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Robust personal authentication using finger knuckle geometric and texture features

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Abstract This paper investigates on the entire finger dorsal surface for human identity that can be extremely beneficial for forensics applications and its related fields. Further, this paper formulates a novel approach to achieve improved performance by simultaneous extraction and integration of finger knuckle geometric and texture features by score level fusion. The geometric features are derived through Angular Geometric Analysis Method (AGAM) which extracts angular-based feature information for unique identification. Similarly, Texture Feature Extraction Methods (TFEM) viz., Completed Local Ternary Pattern (CLTP) generation method, 2D Log Gabor Filter (2DLGF) method and Fourier – Scale Invariant Feature Transform (F-SIFT) method are incorporated to derive the local texture features of an acquired finger back knuckle surface. The experimental results indicate that integration of geometric and local texture features of finger knuckle regions shows decrease in error rate by 27% (in average) when compared to the existing benchmark system taken for comparison.

1. Introduction

Biometric identification through physiological features such as fingerprint, palm print, iris, face and hand geometry has been widely used in highly critical security applications and forensics applications [1]. The high level security applications include access control in physical or logical systems that impose new challenge of handling large volume of biometric data for rapid and precise personal verification whereas, forensics applications need to identify a person using a scale, rotational and transformational variant images of their morphological characteristics [2].

However, the researchers have proposed comprehensive models for personal recognition which uses well promising methods to exploit the highly unique patterns present in the inner and outer surfaces of the hand and these systems are universally accepted as hand-based biometric system [3]. In the recent past, hand based biometric systems have drawn considerable attention of researchers due to its merits such as (i) hand traits can be easily captured using low cost acquisition devices, (ii) hand traits have highly discriminative features which are

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potential enough for personal recognition, (iii) hand traits have high user acceptance rates since they were captured in a non-intrusive (touch-less) manner and (iv) they yield high performance in terms of both speed and accuracy [4]. In the literature, various personal recognition algorithms using hand traits such as fingerprint, palm print, hand shape features, hand vein structures and finger knuckle print [5–9] have been proposed.

Among these hand traits, finger knuckle biometric trait was gaining importance in critical security applications since (i) it possesses distinctive and stable features such as lines, curved lines, contours and wrinkles for identification, (ii) unlike fingerprint, the patterns of finger knuckle surface were present in the inner surface of the hand which is very difficult to be spoofed, (iii) unlike palm print, finger knuckle surface patterns can be acquired by capturing smaller area which contains more number of features for identification, (iv) unlike hand vein systems, finger knuckle surface contains highly discriminative texture patterns that are easily acquirable by means of a low resolution cameras and (v) when compared with hand geometry systems, the finger knuckle surface can be captured in a touch-less environment without pegs [10].

Most of the works in the literature investigate on finger knuckle recognition methods for access control applications and hence only the knuckle patterns of central bend area of finger dorsal surface were taken for consideration. In contrast, this paper focuses on incorporating entire finger dorsal surface that can be extremely beneficial for forensics applications and identification of suspects in criminal investigations. The entire finger back surface consists of two most prominent joints viz., Proximal Inter Phalangeal (PIP) joint and Distal Inter Phalangeal (DIP) joint which are present in the middle and tip surface of the finger respectively. This joint makes the finger to bend uni-directionally toward palm side of the hand and that flexion shrinks on the skin surface create unique patterns which are highly potential enough to identify an individual. A knuckle pattern of entire finger dorsal region is referred as Finger Back Knuckle Surface (FBKS).

Unlike other security applications, forensics applications further impose a challenge of handling distorted (wounded or burned) and deformed (scale, rotation and transformation variant) knuckle images. In the literature, there were no known attempts to examine entire finger dorsal surface for biometric identification with effective algorithms that could able to handle distorted and deformed knuckle images. In addition to this, local features of a knuckle image are robust against noise and deformations since they derive feature information of a block or sub-band of a knuckle image which possesses lower degree of intra-class variations. Thus, local features have higher degree of discriminatory power for matching knuckle biometric images. However in the literature, very few attempts were made to analyze the knuckle image patterns based on three local features to the best of our knowledge. Hence, we are motivated to formulate a complete finger knuckle biometric framework which derives geometric features based on angular geometric analysis and local texture features through three texture analysis methods and further integration of these geometric and three local texture features is done by means of score level fusion method in order to derive final authentication decision.

The major contributions of this paper are given as follows:

(i) This paper investigates on the entire finger back knuckle surface for personal identification. This work contributes efficient segmentation methodology which simultaneously segments proximal and distal knuckle regions from the captures of FBKS image. Integration of proximal and distal knuckle features is carried out to attain improved performance in personal identification.
(ii) This paper investigates on performance improvement that could be achieved by utilizing angular geometric feature information in addition to that of the general shape information such as finger knuckle length, width, area and perimeter.
(iii) This paper further investigates on statistical-based texture analysis method viz., Completed Local Ternary Pattern (CTLP) method that extract local phase features of finger knuckle surface. The extractions of local features are performed since they are robust enough in handling deformations of very low degree.
(iv) Additionally, this paper also investigates on transform based texture analysis methods viz., 2D Log Gabor Filters (2DLGF) and Fourier-Scale Invariant Feature Transform methods (F-SIFT) for extracting finger knuckle local phase and orientation information for further improvement in authentication accuracy of the system.
(v) Finally, this paper contributes a complete personal authentication system that considers entire finger back knuckle surface as input, then simultaneously extracts and integrates angular geometric features and local texture features of both proximal and distal knuckle surfaces for personal authentication. This paper also presents a systematic analysis to ascertain the performance of the proposed textural analysis method in terms of scale, rotation and transformation invariant properties.

The organization of the paper is as follows. Section 2 presents a thorough and comprehensive analysis of existing finger knuckle preprocessing, feature extraction and classification methods. Section 3 presents the design of the proposed personal authentication and image acquisition setup for capturing finger knuckle images. Section 4 illustrates the steps involved in preprocessing and ROI segmentation process. Section 5 presents angular geometric analysis method that extracts angular knuckle features. Section 6 presents texture feature extraction methods that extract local texture feature information from finger knuckle surface which are robust against deformations. Section 7 presents various integration rules for combining matching scores of geometrical and texture analysis methods implemented on FBKS. Extensive experimental analysis conducted to assess the performance of proposed personal authentication system and their detailed results analyses is presented in Section 8. Section 9 concludes the paper with future plan for study.

2. Existing work

In the literature, researchers have proposed various promising feature extraction methods for hand based biometrics. These methods are broadly classified into two categories viz.,

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geometric analysis based feature extraction methods and texture analysis based feature extraction methods [11]. Generally, geometrical analysis methods utilize several edge detecting approaches for extracting features such as edges, lines, creases, and wrinkles, from the hand biometric traits. The extracted feature points were converted into a form of geometrical feature information to represent the feature vector of that particular image for matching [12]. Further, in case of texture analysis methods, the feature information is extracted by means of spatial variations exhibited by the captured finger knuckle image. In this texture analysis, various mathematical models are used for analyzing the different spectral values that are iterative in a region of large spectral scale [13].

Many researchers have also explored finger knuckle texture feature extraction methods that are further classified into (i) sub-space based methods, (ii) coding based methods and (iii) statistical based methods. In sub-space based feature extraction method, captured finger knuckle images are projected into sub-spaces build from training data. Thus, the projected sub-spaces were explored to generate sub-space coefficients by means of various techniques. In a coding-based texture feature extraction method, each field of code-map is assigned a bitwised code based on the quantization obtained through the image's responses toward a set of filters. Similarly, statistical based texture analysis methods attempt to represent the texture patterns of finger knuckle image by means of non-deterministic properties that quantifies the distributions and relationships between the gray-level of a finger knuckle image [14]. Some of the geometric and texture analysis methods implemented for finger knuckle feature extraction were discussed below.

Woodard and Flynn [15] were the first authors to introduce finger knuckle print as a biometric trait by capturing it in a 3D sensor. Feature extraction for identification is carried out by means of geometric methods that extract the curvature shape information of the finger knuckle print. In addition to this, Kumar and Ravikanth [16] have proposed a novel framework for personal authentication using finger knuckle surface based on textural analysis and edge detection methods (FGFEM). Texture exhibited by the knuckle image was derived by means of sub-space based approaches such as principle component analysis, independent component analysis and linear discriminant analysis. Kumar et al., in the second work [17], introduced a new modality known as hand vein structure for personal authentication. In this, dorsum surface of the hand is captured using infra red imaging system (DTFEM). The captured image is subjected to histogram equalization for enhancement and the structure of the vein is studied using key point triangulation method. This paper also focuses on incorporating the simultaneous extracted of knuckle shape information to achieve better performance. Kumar and Zhang [18] have further explored the finger knuckle surface by incorporating the quality feature of the trait which is highly dependent on the capturing device. This is achieved by means of quality dependant fusion (KGFEM), in which the quality of the data acquired from the captured image is quantified for the estimation of matching scores.

Furthermore, Zhang et al., in 2011 [19], proposed a biometric system which implements a novel approach for feature extraction and representation based on texture analysis of finger knuckle print. Authors suggested a new method for feature recognition based on Riesz transform and used a 6 bit coding scheme namely RieszCompCode to encode it. Further, in 2012 [20], authors have contributed a new FKP recognition scheme which extracts both local and global feature information of FKP images. Zhang et al., in [21] investigated a feature extraction mechanism to extract local features of FKP based on phase congruency model (LFI). This work computes the phase congruency, local orientation and local phase information of the subjected FKP image using a set of quadrature pair filters such as two dimensional complex Gabor filter or log-Gabor filters. In addition to this, Zhang and Hongyu in [22] proposed a novel coding scheme based on Riesz transform for encoding the local feature information of palm print and finger knuckle print images. Hegde et al., in [23] implemented a real time personal authentication using finger knuckle print. The features of the finger knuckle surface were extracted using three unique algorithms viz., radon transform, Gabor Wavelet transform and correlation based matching. Aoyama et al. [24] proposed a novel finger knuckle print recognition algorithm based on local block matching. The captured finger knuckle print was subjected to two dimensional discrete Fourier transforms to obtain phase information required as feature information.

Shariatmadar and Faez [25] proposed a new finger knuckle print recognition scheme for personal authentication by subjecting finger knuckle print into bank of Gabor filters from which binary patterns are generated and represented in the form of histograms. Additionally, Gao et al. [26] address the issue of handling scaling, rotational and translation variant FKP which is a result of flexibility in positioning the finger knuckle during capturing process. This variance in scaling, rotation and transformation is handled by reconstructing the captured finger knuckle image using dictionary learning method. Gao et al., in their further work in [27] presented a novel mechanism which integrates multiple orientation coding and texture feature information obtained from finger knuckle print image for personal recognition (LGIC). Yet another method for verifying human identities using finger knuckle surface was proposed by Kumar in 2014 [28]. In this work, the author has explored minor finger knuckle patterns along with major finger knuckle print in order to achieve improved performance in personal recognition. Texture patterns of finger knuckle surface were extracted by means of Local Binary Patterns (LBPs), Improved Local Binary Patterns (ILBPs) and 1D Log Gabor Filters.

2.1. Extracts of the literature

From the survey conducted, it has been inferred that the existing feature extraction methods have the following limitations:

(i) The existing geometric analysis based feature extraction approaches for hand traits extract feature information such as, finger length, finger width, palm length, palm width, palm area and perimeter that possess lower degree of discrimination and may lead to inaccurate authentication within the larger population.
(ii) The existing statistical methods like local binary patterns and improved local binary patterns are sensitive toward noise and illumination of the captured image.

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(iii) The existing local phase information extraction methods like Gabor filters fail to handle larger bandwidth of an image and also 1D log Gabor filters capture only horizontal patterns of finger knuckle image which are highly sensitive toward deformations.
(iv) Even though, the existing transform based texture analysis methods, such as SIFT method was robust against deformations, it extracts features based on gradient information which is not well suited for finger knuckle images.
(v) Moreover, there are no known attempts to integrate geometric/shape oriented features and three texture features of finger knuckle surface in order to improve the performance in terms of accuracy and robustness against deformations of knuckle images.

Hence, we are motivated to implement a complete finger knuckle biometric framework based on angular geometric and three different texture analysis methods for identifying an individual.

3. The proposed system design

This paper contributes a complete personal authentication system using entire finger back region. The proposed personal authentication system captures finger knuckle surface through peg-free and touch-less imaging system and employs efficient feature extraction algorithms which are robust against noise and image deformations. Moreover the proposed system also handles the problem that arises due to the presence of wounds or burns on the finger knuckle surface. The two main aspects of the proposed system are (i) extraction of angular based knuckle shape features in order to achieve better precision rate, (ii) extraction of local phase features through three texture analysis methods which are robust enough to authenticate deformed knuckle images. The following Fig. 1 illustrates the block diagram of the proposed personal authentication system using finger back knuckle surface.

Initially, the captured FBKS images are subjected to preprocessing and ROI segmentation process. Further, simultaneous extractions of geometric and local texture features from the FBKS images are done through AGAM and TFEM approaches respectively. Furthermore, matching of finger knuckle images are performed by manipulating distance based metrics and phase only correlation between registered templates and input image feature vectors. Finally, the obtained matching scores from AGAM and three TFEM approaches are fused to obtain final authentication decision. This work attempts to develop an image acquisition setup similar to that of the image capturing system discussed in [16]. The developed acquisition system is a peg-free and touch-free imaging system that captures a FBKS image by placing it on the white surface which is uniformly illuminated in front of the 4 mega pixel digital camera and the resolution of captured image is 1280×990 pixels. The acquired FBKS images of index, middle, ring and little finger regions are shown in Fig. 2.

4. Preprocessing and ROI segmentation

The proposed finger knuckle biometric system captures entire finger knuckle surface by means of a non-intrusive and peg-free environment. The captured finger dorsal region of a human hand consists of three phalangeal joints viz., Metacarpo phalangeal joint (connects the finger region with the hand surface), Proximal Inter Phalangeal (PIP) joint (present in the middle surface of the finger region) and Distal phalangeal joint (present in the tip surface of the finger back region). This paper mainly focuses on incorporating both proximal and distal knuckle patterns for personal recognition. Hence, in this stage of preprocessing step, we attempt to extract proximal and distal knuckle regions separately from the captured finger back knuckle surface. Fig. 3 illustrates the steps for ROI segmentation process from the captured entire finger back knuckle surface image.

In preprocessing, each acquired finger knuckle surface image is subjected to thresholding operation in order to obtain binarized images. In binarization operation each and every pixel in the finger knuckle surface image is converted into one bit information based on the thresholding limit τ which can be derived using Sauvola's thresholding function [29] given by (1)

$$\tau(x,y) = \mu(x,y)[1 + k(\delta(x,y)/R) - 1] \quad (1)$$

where
$\mu(x,y)$ – represents the mean value of pixel present in the obtained finger knuckle surface image,
$\delta(x,y)$ – represents the standard deviation value of pixel of the finger knuckle surface image,
R – Maximum value of standard deviation,
k – Bias value.

Here R value is considered as 128 as the captured finger knuckle surface is converted into gray scale and the value of k is considered as 0.3 because the boundary of the image can be distinctly identified at only this point.

The mean and standard deviation of pixel values of the captured finger knuckle surface image is derived through integral sum method which is given in (2):

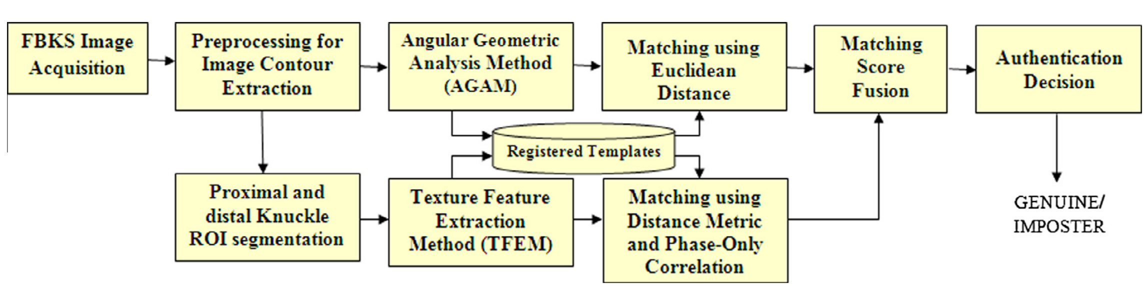

Figure 1 Block diagram of proposed personal authentication system.

Figure 2 Captured finger back knuckle surface of fore finger, middle finger, ring finger and little finger.

$$\mu(x,y) = S(x,y)/I_1 * I_2 \quad (2)$$

where

(x, y) – represents the pixel location.

$S(x, y)$ – represents the sum intensities of the pixels present in the surrounding region in the form of rectangle and $I_1 {}^* I_2$ defines the size of the captured finger knuckle surface image.

The resultant binarized image is further subjected to contour tracing in which the largest possible contour of the finger knuckle is traced out for framing the exact boundary of the finger knuckle image. The derived contour image is subjected to angular geometric analysis for shape oriented feature extraction (detailed in Section 5).

Besides this, each FBKS contour image is marked with its central line representing the length of the finger knuckle region starting from the tip of the finger knuckle toward to its end. Fig. 4 shows the captured FBKS, binarized FBKS image, contour image of FBKS, contour image of FBKS represented with its central-line and edge-map of the FBKS image.

Further, the FBKS image is subjected to canny edge detection algorithm [30] in order to extract region of interest. As shown in Fig. 4(e), the regions present in the center and adjacent side of the symmetric central-line are densely populated with high intensive pixels. Therefore, this region is extracted proportionally on either side of the central-line from a finger knuckle region at a distance of one-third of the finger knuckle length to three-fourth of the finger knuckle length from its base region. Nearly, 110×220 pixel values have been extracted for proximal knuckle region. Similarly, the high intensive pixel region present in tip surface of the finger is extracted by segmenting 80×170 pixel values from either side of the central line for distal knuckle region. Fig. 5 illustrates the captured finger knuckle surface regions with their corresponding proximal and distal ROI images. The proximal and distal knuckle regions of each finger knuckle surface are subjected to Texture Feature Extraction Method (TFEM) detailed in Section 6.

5. Angular Geometric Analysis Method (AGAM)

The main objective of this study was to evaluate the improved performance induced by the integration of geometric and texture features of a finger knuckle biometric system. The geometric measurements are extracted from the ROI images of proximal and distal knuckle regions using Angular Geometric Analysis Method (AGAM) as discussed in [31]. As detailed in [31], the angular geometric analysis method extracts six geometric features from proximal knuckle and six from distal knuckle region. Hence totally, 12 geometric measurements were derived from a finger knuckle surface which includes, two finger knuckle length, six finger knuckle widths and four finger knuckle angular information. The distance between the input finger knuckle geometric measures (fks_i) and the registered feature vector (fks_r) is computed through Weighted Euclidean Distance rule, which is given by (3)

$$D(fks_i, fks_r) = \sqrt{\sum_{k=1}^{l} w_k (fks_i(k) - fks_r(k))^2} \quad (3)$$

where

i – Notation used to represent feature vector of an input image.

r – Notation used to represent feature vector of a registered image.

fks_i – represents the geometric measurement vector of an input finger knuckle surface image.

fks_r - represents the geometric measurement of registered finger knuckle surface image.

w_k – corresponds to the weight which is assigned a lower value for lower variance between input and registered value and assigned higher value for higher variance between input and registered value. w_i takes the value between $0 < w_k < 1$ and $\sum_{k=1}^{n} 1$.

The key significance of the proposed angular geometric analysis method is that it extracts angular-based feature information which is highly potential enough to distinguish the individuals.

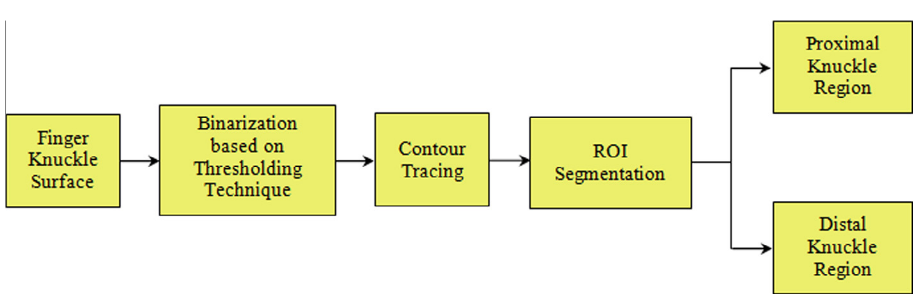

Figure 3 Block diagram illustrating ROI segmentation steps in personal authentication system.

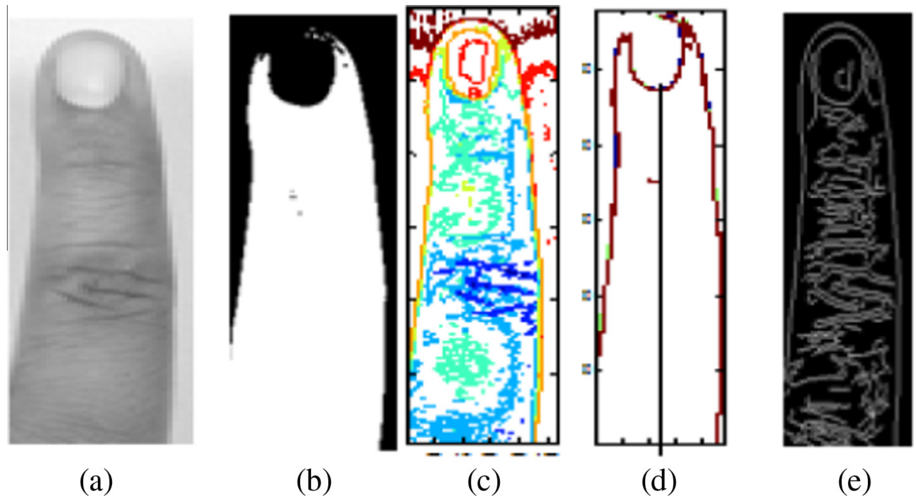

Figure 4 (a) Acquired FBKS image (b) binarized image of FBKS (c), (d) representation of contour extracted from binarized FBKS image. (e) Contour image of FBKS.

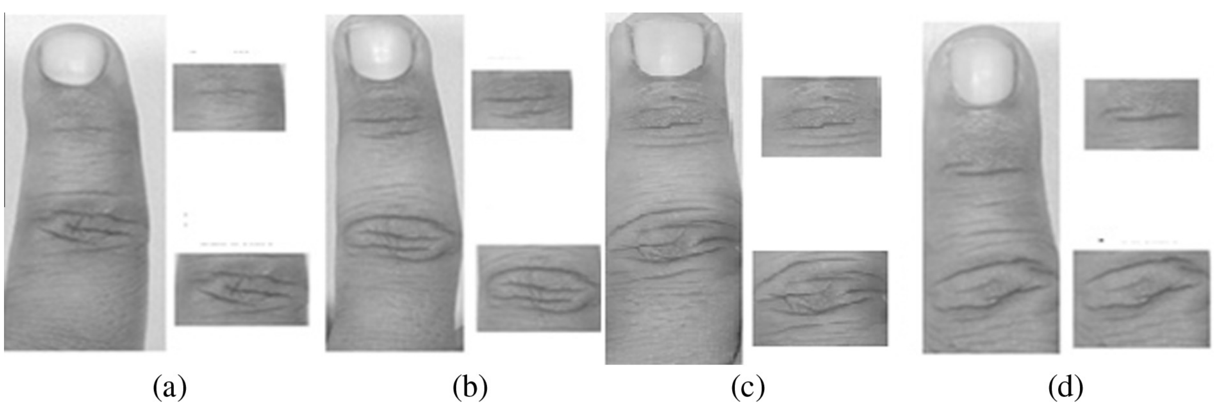

Figure 5 Finger knuckle surface with corresponding proximal and distal knuckle regions for (a) index finger knuckle region, (b) middle finger knuckle region, (c) ring finger knuckle region and (d) little finger knuckle region.

6. Texture Feature Extraction Method (TFEM)

This section reports about the investigation of texture feature analysis for finger knuckle recognition. The focus of this work is on simultaneous extraction of geometrical and local texture feature information. Generally, local texture feature extraction is known as a measure of texture information computation within a local sub-band which encodes the details of the trait in the specific area. Local texture features of a finger knuckle surface represent more detailed texture information within the specified area and also robust against small scaling and rotational changes in the captured finger knuckle image. Hence, in this section, the extraction of local texture feature information from both proximal and distal finger knuckle regions is performed using three different texture analysis methods viz., (i) Completed Local Ternary Patterns (CLTP), (ii) 2D Log Gabor Filters (2DLGF) and (iii) Fourier – Scale Invariant Feature Transform (F-SIFT). In fact, the texture information obtained through these methods reflects different aspects of feature information such as (i) representation of multi-scale and multi-orientation texture patterns, (ii) representation of local phase information and (iii) representation of local orientation or magnitude information respectively. Moreover, this local texture feature information provides most prominent results even they are implemented independently and at the same time performance of the finger knuckle biometric system can further be improved by combining these three local features. The following subsections discuss on implementation details of aforementioned texture feature extraction methods.

6.1. Completed Local Ternary Pattern (CLTP)

In 2010, Tan and Triggs, contributed an enhanced local texture feature sets known as Local Ternary Patterns (LTP). This texture coding scheme encodes the neighboring pixel value into 3-valued code known as trits. Further, this scheme is highly insensitive toward scaling and rotational variances of an image. The LTP scheme encodes the local texture patterns of a knuckle image and represents it in the form of multi-scale texture patterns similar to that of Local Binary Patterns (LBPs). This work incorporates Completed Local Ternary Pattern (CLTP) as discussed in [32] for representing local knuckle texture features. This method is quite popularly used in texture classification, human action recognition, object recognition and identification. Hence, CTLP can be implemented on the FBKS regions in order to extract multi-scale texture patterns of knuckle surface.

In the captured FBKS image, the ternary patterns for centered pixel C_P with neighboring pixel N_P around the radius R are calculated through (4),

$$s(C_P, N_P) = \begin{cases} 1, & (C_P - N_P) \geqslant t \\ 0, & -1 < (C_P - N_P) < t \\ -1 & (C_P - N_P) < -t \end{cases} \tag{4}$$

where

t – denotes threshold.

The LTP code for the corresponding centered pixel C_P is computed by assigning binomial weight 2^P to (1) which can be given as (2)

$$LTP(R) = \sum_{p=0}^{P-1} 2^P s(C_P, N_P), \tag{5}$$

where

C_P – represents the gray scale value of centered pixel.

N_P – represents gray scale value of neighboring pixel present on a circular region of radius as R.

P – represents the number of neighbors.

p – represents the gray value of the center pixel and the gray value of the neighboring pixel in a circular region of radius as R $p = \{0, 1, 2, 3, \ldots, P-1\}$.

In this coding technique, local ternary patterns for a sub-band of finger knuckle surface are obtained through thresholding process as described above. The derived local ternary patterns are categorized into two LBPs viz., upper patterns and lower patterns.

The derived local ternary patterns are categorized into two complementary patterns viz., (i) S_P^{upper} (S_P^u) and S_P^{lower} (S_P^l) as two sign components (ii) M_P^{upper} (M_P^u) and M_P^{lower} (M_P^l) as two magnitude components which can be given by (6) and (7):

$$S_P^u = S(N_P - (C_P + t)), \quad S_P^l = S(N_P - (C_P + t)) \tag{6}$$

$$M_P^u = |N_P - (C_P + t)|, \quad M_P^l = |N_P - (C_P - t)| \tag{7}$$

Then, S_P^u and S_P^l are incorporated to build $CLTP\_S_P^u(R)$ and $CLTP\_S_P^l(R)$ respectively which is given in (8)–(11):

$$CLTP_{S^u(R)} = \sum_{p=0}^{p-1} 2^P S(N_P - (C_P + t)) \tag{8}$$

$$S_P^u = \begin{cases} 1, & N_P \geqslant C_P + t \\ 0, & Otherwise \end{cases} \tag{9}$$

$$CLTP_{s^l(R)} = \sum_{p=0}^{P-1} 2^P S(N_P - (C_P - t)) \tag{10}$$

$$S_P^l = \begin{cases} 1, & N_P < (C_P - t) \\ 0, & Otherwise \end{cases} \tag{11}$$

$CLTP_{S^u(R)}$ and $CLTP_{s^l(R)}$ are concatenated and given in (12):

$$CLTP_{S(R)} = \left[CLTP_{S^u(R)} + CLTP_{S^l(R)} \right] \tag{12}$$

Similarly, CLTP for two magnitude complementary patterns is derived as M_P^u and M_P^l, then the concatenated pattern is given as (13):

$$CLTP_{M(R)} = \left[CLTP_{M^u(R)} + CLTP_{M^l(R)} \right] \tag{13}$$

These two concatenated CLTP are combined into joint or hybrid distributions to derive the final complemented local ternary pattern which is given as (14)

$$CLTP = \left[CLTP_{S(R)} + CLTP_{M(R)} \right] \tag{14}$$

Matching between two knuckle images is performed by means of dissimilarity measuring framework of local ternary patterns. In this work, dissimilarity measure between two histograms of CLTP is derived by means of Chi-Square statistic. Let χ^2 of two histograms $H_1 = h_{1\ldots i}$ and $H_2 = k_{1\ldots i}$, where $i = 1, 2, 3\ldots B$ can be given as (15)

$$\chi^2(H_1, H_2) = \sum_{i=1}^{B} \frac{(h_i - k_i)^2}{h_i + k_i} \tag{15}$$

If the value of χ^2 is least value, then it shows the registered and input finger knuckle images matche correctly while larger value of χ^2 shows larger level of dissimilarity between the registered and input images.

6.2. 2D Log-Gabor filters (2DLGF)

Log Gabor filter overcomes the disadvantage Gabor filter [33] by removing DC components which could able to handle larger bandwidth of even more than one octane. Moreover, log-Gabor functions are more beneficial since it has symmetry on log frequency axis. At the same time, 1D log Gabor filter which is used in work [34], captures only the horizontal patterns of an knuckle image, whereas 2D log Gabor spatial approach could be able capture two dimensional characteristics of the knuckle patterns.

The 2D Gabor filter is a band pass filter that extracts two dimensional information such as frequency and orientation information using four parameters which are highly suitable for finger knuckle recognition. The 2D log Gabor spatial filters capture local texture features of finger knuckle image which is known as local phase information. The proximal and distal regions of knuckle images were subjected to 2D log Gabor filter [21] defined in (16),

$$G[f, \theta] = \exp\left(-\frac{(\log(f/f_0))^2}{2\sigma_f^2} \right) \exp\left(\frac{(\theta - \theta_0)^2}{2\sigma_\theta^2} \right) \tag{16}$$

where

$[f, \theta]$ – represents the normalized polar coordinates of the corresponding Cartesian coordinates (x, y) in a region of a knuckle image.

f_0 – represents the center frequency of the filter.

σ_f – represents radial bandwidth parameter for the filter.

θ_0 – represents center orientation frequency for the filter.

σ_θ – represents orientation bandwidth parameter for the filter.

in which, σ_f and σ_θ are constants that are used to derive the radial and angular bandwidth respectively which are derived by using (17) and (18)

$$B = 2\sqrt{2/\log 2}(\|\log(\sigma_f/f_\theta)\|) \tag{17}$$

$$B_\theta = 2\sigma_\theta\sqrt{2\log 2} \tag{18}$$

The filtered FBKS images are analyzed to derive local phase information similar to that detailed in [21] which can be given as projected image obtained by (19)

$$P_n(c,\theta) = F^{-1}[F(T(c,\theta)) \times G_n(f,\theta)], \quad \theta = \frac{\pi}{2}..\frac{3\pi}{2} \tag{19}$$

where F and F^{-1} denote Fourier and inverse Fourier transforms. $G_n(f,\theta)$ represents 2D log Gabor filters at scale n. Both even and odd symmetric responses of filters are represented as matching template.

The parameters were empirically obtained by means of gallery set of FBKS images. The parameter values were chosen according to the lower values of EER. The center frequency is taken as 46, the value of $\sigma_0 = 0.56$, the value of σ_f is taken same as the σ_0 and the value of $f_0^1 = 0.69$, $f_0^2 = 0.169$, $f_0^3 = 0.094$.

The matching is done by means of estimating the normalized Hamming distance between registered and input knuckle images which can be given in (20):

$$S_{M,N} = \frac{\sum_{x=1}^{I}\sum_{y=1}^{J}\{M_r(x,y) \oplus N_r(x,y) + M_i(x,y) \oplus N_i(x,y)\}}{2 \times I \times J}, \tag{20}$$

where M and N are the registered and Input knuckle images of size $I \times J$.

6.3. Fourier – Scale invariant feature transform

Scale invariant Feature Transform (SIFT) is one of the popular transform based texture analysis method proposed in [35] for extracting knuckle texture features. This SIFT method is also reported as one of the efficient method which produces lowest equal error rate in personal recognition. However, SIFT method extracts features based on the key point descriptor obtained through gradient information that cannot be implemented for distorted finger knuckle images. This limitation can be overwhelmed by extracting features based on the characteristics of the knuckle texture patterns. Hence, in the proposed method, initially Fourier transform is incorporated for characterizing the finger knuckle texture patterns since it has the property of addressing repeated structures/patterns of an image. Secondly, SIFT descriptor is applied to derive the key points to represent the feature information and finally, matching is done through the phase only correlation of derived features points. This Fourier SIFT (F-SIFT) mechanism is a robust method against distortions and deformations which has been proved using iris texture patterns in [36].

The scale space analysis of the captured knuckle image is performed in order to find the key points through the cascade filter approach. The Gaussian kernel $G(x, y, \sigma)$ implemented on a knuckle image to derive its scale space is given in (21),

$$L(x,y,\sigma) = G(x,y,\sigma) * K(x,y), \tag{21}$$

where

$K(x,y)$ – represents the captured finger knuckle image,
σ – represents the width of the Gaussian filter,

The difference in nearby scale space can be estimated by means of difference of Gaussian parameter which can be given as in (22)

$$D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma), \tag{22}$$

where
k – represents constant multiplication factor defined by nearby scales space values.

The key points are derived by means of maximum and minimum difference of Gaussian images as described in [36]. From the obtained key points the incorporation of phase information based on the Fourier transform to quantify the texture pattern of the finger knuckle surface. Each sub-band descriptor is obtained through (23)

$$\begin{aligned} K_i(M,N) &= \frac{1}{W^2}\sum_{n_1-(x-\frac{W}{2})}^{(x+\frac{W}{2})}\sum_{n_2-(x-\frac{W}{2})}^{(x+\frac{W}{2})} I(n_1,n_2)e^{-2\pi\left(\frac{n_1 M}{W}+\frac{n_2 N}{W}\right)} \\ &= A(M,N)e^{2\theta(M,N)} \end{aligned} \tag{23}$$

where
$W \times W$ – represents the size of the sub-band,
(x, y) – represents the key point centered at (x, y),
$\emptyset$ – represent direction,
$A(M, N)$ – represents the amplitude component for each sub-band,
$\theta(M,N)$ – represents the phase component for each sub – band.

The matching between the gallery and probe set of knuckle images is performed through Phase-Only Correlation (POC) functions in which ith sub-band of probe image is matched with jth sub-band of gallery image.

Let $A_i(M, N)$ and $\theta_i(M, N)$ represents the amplitude and phase components of Fourier transform derived from the ith sub-band. Similarly, $A_j(M, N)$ and $\theta_j(M, N)$ is the representation of the jth sub-band.

The cross phase spectrum among the two key points K_{pi} and K_{pj} is obtained through (24) and (25)

$$CPS_{ij}(M,N) = \frac{K_{pi}(M,N)\overline{K_{pj}(M,N)}}{|K_{pi}(M,N)K_{pj}(M,N)|} \tag{24}$$

$$CPS_{ij}(M,N) = e^{i\{\theta_i(M,N)-\theta_j(M,N)\}}, \tag{25}$$

where
$K_{pi}(M,N)$ – represents the complex conjugate.

The phase-only correlation is obtained by taking inverse Fourier transform for $CPS_{ij}(M, N)$ which can be given as (26)

$$POC_{ij}(n_1,n_2) = \frac{1}{W^2}\sum_{n_1-(x-\frac{W}{2})}^{(x+\frac{W}{2})}\sum_{n_2-(x-\frac{W}{2})}^{(x+\frac{W}{2})} CPS_{ij}(n_1,n_2)e^{-2\pi\left(\frac{n_1 M}{W}+\frac{n_2 N}{W}\right)} \tag{26}$$

The matching between two finger knuckle images (based on their key points) is performed by analyzing the derived POC function of their corresponding key points. If the two key points are derived from the similar finger knuckle texture pattern, then the POC function will result in a sharp peak value,

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whereas if the key points are from different texture, then the POC value decreases considerably. Further, the height of the peak is quantified and compared with the threshold (τ), if it is greater than a threshold then the considered key points are said to be similar. In the same manner, all other key points of the probe set knuckle image are matched for identifying an individual.

7. Integration of geometric and three local phase features

In this section, we discuss fusion process that combines matching scores obtained by means of angular geometric analysis and three texture feature extraction methods (CLTP, 2DLGF and F-SIFT) from all classes of FBKS regions to achieve better performance. Since, texture pattern exhibited by all the finger knuckle regions is found to be different, the matching scores obtained from these regions are combined to yield high accuracy equivalent to that of multi-modal biometric system. In this work, we employ three basic rules, viz., (i) sum of matching scores (SUS) (ii) weighted sum of matching scores (WSS) and (iii) multiplication of matching scores (MUL) for combining matching scores since these rules are computationally efficient. The combined matching score (C_M) obtained through SUS, WSS and MUL rule is given by (27), (28) and (29) respectively.

$$C_M = \sum_{j=1}^{n} D_{ij} \tag{27}$$

$$C_M = \prod_{j=1}^{n} D_{ij} \tag{28}$$

$$C_M = \sum_{j=1}^{n} W_i \times D_{ij}, \tag{29}$$

where

$$W_i = \frac{\frac{1}{\sum_{j=1}^{n}\left[\frac{1}{\mathrm{EER}_j}\right]}}{\mathrm{EER}_i}$$

In all the above equations, the D_{ij} represents matching score derived from the ith user using jth classifier. Here, the EER refers to equal error rate, a point at which false acceptance rate and false rejection rate become equal. The value of w_i is assigned highest value when the EER obtained for the subject i in a classifier is minimum.

8. Experimental analysis and results discussion

The performance of the proposed geometric and texture feature extraction methods is analyzed by conducting various experiments using a newly created biometric data on finger knuckle surface (FBKS-DB). This database consists of finger knuckle surface images captured from 150 subjects using the acquisition setup as detailed in Section 3. This finger knuckle database was collected from 80 males and 70 female subjects belonging to the age group of 18–40 years. The database was collected in three different sessions with a time interval of 5–6 weeks. In each session, three images of finger knuckle regions from four fingers viz., fore finger, middle finger, ring finger and little finger are captured for processing. Thus, 12 images are collected from each subject in one session. Hence, totally 36 images are collected from one subject in all the three sessions. Finally, the finger knuckle dataset comprises of $150 \times 36 = 5400$ images in which 600 (150×4) images were different finger knuckle regions.

In all the experiments conducted in this study, the images collected during the first session are taken as gallery set, whereas images collected during the second and third session are considered as probe set. The evaluation metrics taken for performance assessment of proposed finger knuckle recognition system are Genuine Acceptance Rate (GAR) and Equal Error Rate (EER). The GAR is derived by assessing the number of genuine matches toward the total number of matches performed by the system. Equal Error Rate is derived by assessing the number of false acceptances and false rejections. The point at which false acceptance rate and false rejection rate become equal derives the ERR of the system. In addition, the Decidability Threshold [37] which is defined as the normalized distance between genuine and imposter matching scores is given by (30)

$$DT = \frac{\mu_g - \mu_i}{\sqrt{\left(\sigma_g^2 + \sigma_i^2\right)/2}} \tag{30}$$

where μ_g and μ_i are the mean values of genuine and imposter matching scores respectively, σ_g and σ_i are the standard deviation values of genuine and imposter matching scores respectively. The number of false acceptances and its false rejection rates are obtained for all possible decidability threshold values and plotted as detection error tradeoff (DET) curve. The obtained DET curve reflects the overall accuracy of the proposed personal authentication system. Hence, in this paper the performance analysis of both AGAM and TFEM approaches is achieved by constructing DET curves.

Experiments are conducted in four different categories viz, Experiment 1: Performance of angular geometric features, Experiment 2: Performance of local phase features, Experiment 3. Performance of Integrated features and Experiment 4: Robustness of local texture features toward deformations. Experiment 5: Computational time analysis of proposed integrated features. Among these, Experiments 3 and 4 are also conducted using published database for entire finger back knuckle surface which is referred to as PolyU Contactless Finger Knuckle Images Dataset (PolyU-FBKS) [38]. This PolyU-FBKS is created by capturing the entire finger dorsal surface which contains the patterns generated by both proximal and distal phalangeal joints and it is referred as major and minor finger knuckle regions respectively. The dataset contains finger back knuckle images acquired from more than 500 people (both male and female) from Hong Kong PolyU university and IIT Delhi campus during the period of 2006–2013. The finger knuckle surface images are captured in a contactless (non-intrusive) manner by means of simple acquisition setup incorporated with hand held camera device. This dataset consists of 2515 of middle finger dorsal regions acquired from 503 subjects and stored in bitmap format.

8.1. Experiment 1 – Performance of angular geometric features

This experiment is conducted to ascertain the performance improvement achieved through angular geometric features of

FBKS. Initially, the experiments were conducted using each type (index, middle, ring and little finger) of finger knuckle images separately and then analyzed for combined performance. For each type of FBKS analysis, the gallery and probe set is considered to be 150 and 900 (150 × 6) respectively. The number of genuine and imposter matches are 5765 and 998,160 respectively. Table 1 depicts the experimental results based on equal error rate and its corresponding decidability index for various geometric approaches which has been exercised on all the four types of finger knuckle regions. Fig. 6(a) –(d) illustrates the DET curves derived based on the experiment results of various geometric approaches implemented on index (IF), middle (MF), ring (RF) and little (LF) finger back knuckle surface respectively.

From the experimental results, it is evident that for index, middle and ring finger knuckle regions the proposed AGAM approach performs much better than the existing FGFEM, KGFEM and DTFEM approaches. But, only for little finger knuckle regions, the performance is slightly degraded due to the unclear texture patterns exhibited by the distal surface of little finger dorsal surface. In average, the decrease in EER of each FBKS type is 29.13%, 31.73%, 30.76% and 22.45% respectively which clearly portrays the superiority of the proposed AGAM approach is due to the incorporation of angular geometric features.

In the combined analysis, all the four finger knuckle regions were used. Therefore, number of images taken for gallery and probe set is 600 (150 × 4) and 3600 (150 × 4 × 6) respectively. In this experiment, each probe set image has been compared with each gallery set images. The number of genuine and imposter matches obtained through this experimental analysis is 9783 and 12, 727, 86 respectively. The experimental results obtained through various combinations of finger knuckle regions with its performance according to three different score level fusion rules (SUS, WSS and MUL) are illustrated in Table 2. Table 2 results illustrates that combining matching scores of two or more finger knuckle regions using weighted sum rule (WSS) yields good results than the other score level fusion rules, since the angle oriented shape information is obtained from four finger knuckle regions are found to be independent and the weights are calculated for these independent sets. In addition, the experimental results in terms of equal error rate and its corresponding decidability indices for various geometric analysis methods are shown in Table 3. Fig. 7 depicts the DET plots combined performance of various geometric methods.

Further, each obtained score is multiplied by their weights and then combined to yield better results. Additionally, the results from Table 3 and Fig. 7 illustrate that the combined performance of the proposed AGAM approach yields better results in terms of lower error rate of 0.71% which is 28%, 29.63% and 30.28% drop when compared to FGFEM, KGFEM and DTFEM respectively. This decrease in error rate is possible since AGAM derives angular based shape oriented features.

8.2. Experiment 2 – Performance of local phase features

This experiment is conducted to prove that derived local features of finger knuckle surface can provide better performance. Initially, the experiment conducted separately with each FBKS regions and then finally combined performance of all the four FBKS regions has been analyzed. For separate FBKS analysis, number of gallery and probe set images were 150 and 600 respectively. The number of genuine and imposter matches were 9945 and 13, 647, 53 respectively. Table 4 depicts the equal error rate and its corresponding decidability indices for the three proposed local feature extraction approaches (CLTP, 2DLGF, F-SIFT) that has been implemented for four FBKS regions. Fig. 8(a) –(d) illustrates the DET curves derived based on the experiment results of proposed texture analysis method implemented on index, middle, ring and little finger back knuckle surface respectively.

From the experimental results, it is evident that for index, middle and ring finger knuckle regions the proposed FKTAM approaches such as CLTP, 2DLGF, F-SIFT produces lowest error rates since all the three local features produces finer representation by encoding more detailed information of the determined local region. But, for little finger knuckle regions, the error rate is slightly increased when compared to all other knuckle regions since the texture pattern area of proximal region is very small when compared to other fingers and also distal knuckle region posses unclear texture patterns.

For combined performance analysis, all the four fingers knuckle regions are utilized. Hence, 900 gallery images and 3600 probe set images. The number of genuine and imposter matches were 26,780 and 14, 727, 689 respectively. Table 5 shows the combined performance obtained by local texture feature extraction methods viz., CLTP, 2DLGF and F-SIFT respectively using three fusion methods (SUS, WSS and MUL). The tabulated results illustrates that the combined performance of four finger knuckle regions using WSS rule yields better performance than the other fusion rules. Similarly, combination of two or three finger knuckle regions also yields higher accuracy.

Table 6 and Fig. 9 illustrates the combined performance of the all classes of FBKS regions using three texture analysis methods. The experimental results show that the proposed CLTP approach produces lowest error rate of 0.49% since it quantifies the multi-scale texture appearances in terms of trits in an efficient way. The CLTP approach drops the error rate

Table 1 Performance of geometric analysis methods based on EER (%).

Feature extraction methods	Index finger knuckle		Middle finger knuckle		Ring finger knuckle		Little finger knuckle	
	EER (%)	DI	EER (%)	DI	EER (%)	DI	EER (%)	DI
FGFEM	3.67	4.6756	3.98	4.6756	4.12	4.6756	4.09	4.6756
KGFEM	3.14	4.7867	3.29	4.7867	4.09	4.7867	4.15	4.7867
DTFEM	2.89	4.9920	3.09	4.9920	3.89	4.9920	3.97	4.9920
AGAM	1.81	3.5461	1.86	3.5461	1.81	3.5461	2.23	3.5461

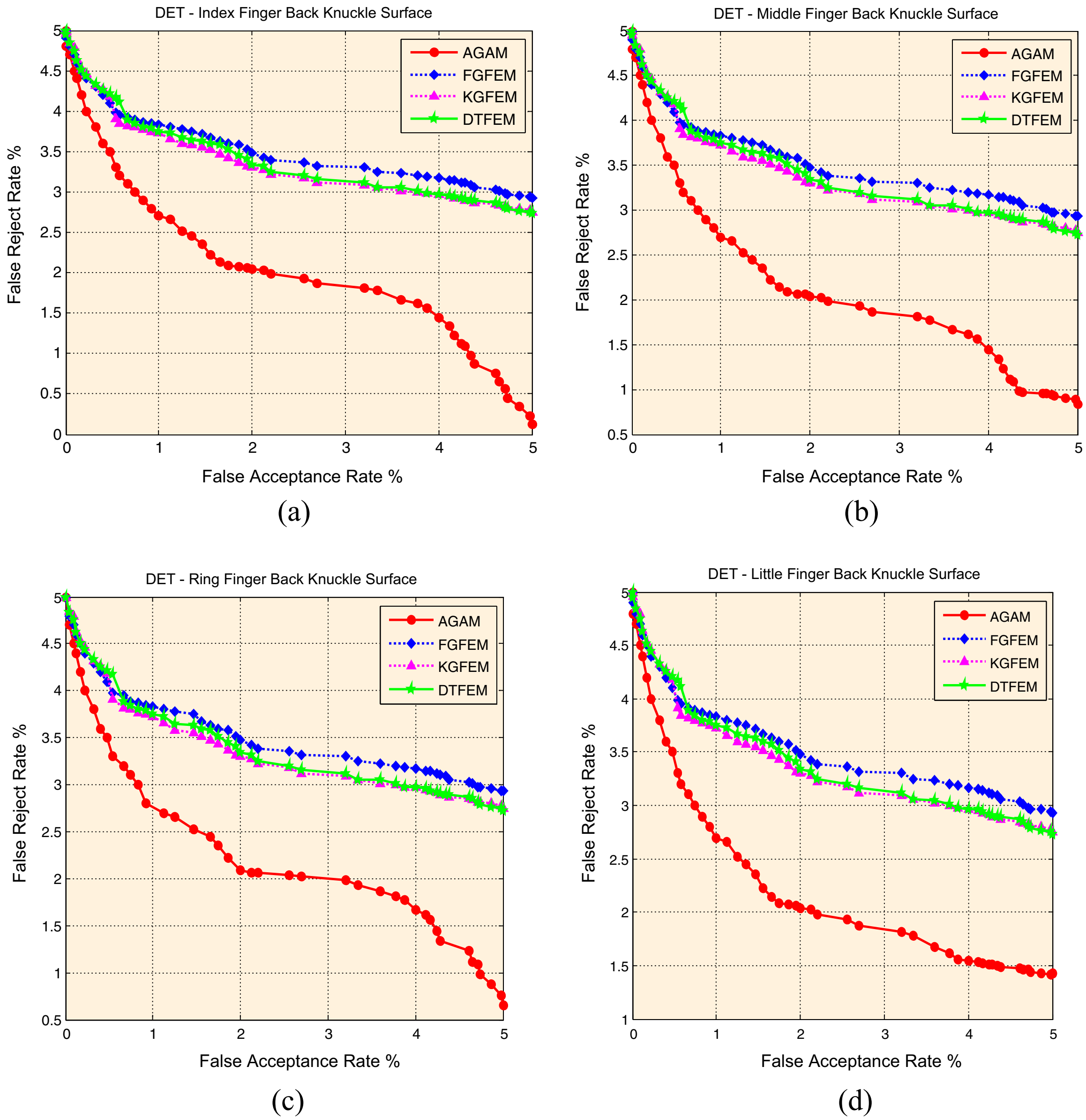

Figure 6 DET curves reflecting the performance analysis of geometric methods implemented on (a) index finger back knuckle surface, (b) middle finger back knuckle surface, (c) ring finger back knuckle surface and (d) little finger back knuckle surface.

by 32.96%, 33.45%, 37.56% when compared to the LBP, ILBP and LTP [28] (local binary pattern, Improved Local Binary Pattern, Local Ternary Pattern) respectively which are some of the state of art method that derives local texture features form finger knuckle surface.

Similarly, the results show that the proposed 2DLGF yields lower error rate of 0.36% since it exploits the local phase information of finger knuckle surface. This approach decreases the error rate by 22% when compared to the Gabor filter method [28] since, (i) log – Gabor filter have zero discrete cosine components which makes the filter to respond independent to the mean value of the signal, (ii) it has logarithmic value of size distribution of features in an image. However, the equal error rate obtained through Fourier SIFT method is 0.35% which is 23% and 19% lesser than that of SIFT and OE-SIFT [35] algorithms.

8.3. Experiment 3 – Performance of Integrated features (geometric and three local phase features)

This experiment is performed to project the superiority of the integrated features (geometric + three local texture features) based on score level fusion with separate analysis of features like, geometric and local texture features. The number of gallery and probe images is considered to be 600 and 3600 respectively. Therefore, the genuine and imposter matches were 9980 and 14, 234, 789 respectively. In this experiment, scores obtained through geometric and texture features are combined using three basic score level fusion rule viz., SUS, WSS and MUL and from the results it is obvious that the MUL rule were promising than the other two rules since independence of data representation is retained in this rule. Hence, for integrating geometric and texture features MUL rule of score level

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Table 2 Combined performance analysis of AGAM approach based on EER (%).

Fingers in fusion	AGAM (EER%)		
	SUS	MUL	WSS
Index + Middle FBKS	1.49	1.41	1.32
Index + Ring FBKS	1.50	1.43	1.30
Index + Little FBKS	1.54	1.46	1.35
Middle + Ring FBKS	1.49	1.42	1.39
Middle + Little FBKS	1.52	1.47	1.35
Ring + Little FBKS	1.58	1.45	1.32
IF + MF + RF	**1.18**	**1.14**	**1.07**
IF + MF + LF	1.38	1.34	1.27
IF + RF + LF	1.32	1.28	1.22
MF + RF + LF	1.38	1.27	1.19
All four finger knuckles	**0.92**	**0.89**	**0.81**

Bold values indicates superior performance exhibited under fusion.

Table 3 Comparative analysis of AGAM approach with existing geometrical methods based on EER (%).

Methods	EER (%)	DI	FRR (%)
FGFEM	1.987	5.4352	3.898
KGFEM	1.834	4.4828	3.782
DTFEM	1.732	3.3456	3.634
AGAM	**1.053**	**4.1217**	**1.787**

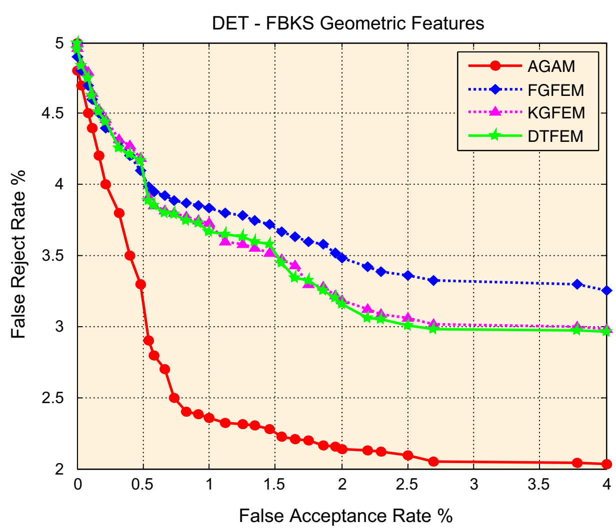

Figure 7 DET curves reflecting the comparative performance analysis of AGAM approach with existing geometric methods.

fusion were implemented. Table 7 illustrates the ERR values obtained from geometric, texture features and integration of geometric and texture features (using MUL rule).

Fig. 10 depicts DET curves derived from the experimental results from geometric features, local textures features and integration of geometric and texture features (using MUL rule). The experimental results suggests that the integration of geometric and three local texture features performs phenomenally better by producing lowest error rate of 0.19% which is 11% and 9% drop when compared to separate analysis of geometric and three texture features. Also, we can infer that integration of three local features at score level fusion using MUL rule yields the error rate of 0.22% which is highly remarkable, since the derived feature information is the integration of multi-scale texture representation (obtained through CLTP), local phase information (obtained from 2DLGF) and local orientation or local magnitude information (obtained through F-SIFT).

The proposed integrated feature extraction approach is compared with two state of art methods, (i) LGIC (local-global information combination) and (ii) LFI (three local feature integration) and in this comparative analysis, it has been found that the proposed approach of integrating geometric and three local texture features performs better by yielding the decreasing error rate of 16.12% and 19.75% respectively. The aforementioned comparative analysis process are also experimented with PolyU-FBKS (published database), yields 13.45% and 15.56% decrease in error rate respectively. This drop in error rate is achieved due to (i) incorporating angle oriented shape features as geometric features and (ii) combining three discriminate local texture features.

8.4. Experiment 4 – Robustness of local texture features toward deformations

This experiment is conducted to ascertain that the derived three local features and their integration are robust against deformed knuckle images. The deformations in finger knuckle images are very common in security applications since these applications incorporate peg-free imaging to enhance user acceptability and in addition, the deformations are also highly possible with forensics applications. The processing of deformed finger knuckle images will result in high intra-class variations which will lead to performance degradation by increasing the false rejection rate. Hence, it is necessary for an efficient feature extraction algorithm to be invariant toward deformations (scaling, rotational and transformational variances) of finger knuckle images.

For this experiment, the number of gallery images are taken as 100 (all finger knuckle types) and 600 images probe set were taken. Let the rotational angle $\varphi = [0, 1, 2, 3, 4, 5]$, similar to the values considered in paper [21]. Each FBKS image is rotated by the degree within a range of $[-\varphi, \varphi]$, in order to create virtual dataset with deformed finger knuckle images. These six virtual datasets were considered for validating the performances of local texture features and their integration for scaling, rotational and transformational invariant. The experimental results were derived in terms of equal error rate and shown in Table 8.

The tabulated results show that increase in the value of α increases the error rate of the authentication system. However, the local features derived by means of F-SIFT and 2DLGF shows only a meager variation in the error rate. At the same time, local features obtained through CLTP shows a slightly higher variation in error rate. In addition, the proposed integrated local features decrease the error rate and exhibits only smaller variations against each deformation which when implemented using FBKS-DB and PolyU-FBKS databases as shown in Tables 8 and 9 respectively.

The deformation considered in this paper is related to only small rotations. The proposed integrated features suffer from

Table 4 Performance of texture analysis methods based on EER (%).

Feature extraction methods	Index finger knuckle		Middle finger knuckle		Ring finger knuckle		Little finger knuckle	
	EER (%)	DI	EER (%)	DI	EER (%)	DI	EER (%)	DI
CLTP	0.927	2.3452	0.864	2.3452	0.789	2.3452	1.223	2.3452
2DLGF	0.863	3.4521	0.872	3.4521	0.865	3.4521	1.199	3.4521
F-SIFT	0.891	3.5461	0.823	3.5461	0.845	3.4521	1.209	3.5461

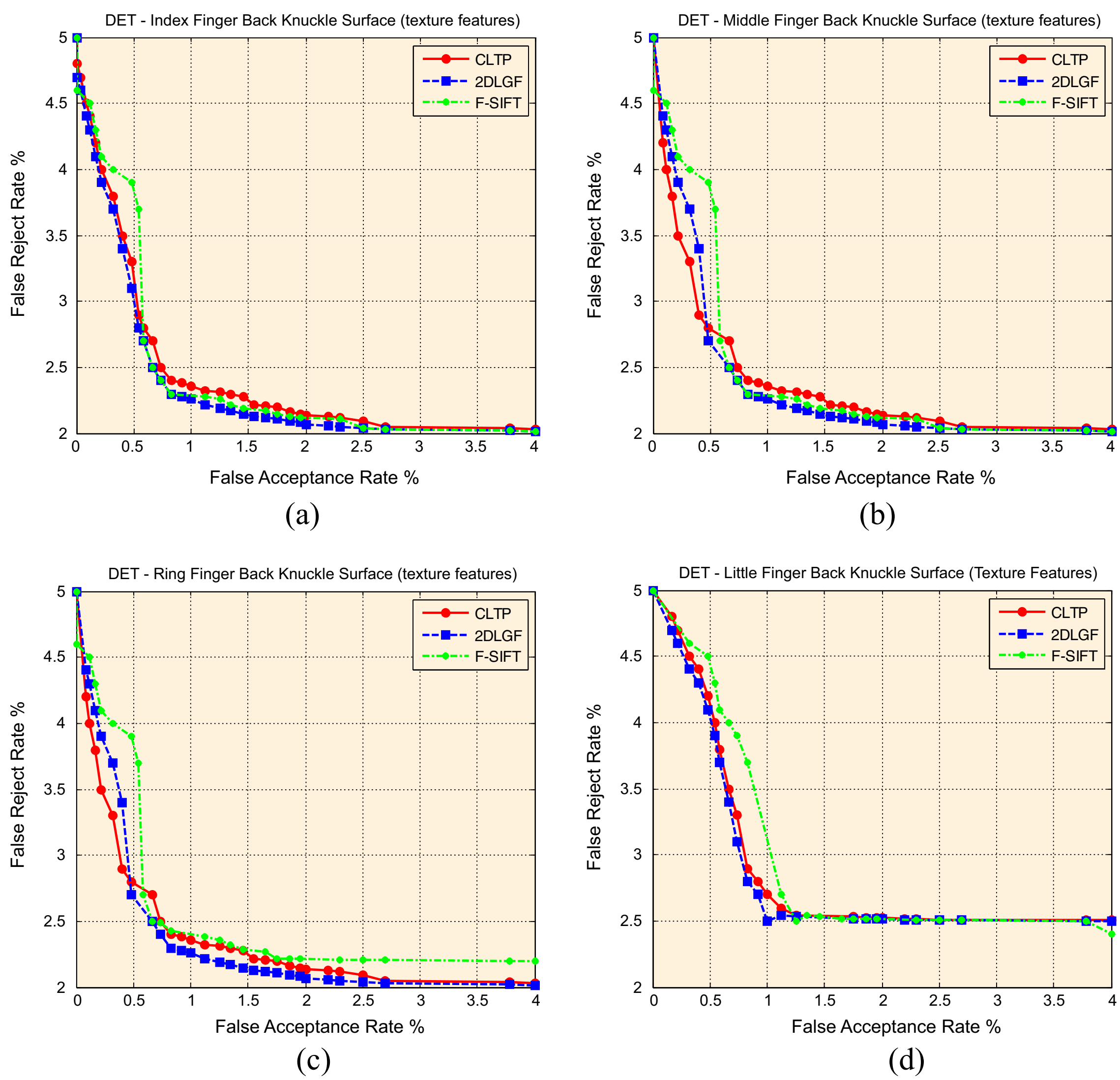

Figure 8 DET curves reflecting the performance analysis of texture analysis methods implemented on (a) index finger back knuckle surface, (b) middle finger back knuckle surface, (c) ring finger back knuckle surface and (d) little finger back knuckle surface.

more intra-class variations which may find its limitations in handling more non-reversible deformations exhibited by the finger knuckle surface.

8.5. Experiment 5 – Computational time analysis of proposed integrated features

The proposed integrated features approach is implemented in VC+ + and executed in the system configuration of Intel core i5 CPU with 5 GHz processor, 8 GB RAM and compiled using GNU compiler with the support of openCV library. The computational time taken for deriving integrated features using FBKS-DB are evaluated by calculating the time taken for deriving the geometric and three local texture features as illustrated in Table 10.

The evaluated computational time for the proposed integrated approach is compared with existing method [39] which is based on Gabor and band-limited phase-only correlation

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Table 5 Combined performance analysis of CLTP, 2DLGF and F-SIFT (TFEM approaches) based on EER (%).

Fingers in fusion	CLTP (EER%)			2DLGF (EER%)			F-SIFT (EER%)		
	SUS	MUL	WSS	SUS	MUL	WSS	SUS	MUL	WSS
Index + Middle FBKS	1.29	1.56	1.14	1.37	1.26	1.12	1.32	1.28	1.22
Index + Ring FBKS	1.28	1.43	1.09	1.35	1.27	1.19	1.22	1.13	1.05
Index + Little FBKS	1.37	1.46	1.22	1.29	1.22	1.16	1.50	1.43	1.30
Middle + Ring FBKS	1.35	1.67	1.29	1.39	1.29	1.17	1.34	1.24	1.17
Middle + Little FBKS	1.39	1.42	1.36	1.43	1.39	1.35	1.54	1.46	1.35
Ring + Little FBKS	1.46	1.39	1.27	1.37	1.23	1.13	1.49	1.42	1.39
IF + MF + RF	**1.09**	**1.04**	**0.89**	**0.98**	**0.97**	**0.88**	**0.88**	**0.91**	**0.86**
IF + MF + LF	1.23	1.12	0.98	1.12	0.97	0.88	1.22	1.27	1.15
IF + RF + LF	1.33	1.22	1.09	1.16	1.07	1.08	1.18	1.15	1.12
MF + RF + LF	1.47	1.56	1.12	1.28	1.17	1.13	1.18	1.24	1.17
All four finger knuckles	**0.74**	**0.77**	**0.59**	**0.71**	**0.67**	**0.43**	**0.69**	**0.63**	**0.51**

Table 6 Comparative analysis of TFEM approaches based on EER (%).

Methods	EER (%)	Decidability index (DI)	FRR (%)
CLTP	0.593	2.3478	1.980
2DLGF	0.426	3.6745	1.765
F-SIFT	0.493	3.7478	1.874

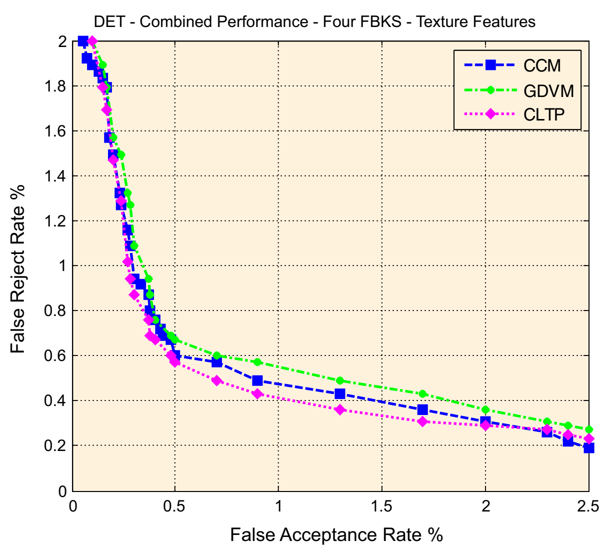

Figure 9 DET curves reflecting the comparative performance analysis of TFEM approaches.

(Gabor-BLPOC). The proposed approach derives integrated features for the entire finger back region by considering both the proximal and distal knuckle regions. Hence, the time taken for the preprocessing and ROI segmentation process is more when compared with the existing approach (because it considers only proximal region). The feature extraction step in the proposed integrated approach is also time consuming when compared with existing one since the proposed method derives geometric and three local texture features for both proximal and distal knuckle regions. However, the total computational time for deriving the entire integrated features and matching in our proposed personal authentication system is 1.074 seconds which is fast enough for its deployment in real time scenario.

Table 7 Comparative analysis of proposed approaches based on EER (%).

Methods	EER (%)	Decidability Index (DI)	FRR (%)
Angular geometric features (obtained through AGAM approach)	0.83	4.3478	0.867
Local texture features (combining three texture features obtained through TFEM approaches)	0.22	3.6745	0.765
Integration of angular geometric + three local texture features	0.19	3.7478	0.874

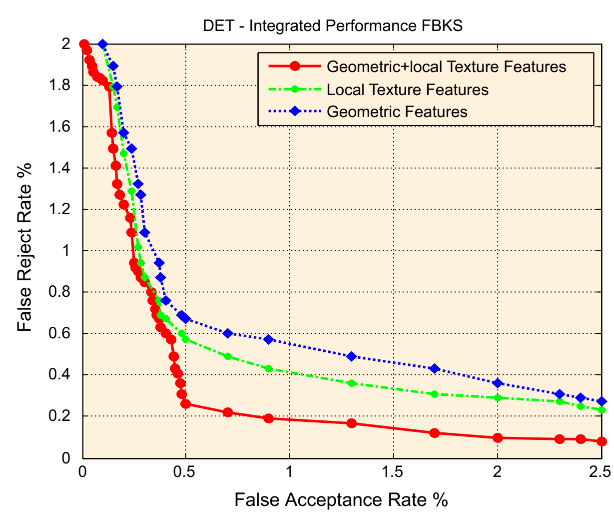

Figure 10 Performance of integrated approach (geometric + texture features).

Table 8 Performance analysis of local texture features and integrated features implemented on the deformed knuckle images from FBKS-DB (derived in terms of EER (%)).

Features	Performance based on EER (%)					
	$\varphi = 0$	$\varphi = 1$	$\varphi = 2$	$\varphi = 3$	$\varphi = 4$	$\varphi = 5$
Local features representing multi-scale texture patterns (obtained through CLTP method)	0.976	1.398	1.783	1.896	1.985	2.134
Local features representing phase information (obtained through 2DLGF)	0.873	1.347	1.673	1.890	1.967	2.098
Local features representing orientation or magnitude information (obtained through F-SIFT method)	0.923	1.234	1.563	1.673	1.765	1.897
Integrated representing the combination of geometric and three local texture features (obtained through integrated approach using score level fusion)	0.195	0.389	0.542	0.654	0.785	0.984

Table 9 Performance analysis of local texture features and integrated features Implemented on the deformed knuckle images from PolyU-FBKS (derived in terms of EER (%)).

Features	Performance based on EER (%)					
	$\varphi = 0$	$\varphi = 1$	$\varphi = 2$	$\varphi = 3$	$\varphi = 4$	$\varphi = 5$
Local features representing multi-scale texture patterns (obtained through CLTP method)	1.762	2.356	2.645	2.896	2.972	3.334
Local features representing phase information (obtained through 2DLGF)	1.872	2.332	2.341	2.890	3.045	3.998
Local features representing orientation or magnitude information (obtained through F-SIFT method)	1.923	2.221	2.783	2.873	2.965	3.297
Integrated representing the combination of geometric and three local texture features (obtained through integrated approach using score level fusion)	0.789	0.934	0.998	1.154	1.251	1.404

9. Conclusions

This paper has presented a novel geometric and texture feature integration approach for personal recognition based on finger back knuckle surface. For an input FBKS image, initially, geometric features were extracted by means of AGAM approach which incorporates triangulation method for deriving angular shape information. Secondly, for texture feature extraction, completed local ternary patterns, 2D log Gabor filter and Fourier-SIFT algorithms were implemented on the capture finger dorsal surface. Finally, the integration of geometric and texture features was done through score level fusion method. Extensive experiments were conducted and results show that, the integrated features produce lowest error rate, which is 27% (in average) lesser than the existing approaches. In addition, this integrated feature derived from FBKS is invariant to scaling, rotational and transformational changes of the finger knuckle image. Hence, we conclude that proposed integrated approach is an step advancement to the existing state-of-art algorithms for finger knuckle biometrics.

Table 10 Computational time analysis of integrated features.

Key processing steps	Time (ms)
Image acquisition and loading	90
Preprocessing and ROI Segmentation	232
Extraction and Matching of geometric features	1.2
Extraction and matching of three location features	752

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