowledge.

Therefore, we are motivated to develop an automated method for finger knuckle print recognition which incorporates both geometrical analysis and texture analysis. The former approach extracts angle based feature information while the latter approach utilizes multi-resolution transform for investigating the performance the biometric system.

The reasons behind utilizing finger knuckle print for recognition rather than using multiple traits or any other hand traits are as follows,

1. Finger knuckle biometric trait contains most discriminative texture patterns that are easily acquirable by means of a low resolution camera.
2. Finger knuckle print has a high degree of user acceptance rate since, it is captured through a contact less image acquisition setup and its high resilience to spoof attacks.
3. The knuckle texture patterns of all the hand fingers are observed to be highly distinctive and hence, the combination of different finger knuckle patterns of a person is expected to perform equivalent to that of the multimodal biometric system.

3. The proposed system

This paper proposes a novel personal recognition system using finger knuckle print. The following Fig. 1 shows the block diagram of the proposed personal recognition system.

Initially, the captured finger knuckle print is preprocessed and region of interest is extracted by means of a robust approach which could handle FKP images with scaling, translation and rotation variant properties. This preprocessing approach also overcomes the problems that could arise due to distorted or impaired knuckle images. Secondly, the extracted ROI image of finger knuckle print is subjected to geometrical and textural analyses for simultaneous extraction of shape and textural feature information. The extracted feature vectors derived through the above methods are passed as input to their associated matching modules for generating matching scores. Finally, the identity of a person is decided based on the fusion of the matching scores derived from two different classifiers.

4. Preprocessing and ROI extraction

The preprocessing is performed with the captured finger knuckle print for locating a specific knuckle region which has substantial features for reliable identification of individuals. The region of interest (ROI) segmentation process is required since the FKP images are collected in various scenarios which may exhibit scaling, translational and rotational variances.

From the captured finger knuckle print (FKP), a sample region size of 90×180 pixels is cropped to get its sub-image. This pixel size is obtained by means of empirical analysis. The obtained sub-image is subjected to canny edge detection algorithm (Bao et al., 2005), which produces its corresponding edge-map image. The following Fig. 2(a–e) shows the originally captured FKP image, sub-image of FKP image, the edge-map image of FKP image, edge-map image of FKP represented with its mid-line and extracted ROI image of FKP respectively.

The ROI is extracted from the FKP image by analyzing the edge-map FKP image based on high intensive pixels as shown in Fig. 2(c). For example, as shown in 2(d), each FKP edge-map image is marked with its mid-line representing the length of the finger knuckle region as shown in Fig. 2(d), the regions present in the center and on either side of the symmetric mid-line are densely populated with high intensive pixels. Therefore, this region is extracted proportionally on either side of the mid-line from a finger knuckle region at a distance of one-third the finger knuckle length to three-fourth the finger knuckle length from the base region of the finger knuckle. The resulting ROI image with an average size of 90×160 is extracted from the sub-image of finger knuckle print image as presented in 2(e) which has rich feature sets from which reliable feature information could be extracted.

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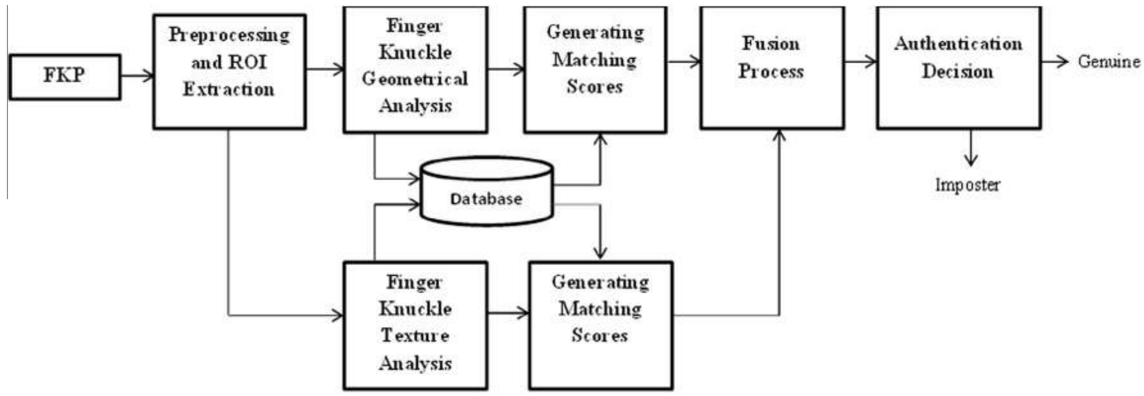


Figure 1 Block diagram of a personal recognition system using finger knuckle print.

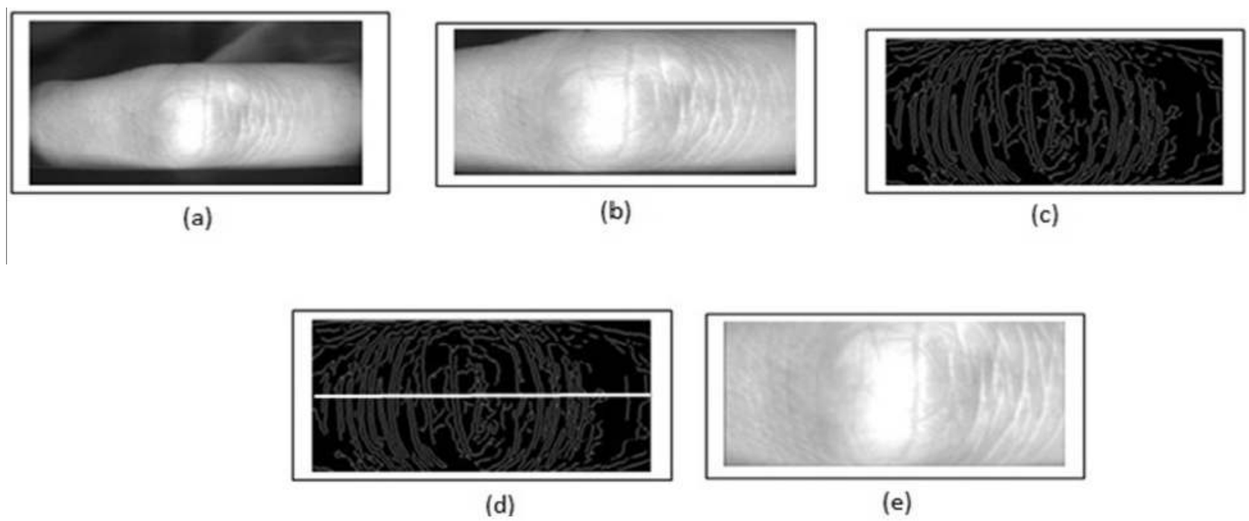


Figure 2 (a) Captured FKP image, (b) sub-image of FKP image, (c) edge-map image of FKP image, (d) edge-map image of FKP represented with its mid-line, (d) extracted ROI image of FKP.

in Fig. 2(c). For example, as shown in 2(d), each FKP edge-map image is marked with its mid-line representing the length of the finger knuckle region. As shown in the Fig. 2(d), the regions present in the center and on either side of the symmetric mid-line are densely populated with high intensive pixels. Therefore, this region is extracted proportionally on either side of the mid-line from a finger knuckle region at a distance of one-third the finger knuckle length to three-fourth the finger knuckle length from the base region of the finger knuckle. This results in ROI image with an average size of 90×160 is extracted from the sub-image of finger knuckle print image as presented in 2(e) which has rich feature sets from which reliable feature information could be extracted.

The correctness of this preprocessing approach is analyzed as follows. The preprocessing and ROI extraction method segments the region by concentrating on the area which contains rich set of features rather than cropping fixed size pixel from a FKP image. Thus, this preprocessing mechanism extracts the knuckle features which are invariant to scaling, translation and rotational properties. Further, this method has the potentiality to process the distorted or impaired knuckle regions without affecting the performance of the system. The problem raised due to injured knuckle surfaces can be overwhelmed in two steps. (i) Identifying the distorted or injured regions in the captured finger knuckle print by calculating its pixel intensities. Since, the distorted regions will have extremely low intensity pixel values, these regions of a FKP image can be identified by comparing the summation of pixel intensities obtained from the distorted regions with the intensity threshold. This threshold is derived from the normal FKP image. (ii) Once the distorted or impaired regions of knuckle are detected, the ROI extraction is performed with the regions that continuously follow the detected surface. Hence, it is concluded that, this method of preprocessing and ROI extraction is an efficient method which aids in improving the performance of the personal recognition system.

5. Finger knuckle geometric analysis

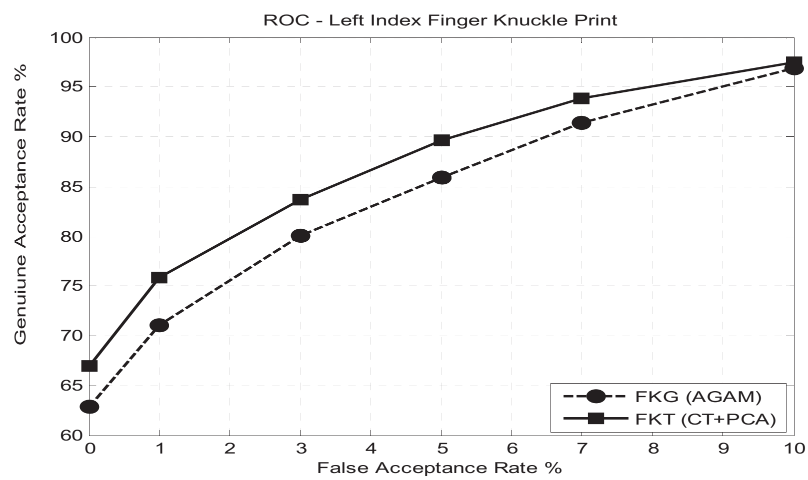
The main objective of our proposed work is to quantify the improvement in performance incorporated by finger knuckle print in a personal recognition system using geometric analysis and textural analysis. Geometrical analysis is performed on the extracted ROI image of the finger knuckle print in order to extract its shape oriented features. As discussed in Usha and Ezhilarasan (2013a,b) the convex curves derived from the FKP images are used for extracting reliable shape oriented features through angular geometric analysis method (AGAM). This method extracts seven features that effectively characterize the shape of the finger knuckle image. These extracted seven shape oriented features includes one finger knuckle length, three finger knuckle widths and two finger knuckle angles. The main advantage of this angular geometric analysis method when compared to the other existing geometric methods is that, this approach focuses on extracting knuckle orientation based feature information which is a highly unique and reliable feature for personal identification. Further, the extracted shape feature information of finger knuckle surface is stored in a feature vector. This feature vector is further normalized to a specific range of feature values. If $V_{G_{ij}}$ is the feature vector obtained through geometrical analysis of the finger knuckle print image, then the normalized feature vector $NV_{G_{ij}}$ is obtained through (1),

$$NV_{G_{ij}} = a + \frac{V_{G_{ij}} - \min(V_{G_{ij}})(b-a)}{\max(V_{G_{ij}}) - \min(V_{G_{ij}})} \tag{1}$$

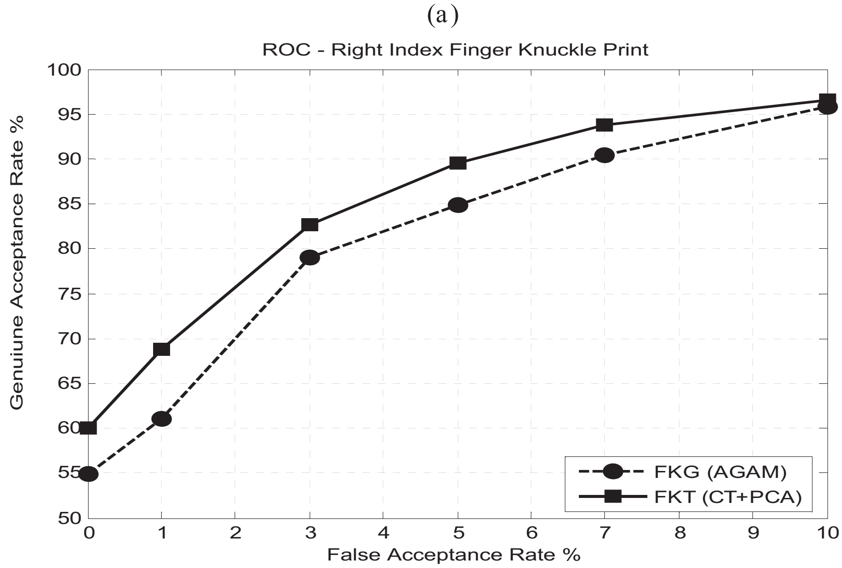
where $V_{G_{ij}} = (V_{G_{i1}}, V_{G_{i2}}, \ldots, V_{G_{i7}})$ is the feature vector that stores seven finger knuckle shape features. The values of 'a' and 'b' are specified according to the range in which feature values are normalized. For example, if the values of 'a' and 'b' are specified as 0 and 1 respectively, then the normalized vector contains values between 0 and 1. This method of normalization is known as unity-based normalization, which is chosen for its simpler computation.

The matching of finger knuckle shape oriented features is carried out by computing the Euclidean distance between the feature vector obtained from the test image $NV_{G(test)}$ and the feature vector obtained from registered image $NV_{G(reg)}$. The computation of Euclidean distance can be given in (2),

$$dist(NV_{G(reg)}, NV_{G(test)}) = \sum_i |NV_{G(reg)_{ij}} - NV_{G(test)_{ij}}| \tag{2}$$

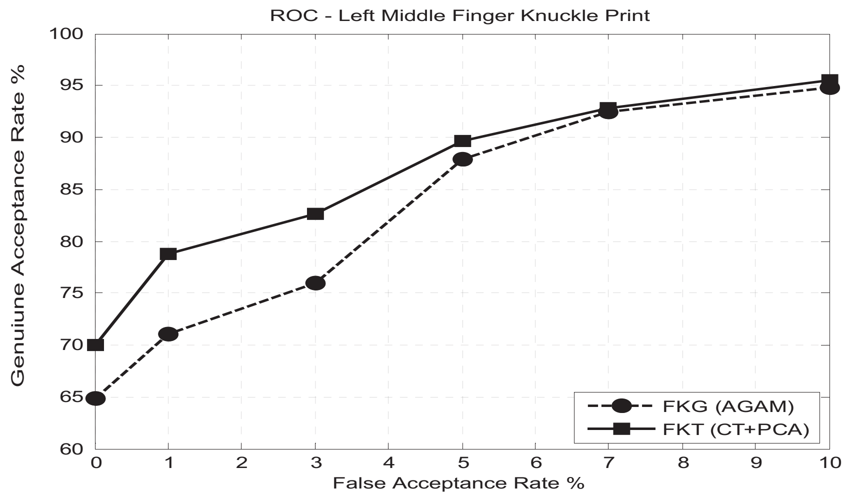


(a)

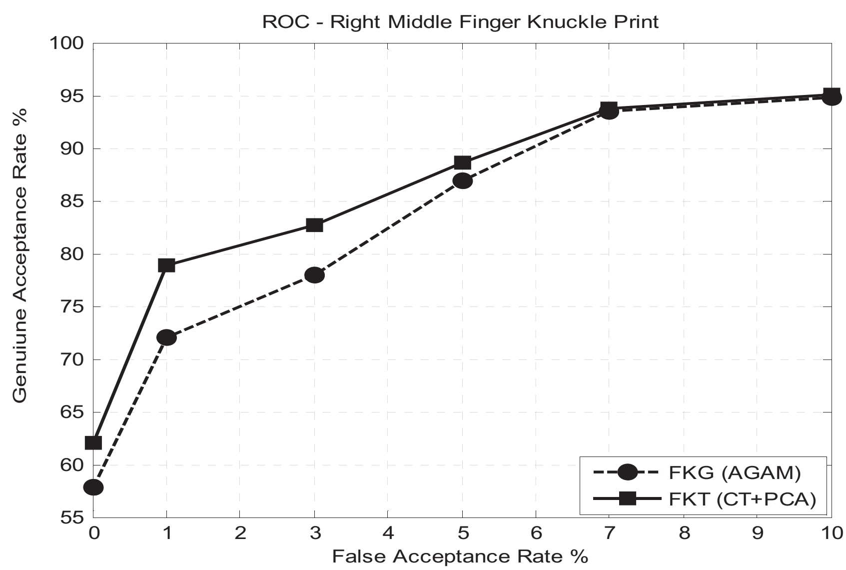


(b)

Figure 3 ROC plots representing individual performance of (a) left index finger knuckle print, (b) right index finger knuckle print, (c) left middle finger knuckle print, (d) right middle finger knuckle print – belongs to PolyU dataset.



(c)



(d)

Fig. 3 (*continued*)

The matching scores were generated according to the minimum matching distance value obtained.

6. Finger knuckle texture analysis

The extracted ROI image of a finger knuckle print is also subjected to fast discrete Curvelet transform for extracting finger knuckle print texture. This Curvelet transform method of image analysis is a multi-resolution, band-pass, direction and functional analysis method which is highly significant in representing curved singularities of an image in a computationally efficient way. Since, the texture patterns of finger knuckle print are in the form of curves, this Curvelet transformation method will be highly suitable for finger knuckle print feature representation.

The extracted FKP ROI image of pixel size 90×160 is subjected to Curvelet transform with scaling factor 4 and orientation factor of 16. The first 16 sub-bands are selected and decomposed into a number of sub-bands which are represented as Curvelet knuckle $c[m,n]$, where, $0 < m < M, 0 < n < N$ can be obtained through (3)

$$C^D(i,j,c_1,c_2) = \sum f[m,n]\psi^D_{i,j,c_1,c_2}[m,n] \tag{3}$$

where $\psi^D_{i,j,c_1,c_2}[m,n]$ is the Curvelet waveform.

This transform derives a vector of coefficients with scale i, orientation j and parameters (c_1,c_2).

6.1. Implementation of Curvelet transform

The implementation of Curvelet transform in the ROI of a finger knuckle print image is performed based on the following steps.

1. The extracted ROI image is subjected to two dimensional Fast Fourier transforms which results in two dimensional frequency planes.

2. The resulting two dimensional frequency planes are divided into number of regions based on the different scaling and orientations.
3. Each region of the Fourier plane is decomposed into concentric circles with various angular divisions representing its scale and orientation parameters.
4. Further, these regions are subjected to inverse Fast Fourier transform in order to determine the Curvelet coefficients based on the particular scaling and orientation parameters.

In this implementation, the value of Curvelet coefficients are obtained by marshaling the Curvelet with the real knuckle image in which regional planes are chosen according to the smoothly tapered regional boundaries. This results in Curvelet coefficients which are better localized with frequency and spatial domain when compared to other transforms.

6.2. Principal component analysis

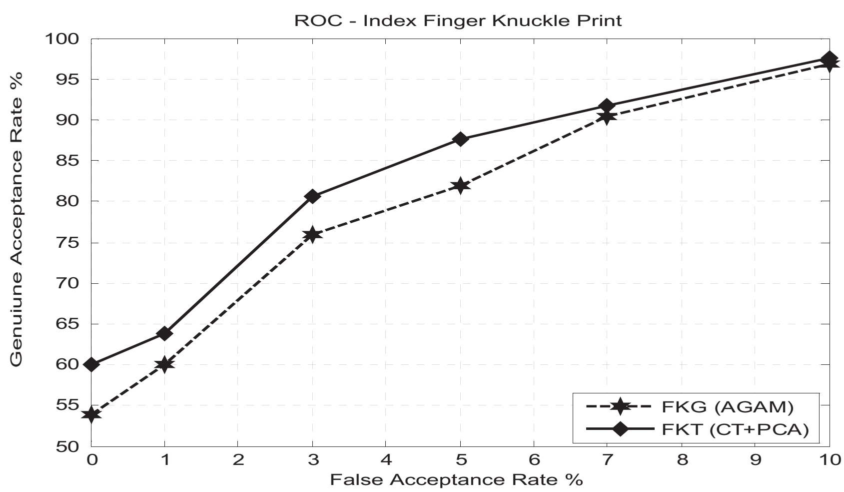
From each Curvelet knuckle region, the Curvelet coefficients are generated and stored. The first sixteen optimal Curvelet knuckles are subjected to principal component analysis (PCA) in order to create feature vectors. This feature extraction process involves the representation of the sub-band coefficients of finger knuckle image in terms of normalized vector σ_j with dimension $m \times n$. Then, the computation of its covariance matrix φ is achieved through (4),

$$\varphi = \frac{1}{C}\sum_{j=1}^{C}\sigma_j\sigma_j^T \tag{4}$$

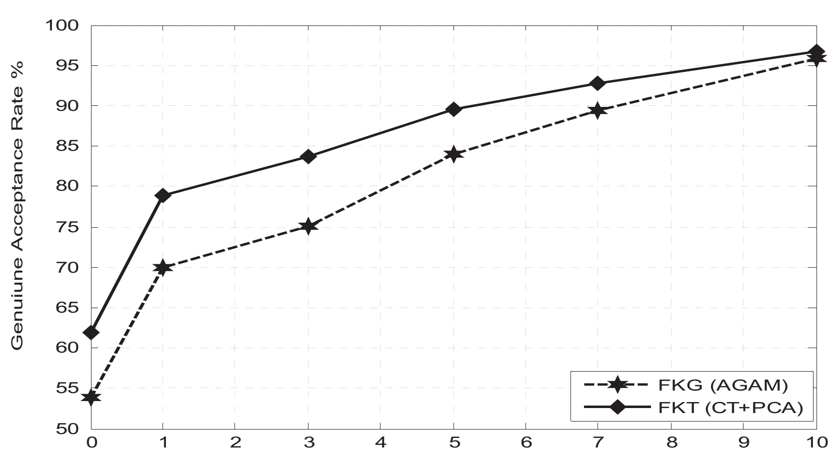
These feature descriptive vectors are then used for generating matching scores for testing images using Euclidean distance.

7. Fusion process

The main objective of this fusion process is to investigate the performance of the system by combining the feature information obtained from different modalities. Since, the finger knuckle features of all the four fingers exhibit different textural patterns; it is meaningful to combine the information obtained

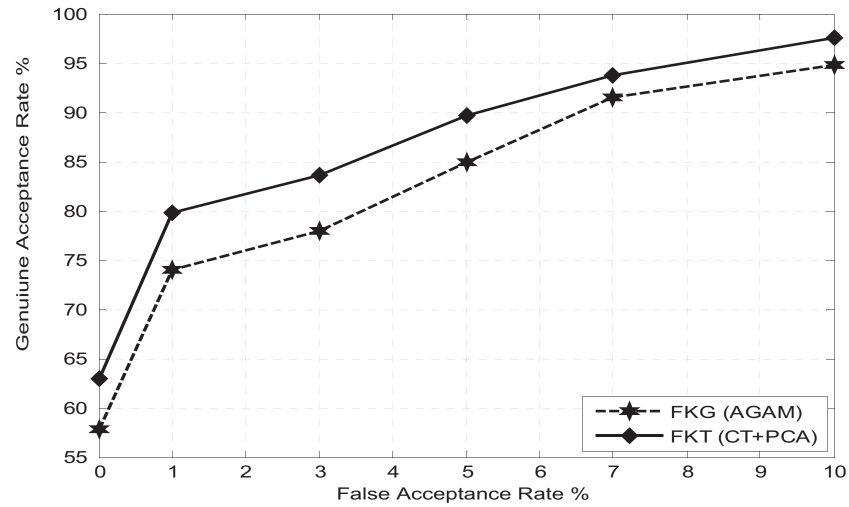


(a)

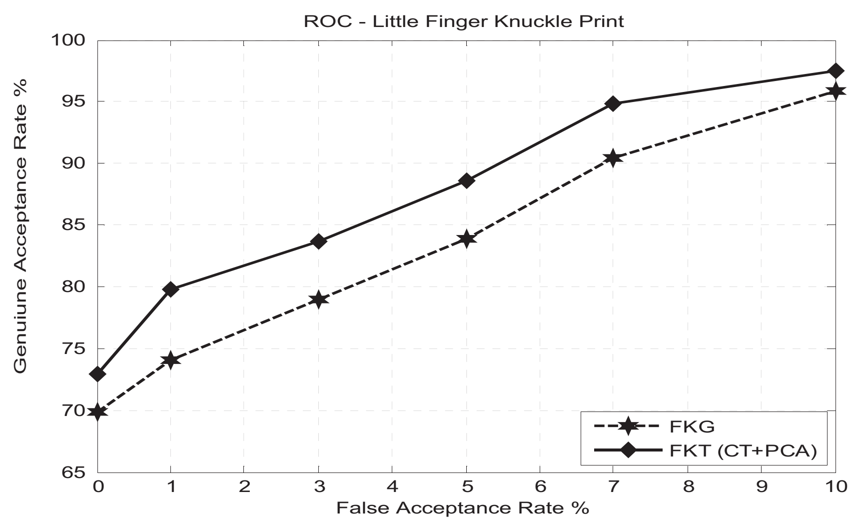


(b)

Figure 4 ROC plots representing individual performance of (a) index finger knuckle print, (b) middle finger knuckle print, (c) ring finger knuckle print, (d) little finger knuckle print – belongs to IIT dataset.



(c)



(d)

Fig. 4 (*continued*)

from each finger knuckle regions using fusion process for evaluating the performance of the proposed system. Thus, this process results in a personal authentication using single biometric trait (FKP) with multiple units. In this paper, the score obtained from each of the four finger knuckle surfaces are fused together using matching score level fusion method to make the system efficient. This matching score level fusion method combines the matching scores obtained from different classifiers using the set of rules defined in that fusion process (Tax et al., 2000; Wayman et al., 2005). In this work, we consider three different factors viz., sum of the matching scores (SUS), weighted sum of the matching score (MUL) and product of the matching scores (SWS) to estimate the integrated performance. The fusion of matching scores D_F obtained using the factor sum of the matching scores is given by (5)

$$D_F = \sum_{i=1}^{n} D_i \tag{5}$$

where, D_i is the score obtained from ith classifier for finger knuckle print matching.

The fusion of matching score D_F is obtained through product rule given by (6)

$$D_F = \prod_{i=1}^{n} D_i \tag{6}$$

where D_i is the score obtained from ith classifier for finger knuckle print matching.

The fusion of matching score D_F is obtained through weighted sum rule is given by (7)

$$D_F = \sum_{i=1}^{n} W_i \times D_i \tag{7}$$

where, D_i is the score obtained from ith classifier for finger knuckle print matching and the value of W_i is obtained through (8),

$$W_i = \frac{\frac{1}{\sum_{j=1}^{n}\left[\frac{1}{EER_j}\right]}}{EER_i} \tag{8}$$

The performance of the proposed finger knuckle is studied by analyzing various combinations of matching scores obtained from all the four finger knuckle samples using both the angular geometric analysis method and textural analysis method.

8. Experimental analysis and results' discussion

The performance of the proposed personal recognition system is evaluated using two different publicly available biometric databases viz., PolyU finger knuckle print database (PolyU Finger Knuckle Print Database) and IIT finger knuckle print database (IIT Delhi Finger Knuckle Database). PolyU FKP dataset consists of finger knuckle print images captured using low cost and low resolution camera in a peg free environment. In this database, the FKP images of left index finger, left middle finger, right index finger and right middle finger of each person were acquired. PolyU database consists of totally 7920 images with 660 different finger knuckle images collected from 165 persons. For this experimentation analysis, the FKP images obtained from 100 subjects are considered as training samples and images obtained from 65 subjects are considered as test images. Hence it results in, 400 FKP images as training samples and 260 FKP images as testing images. Similarly, IIT FKP database consists of finger knuckle images captured using low resolution camera in a contact free manner. In this dataset, FKP images of index finger, middle finger, ring finger, little finger and thumb finger were captured. Further, this data set consists of 790 FKP images obtained from 158 persons. For this experiment, we consider, FKP images obtained from 100 users as training samples and FKP images obtained from 58 users for testing process. Furthermore, in this experiment, we consider knuckle regions of all four fingers excluding the thumb.

Extensive experiments are conducted to prove the superior performance of the proposed personal recognition system. The performance evaluation of the proposed system is carried out by considering the individual finger knuckle and also through their combinations. In angular geometric analysis, all the feature vectors which have non-zero values are considered for feature extraction. Nearly, 400 feature vectors obtained from training samples of each finger knuckle image were stored in the database. In case of texture analysis, Curvelet transform is used to decompose the finger knuckle image into sub-bands. Here, Curvelet transform at a scaling factor of 4 and orientation factor of 16 is implemented for feature analysis, which results in 16 Curvelet-knuckle images and the principle component analysis is applied on the sub-bands which derive the covariance vector from its generated Curvelet coefficients. Thus, we obtain nearly 400 feature vectors from the training samples of each dataset.

The receiver operational characteristics (ROC), illustrating the performance obtained through geometrical and textural analysis methods on four finger knuckles of PolyU FKP dataset are shown in Fig. 3.

The ROCs obtained from left index finger knuckle and right index finger knuckle are depicted in the Fig. 3 (a) and (b), suggesting that the proposed texture analysis method using Curvelet transform and PCA shows improvement in the genuine acceptance rate from 0.57% to 1.08% than the angular geometric analysis method at a lower rate of FAR. While, at the same time, the ROCs obtained from left and right middle finger knuckle regions are shown in Fig. 3(c) and (d) in which the performance of the textural method and geometrical method are equivalent.

Similarly, the ROCs obtained through geometric and texture analysis method implemented on four finger knuckle of

Table 1 Performance analysis of proposed personal recognition system using PolyU FKP dataset.

Various combinations	Genuine acceptance rate (%)			ERR (%)	DT
	FAR 0.1%	FAR 0.5%	FAR 1%		
$SUS(FKG_i)$	82.98	84.32	85.09	4.68	3.12
$MUL(FKG_i)$	83.78	84.89	85.76	4.65	2.98
$SWS(FKG_i)$	84.76	85.67	86.98	4.23	2.65
$SUS(FKT_i)$	85.75	86.04	87.75	3.87	2.87
$MUL(FKT_i)$	86.34	86.98	88.34	3.76	2.45
$SWS(FKT_i)$	86.98	87.45	89.62	2.82	2.41
$SUS(FKG_i, FKT_i)$	87.82	88.93	91.36	2.72	2.21
$MUL(FKG_i, FKT_i)$	88.25	89.35	92.77	2.50	2.12
$SWS(FKG_i, FKT_i)$	89.17	90.22	93.34	2.36	2.17
$SUS(MUL(FKG_i), MUL(FKT_i))$	90.18	91.56	94.63	1.83	1.74
$SUS(SWS(FKG_i), SWS(FKT_i))$	91.54	93.75	95.54	1.67	1.95
$SWS(SUS(FKG_i), SUS(FKT_i))$	92.66	94.85	96.74	1.24	1.44
$SWS(MUL(FKG_i), MUL(FKT_i))$	93.82	95.73	97.94	1.13	1.32
$MUL(SUS(FKG_i), SUS(FKT_i))$	94.57	96.65	98.94	0.94	1.23
$MUL(SWS(FKG_i), SWS(FKT_i))$	96.4	97.2	99.67	0.78	1.12

Table 2 Performance analysis of proposed personal recognition system using IIT FKP dataset.

Various combinations	Genuine acceptance rate (%)			ERR (%)	DT
	FAR 0.1%	FAR 0.5%	FAR 1%		
$SUS(FKG_i)$	81.45	82.43	83.59	5.73	3.74
$MUL(FKG_i)$	82.12	83.24	84.23	5.54	3.52
$SWS(FKG_i)$	83.13	84.90	85.27	5.34	3.12
$SUS(FKT_i)$	84.12	85.26	86.34	4.95	2.98
$MUL(FKT_i)$	85.23	86.12	87.89	4.68	3.12
$SWS(FKT_i)$	86.12	87.24	88.24	4.37	2.98
$SUS(FKG_i, FKT_i)$	87.26	88.45	89.23	4.12	3.87
$MUL(FKG_i, FKT_i)$	88.04	89.78	89.98	3.80	3.42
$SWS(FKG_i, FKT_i)$	89.67	90.34	90.13	2.76	3.43
$SUS(MUL(FKG_i), MUL(FKT_i))$	90.09	91.39	92.56	2.34	3.26
$SUS(SWS(FKG_i), SWS(FKT_i))$	91.23	92.45	93.23	2.07	3.98
$SWS(SUS(FKG_i), SUS(FKT_i))$	92.58	93.67	94.27	1.85	2.68
$SWS(MUL(FKG_i), MUL(FKT_i))$	93.80	94.78	96.29	1.73	2.45
$MUL(SUS(FKG_i), SUS(FKT_i))$	94.13	95.82	97.49	1.15	1.98
$MUL(SWS(FKG_i), SWS(FKT_i))$	95.30	96.40	98.27	0.94	1.35

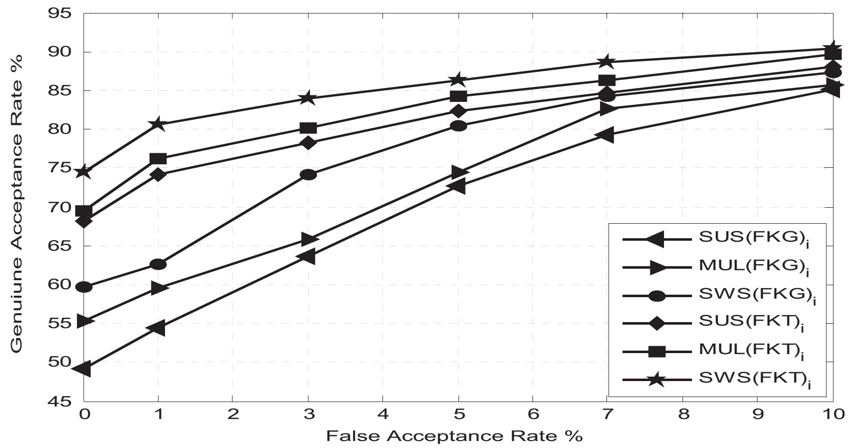


Figure 5a ROC plots for combined performance representing fusion of matching score obtained either through geometrical or textural analysis which are derived from finger knuckle regions of PolyU dataset.

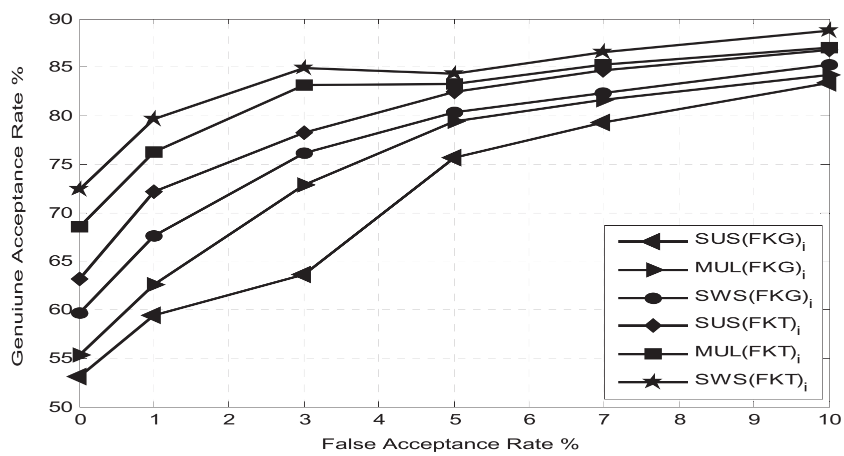


Figure 5b ROC plots for combined performance representing fusion of matching score obtained either through geometrical or textural analysis which are derived from finger knuckle regions of IIT dataset.

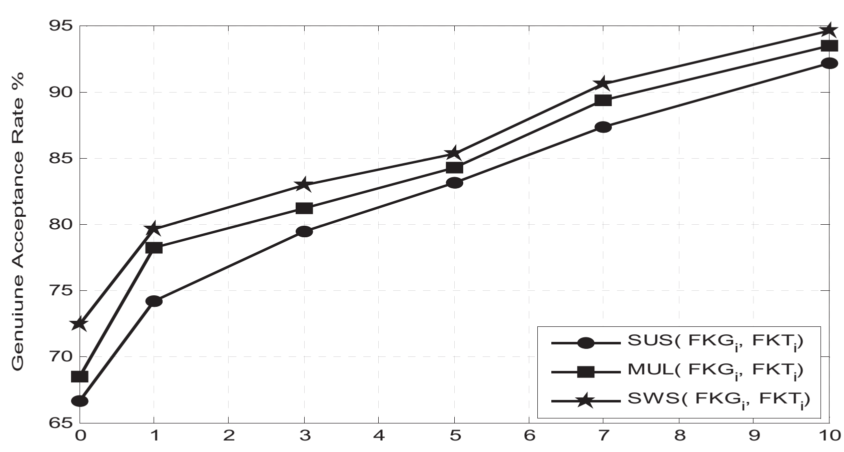


Figure 5c ROC plots for combined performance representing fusion of matching scores obtained from both geometrical and textural analyses which are derived from finger knuckle regions of PolyU dataset using basic fusion rules.

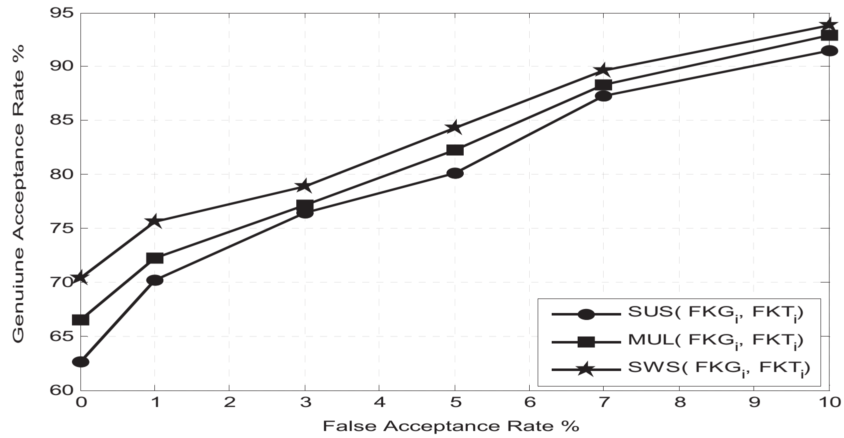


Figure 5d ROC plots for combined performance (d) fusion of matching scores obtained from both geometrical and textural analyses which are derived from finger knuckle regions of IIT dataset using basic fusion rules.

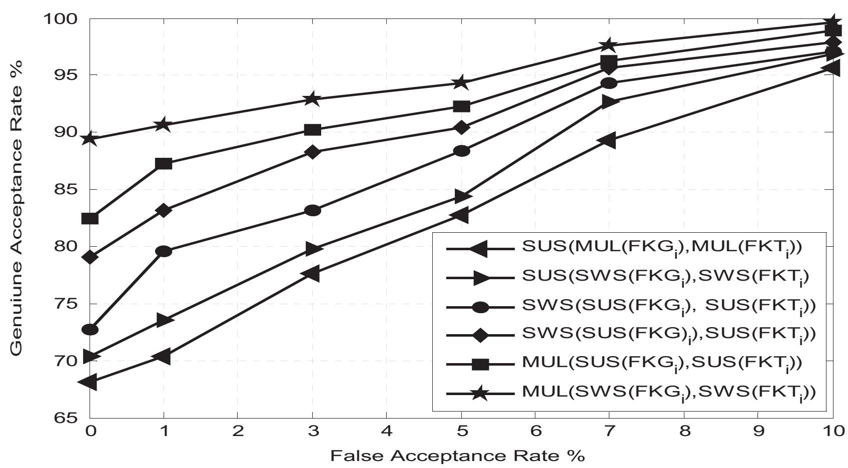


Figure 5e ROC plots for combined performance representing fusion of matching scores obtained from both geometrical and textural analyses which are derived from finger knuckle regions of PolyU dataset using hybrid rules.

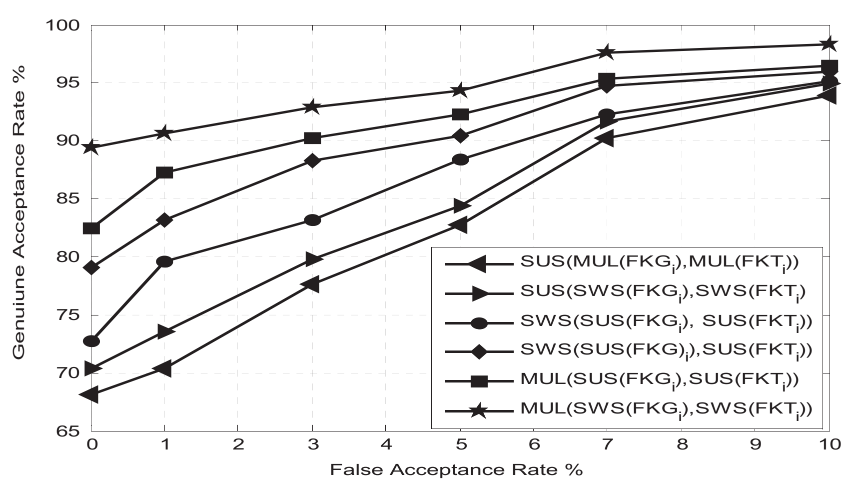


Figure 5f ROC plots for combined performance representing fusion of matching scores obtained from both geometrical and textural analyses which are derived from finger knuckle regions of IIT dataset using hybrid rules.

IIT FKP dataset are presented in the Fig. 4. The ROCs obtained from index, middle and ring finger knuckle regions as shown in Fig. 4(a)–(c) portray that the proposed textural analysis method based on Curvelet transform and PCA shows higher GAR values of 98.14%, 98.46% and 98.91% respectively, which differs in an average value of 0.68–1.45% from angular geometric analysis method. However, our proposed angular geometric analysis method (AGAM) produces high recognition rate of 97.46% with a lower false acceptance rate of 0.04% than the existing geometric analysis methods as detailed in Kumar and Ravikanth (2009) and Kumar and Zhang (2010), since AGAM produces angular based feature information which has high potentiality toward the reliable identification of individuals. It is also observed that the performance of the little finger knuckle region in terms of GAR is 82.45%, which is not appreciable when compared to the other finger knuckle regions, this may be due to its small size and unclear texture patterns.

The matching scores generated by the individual finger knuckle regions are combined using fusion methods viz., sum rule (SUS), product rule (MUL), and sum weighted rule (SWS) as discussed in Section 7, for analyzing the combined performance. In addition to the basic fusion methods, we also incorporate hybrid rules which combine any two fusion strategies as describe above. For example, matching scores obtained either through geometric analysis method or textural analysis from individual finger knuckles are combined using weighted sum rule and then product rule is applied for further integration process in order to generate resultant matching score. The following Table 1 illustrates the experimental results obtained through the various combinations of matching scores that correspond to the geometrical and textural analyses derived using PolyU FKP database. The value of 'i' in the table can be given as $i = 1, 2, 3$ and 4 representing four finger knuckle regions of PolyU dataset viz., left index finger knuckle, left middle finger knuckle, right index finger knuckle and right middle finger knuckle. From the tabulated results, it is evident that the combination of matching scores obtained from individual finger knuckle regions using geometric and texture analysis method by means of a hybrid rule (combination of weighted sum rule and product rule) yields better performance.

Similarly, the experimental results generated for analyzing the combined performance, derived using IIT FKP dataset are illustrated in the Table 2, where $i = 1, 2, 3$ and 4 represents the four different finger knuckle regions of index finger, middle finger, ring finger and little finger as stored in IIT FKP dataset. From the tabulated results, it is obvious that, the combination $MUL(SWS(FKG_i), SWS(FKT_i))$ shows higher GAR of 98.27% at lower rate of FAR than any other combination.

Further, this thorough experimental analysis aids in deriving a decidability threshold (DT) using (9), which is used to ascertain the performance of the proposed system.

$$\mathrm{DT} = \frac{2^{\mu_d - d_l - d_u}}{d_l - d_u} \tag{9}$$

where μ – Mean value of the genuine and imposter matching scores obtained through combined performance analysis. d_l – Highest value of matching score obtained through combined performance analysis. d_u – Lowest value of matching score obtained through combined performance analysis.

The experimental results illustrating the equal error rate along with its decidability threshold for various combinations derived using PolyU and FKP dataset are also presented in Tables 1 and 2 respectively. The lowest EER value is 0.78% with DT 1.12, which is obtained from the best combined performance, $MUL(SWS(FKG_i), SWS(FKT_i))$ as discussed earlier.

The ROCs illustrating the combined performance of all the four finger knuckle regions of PolyU and IIT FKP datasets are shown in Fig. 5. The ROC shown in Figs. 5(a) and (b) illustrates that, there is a significant improvement in the performance when the matching scores obtained either through geometrical or textural analysis from individual finger knuckle regions are combined using three basic rules of fusion process. Moreover, the application of weighted sum rule shows better performance than any other rule of combinations. From the Figs. 5(c) and (d), it is observed the combinations of matching scores obtained through textural analysis methods from individual finger knuckle regions is further combined with matching scores obtained through geometrical analysis yields high genuine acceptance rate of 92.89% using weighted sum rule. This weighted sum method of combining matching scores improves genuine acceptance rate from 8% to 12% when compared with other two fusion methods, since it combines the matching scores from the correlated texture patterns for which the errors from the different matching modules are independent. The ROCs illustrating the combined performance based on the hybrid rule are shown in the Figs. 5(e) and (f). These experimental results demonstrate that there is a substantial increase in performance when the matching scores are combined using hybrid rule. The best performance yielded through the hybrid rule which incorporates both weighted sum scheme and product scheme is 99.67% using PolyU dataset and 98.27% using IIT FKP dataset. This could be possible because, the combined fusion score obtained from geometrical and textural analyses are further combined using product scheme which yields maximum results when the data representation is independent.

The comparative analysis of ROCs obtained from various combinations clearly suggests that the combination of shape oriented features and texture analysis results in better performance than its individual performance.

The following Table 3 illustrates the comparative analysis of the results of the proposed methodology with the reported results of the existing works based on PolyU FKP dataset. The proposed personal recognition method incorporates both geometrical and texture analyses using finger knuckle print is compared with the other geometric and texture analysis methods implemented on finger knuckle print biometric trait.

The existing methods experimented with PolyU database were taken in order to perform comparative analysis with the proposed method. The existing methods presented in Table 3 correspond to transform based textural analysis methods using FKP and various other hand biometric traits. In this comparative analysis, it is observed that, our proposed angular geometric analysis method (AGAM) produces a high recognition rate of 97.46% with a lower error rate of 0.68%, since the proposed AGAM extracts angular based feature information which has greater potentiality toward reliable identification of individuals.

Further, the comparative analysis of the performance of the proposed personal recognition system based on textural analysis using Curvelet transform and principal component

Table 3 Comparative analysis of proposed personal recognition method with the existing approaches for finger knuckle print using PolyU dataset.

Si. no	References	Methodology incorporated for feature extraction, matching and fusion	Specification of database used for experimentation	Reported results based on EER (%) values
1	Shen et al. (2010)	Extraction of magnitude and phase information using 2D Gabor filters	1200 (left index finger knuckle obtained from 100 subjects)	2.23
2	Zhang et al. (2011)	Competitive coding scheme based on Riesz transform	3960 (gallery and probe set)	1.26
3	Yang et al. (2011)	Generation of phase correlation function based on discrete Fourier transform	7920	1.29
4	Hegde et al. (2011)	Competitive coding scheme using random transform and Gabor wavelet transform	3960 (gallery and probe set)	1.49
5	Zhang et al. (2012)	Coding scheme based on Riesz transform which encodes local feature information of palm print and FKP	3960 (gallery and probe set)	Rcode1: 1.661 Rcode2: 1.610
6	Gao et al. (2013)	Reconstruction of query FKP images with the aid of template samples using dictionary learning techniques	3960 (gallery and probe set)	1.10
7	Hegde et al. (2013)	Computation of Eigen values by subjecting the FKP image to random transform and matching by calculating the minimal distance value	3960 (gallery and probe set)	1.28
8	Shariatmadar and Faez (2013)	Binary patterns generation using Gabor filtering method	3960 (gallery and probe set)	1.69
9	Gao et al. (2014)	Integration of multiple orientation code and texture feature information	3960 (gallery and probe set)	1.048
10	This paper	Shape oriented features are extracted using angular geometric analysis and textural feature information are represented by means of Curvelet transform and principal component analysis	PolyU FKP database with 660 images obtained from 165 subjects. In which 400 images were taken for training process and 260 images for testing process	0.78
			IIT FKP database with 632 images obtained from 158 users. In which 400 images were taken for training process and 232 images for testing process	0.94

Table 4 Performance analysis of proposed personal recognition system based on computational complexity.

Key process	Time (ms)
Image loading	90
Image processing and ROI extraction	180
Geometric analysis based shape oriented feature extraction	1.2
Texture analysis based feature extraction	140
Score generation	20

analysis (PCA) is carried out with the benchmark systems as discussed in the table entries. This analysis shows that, our proposed Curvelet transform based texture analysis method produces a high accuracy rate of 98.72% with a lower error rate 0.52%, since Curvelet transform has better ability to represent edge curves in an image. Also, the bench mark system taken for comparison were implemented based on Gabor filters, Gabor Wavelet transform, Riesz transform and Random transform, which have serious drawbacks such as Wavelets fail to handle higher dimensional singularities and requires more number of parameters to reconfigure discontinuities present in various image structures. These drawbacks were overwhelming in the proposed method since Curvelet transform optimally represents the curved singularities in the knuckle image and also the principal component features of each Curvelet knuckle images are taken as feature information.

Furthermore, the comparative analysis from Table 3 clearly portrays that, the proposed method for personal recognition using finger knuckle shape oriented features and texture feature analysis outperforms all other existing methods by producing the lowest error rate of 0.78% using PolyU FKP database and 0.94% using IIT FKP database. The recognition rate produced by this combined performance is 99.67%, which is found to be remarkable as compared with existing methods.

The proposed system is implemented in VC++ and executed in the system configuration of Intel core is CPU with 5 GHz processor, 4 GB RAM and compiled using GNU compiler with the support of open CV library. The computational complexity of the system is evaluated by calculating the time taken to execute each step of personal recognition process as listed below in the Table 4.

The total execution time for the entire process of verification was 3.32 s. In the computational analysis, it is perceived that the process of image loading and ROI extraction is very critical and computationally costlier than that of the other processes. Similarly, textural analysis process also consumes more amount of time than the geometrical analysis method. However, the overall speed of the proposed personal authentication system was found to be appreciable and suitable for real time environment.

Finally, it is also evident that, this personal finger knuckle recognition mechanism innovates a new fusion methodology based on hybrid rule to integrate the scores obtained through geometric and texture analysis methods. Further, this results in the highest verification accuracy rate of 99.46% with the lowest rate of 0.78%.

9. Conclusion

This paper investigates a novel approach for reliable personal recognition based on simultaneous extraction and integration of finger knuckle shape oriented and texture features. The proposed method of FKP recognition includes preprocessing of finger knuckle images, ROI extraction, extraction of angular based geometrical feature information and Curvelet knuckle based textural feature information for achieving better performance. In addition to this, the proposed system handles distorted or impaired knuckle regions and extracts reliable feature information for personal identification. Further, the performance of the proposed system is thoroughly studied using PolyU and IIT databases in which 660–632 finger knuckle images are considered for processing. The experimental results demonstrates that the finger knuckle texture features have highly distinctive information for biometric verification that produces high accuracy rate of 98.72% using PolyU dataset when compared to the finger knuckle shape oriented features which produces an accuracy rate of 97.46%. In addition, the experimental results further demonstrate that, the significant improvement in performance can be achieved by integrating the matching scores obtained from finger knuckle shape oriented features and texture features using hybrid rule which produces a high accuracy rate of 99.46% with lowest error rate of 0.78%. The comparative analysis of the results obtained from the proposed method with the reported results of existing methods, makes it clear that our proposed method decreases the error rate in an average value of 59%, which is said to be a significant improvement to the existing state of art as far as the Intra-model biometric system is concerned. Future work would involve personal recognition by experimenting with newly acquired large scale database of entire finger dorsum knuckle surface images obtained from 700 to 1000 subjects.

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