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Research paper

Finger knuckle biometrics for personal identification using statistical and feature based approaches

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Abstract

Texture pattern observed on finger knuckle joint is called as Finger Knuckle Print (FKP). FKP can be extracted from inner side or back side of finger surface. FKP is extremely unique and makes the knuckle surface an emerging biometric modality. The FKP may be useful in user identification and has attracted attention of very few researchers. Our proposed work is based on FKP of back side of finger surface. The objective of this work is to investigate and develop a systematic approach for identifying a person using his/her finger knuckle print. Three different methodologies are employed for FKP identification process. Statistical approach (Principal Component Analysis) and feature based approaches (Gabor based coding scheme and Radon like features) are used to accomplish this objective. Nearest Mean Classification, Angular distance matching and Dynamic Time Warping methods are used for finding similarity between enrolled FKP and test FKP images. Performance comparison of proposed three methodologies is done by computing different performance measures such as FAR, FRR, EER, Di and CRR. Proposed methods are producing EER 0.2 using statistical approach and 0.03 using feature based approach.

Keywords: *Finger Knuckle Print (FKP); Principal Component Analysis (PCA); Radon Like Features (RLF); EER (Equal Error Rate); DI (Decidability Index); CRR (Correct Recognition Rate).*

1. Introduction

The skin design on the back side of finger joint is called as finger knuckle print (FKP) and it is highly rich in texture due to skin folds and creases. FKP can be used for person identification as it is easily accessible and provides stable features. In addition to this FKP image acquisition is contactless that is without touching any scanner surface. Unlike face FKP is also invariant to emotions and other behavioral aspects such as fatigue. Due to which FKP could be highly acceptability in the society [1]. The user acceptance for employing finger knuckle in human identification is expected to be very high as there is no personal information (such as life-line, study-line occurs in palm print) associated with finger knuckle creases. In addition to this another advantage of using FKP is its smaller surface area that reduces computational time and cost [2]. The usage of finger knuckle for personal identification has shown promising results and generated lot of interest in biometrics. However, the research efforts to investigate the utility of finger knuckle patterns for personal identification have been very limited. As a result; there is no known use of knuckle pattern in commercial or civilian applications [3].

2. Literature review

Kumar A and Ravikanth (2009) [1] [4] examines an innovative method for individual identification using FKP. They utilized texture pattern formed on the back side of finger knuckle joint for identifying a person. FKP is highly unique and proved as a distinct biometric modality. Authors applied subspace methods such as Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) .Geometrical features of finger are also extracted from the same image at the same time and integrated for user-identification person. Authors evaluated system based on EER and is was 1.39. Kumar A and Zhou Y (2009) [5] explore a novel methodology for effective personal identification using KnuckleCodes. The improved knuckle images are then used to produce KnuckleCodes using Localized Radon Transform that can competently distinguish random curved lines and creases. The likeness between two KnuckleCodes is computed using the minimum matching distance that uses variations resulting from translation and positioning of finger. Performance is then evaluated by computing EER (1.14) and CRR (98.6). Lin Zhang, Lei Zhang and David Zhang (2009) [6 - 9] built device to acquire the Finger Knuckle Print images, and then an effective algorithm is presented to process the acquired data .The local convex direction map of the FKP image is retrieved based on which a coordinate system is defined to align the images. Then Region of Interest (ROI) is cropped for feature extraction. Their evaluation parameter was EER (0.4) and DI (4.53). G S Badrinath, Nigam A and Gupta P (2011) [10] introduces Finger-knuckle-print based Recognition System by fusion of SIFT (Scale Invariant Feature Transform) and SURF (Speeded up Robust Features) Matching Scores. Nearest neighbour ratio method is used to match corresponding features of the enrolled and the test FKP image. After that weighted sum rule is used to fuse derived SIFT and SURF matching scores. EER of their system using SIFT and SURF is given as 1.9 and 0.317. Y. Hongyang, Y. Gongping, W. Zhuoyi [2015] [11] suggested a new Finger knuckle print extraction technique based on two stage center point detection. A center point initial detection is created to capture the center point initially. Then efficient center point positioned algorithm is proposed by them to locate center point more precisely in real time. To verify efficiency of proposed method they used Hong Kong Polytechnic University (PolyU) database. K. Mahesh and K. Premalatha [2014] [12] proposed FKP recognition by extracting local and global feature using Discrete Orthonormal Stockwell Transform [13 - 17]. In existing work all three evaluation parameters are not considered together whereas in proposed work of FKP identification, evaluation is based on all three parameters that is EER, CRR and DI.

3. Methodology

Feature extraction and matching methods used in pattern recognition task plays an important key role for any biometrics authentication system. Proposed research is focusing on implementing different methods that can be used for FKP feature extraction and matching. First method presented using Principal Component Analysis (PCA) and nearest mean classification. Second method presented using Gabor filter based coding scheme and angular distance matching. Third method presented here using Radon like Features (RLF) and Dynamic Time Warping (DTW).

3.1. FKP identification method i – principal component analysis and nearest mean classification

Work flow diagram using Method I as shown below.

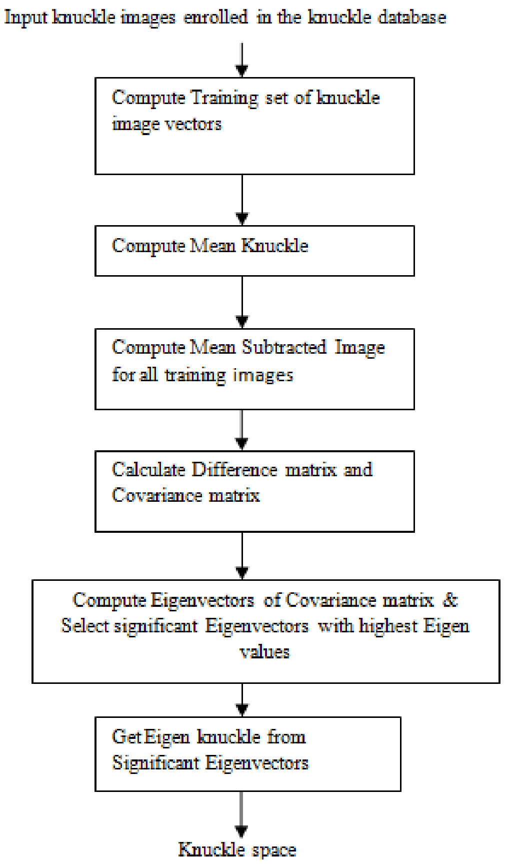

Fig. 1: Work Flow Diagram for Finding Knuckle Space.

Algorithm: Nearest Mean Classifier

Input:
M1, M2…..Mm (Mean of each class)
T (Input Knuckle to classify)
Output:
C (Class to which T is assigned)
D (Distance from class C)
Begin
Step 1: D=∞
Step 2: for i=1 to m do
If Euclidean distance (ci,t)<D then
C= i
D= Euclidean distance (ci,t)
End

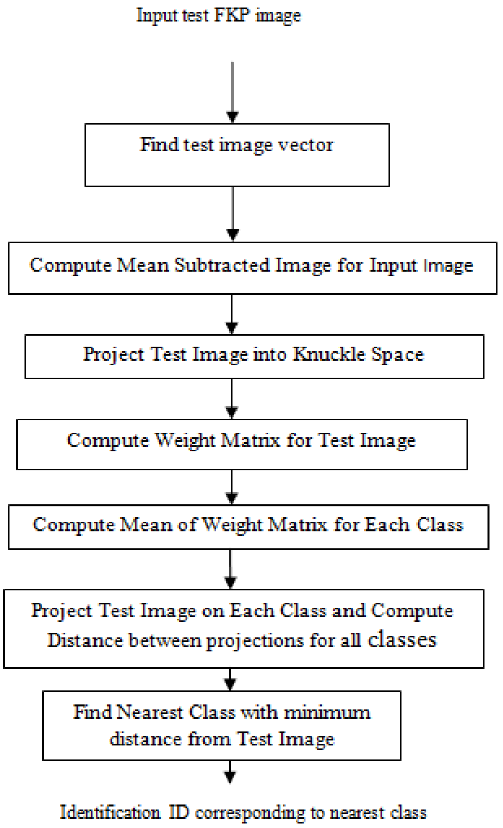

Fig. 2: Work Flow Diagram to Classify Knuckle Image Using NMC.

3.2. FKP identification method ii – Gabor filter based coding scheme & angular distance

Gabor filters have maintained their popularity for feature extraction in the applications of computer vision and image analysis. The reason that draws attention towards Gabor filter is the similarity of Gabor filter and the receptive fields of simple cells in the visual context. Gabor filter is more successful in many biometric applications such as face detection and recognition, iris recognition, fingerprint matching and palm recognition.
Proposed work is based on Gabor filter based coding scheme for extracting the image local orientation information. This information represents the FKP features. Angular distance matching method is then used to measure the similarity between two FKP images. Figure below presents the work flow diagram.

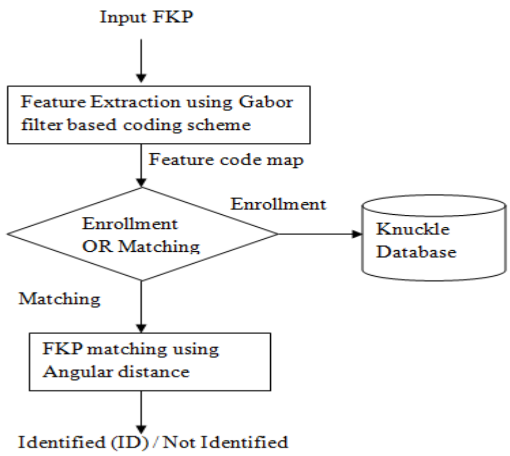

Fig. 3: Work Flow Diagram for FKP Identification Using Method II.

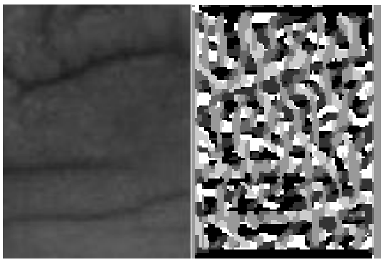

Fig. 4: Knuckle Images and Corresponding Image Code Map.

Algorithm: FKP image code map:

Input: Img (R×C)
Gf $_{real}$
Output: Code $_{Image}$
Algorithm:
Begin
For each pixel Img(x,y) do

$$Code_{Image(x,y)} = \arg\max j\{abs(Img(x,y) * Gf_{Real}\ (x, y, \theta_j))\}$$

Where $\theta_j = \frac{j\pi}{6}$, $j = 0$ to 5

End

Algorithm: matching angular distance:

```
Input:
        P (R×C matrix)
              Q (R×C matrix)
              PM (ones R×C matrix)
              PM (ones R×C matrix)
Output:
              Distance

Begin
 Step1: N = 0, D=0
 Step 2: for i=1 to R do
        for j=1 to C do
              if P(i,j)>=Q(i,j) then
              g = min(P(i,j)-Q(i,j),Q(i,j)-P(i,j)+6);
              else
        g = min(Q(i,j)-P(i,j),P(i,j)-Q(i,j)+6);
              end
 N = N+ Pm(i,j)*Qm(i,j)*g;
 D= D+ Pm(i,j)*Qm(i,j);
 end
 end

 Step 3: Distance =N/ (3*D);
End
```

3.3. FKP identification method iii- radon like features (RLF) and dynamic time warping (DTW)

This method is presenting Radon like feature extraction method for knuckle images. Further dynamic time warping is used to compare two knuckle images. Figure below shows the work flow for proposed method III.

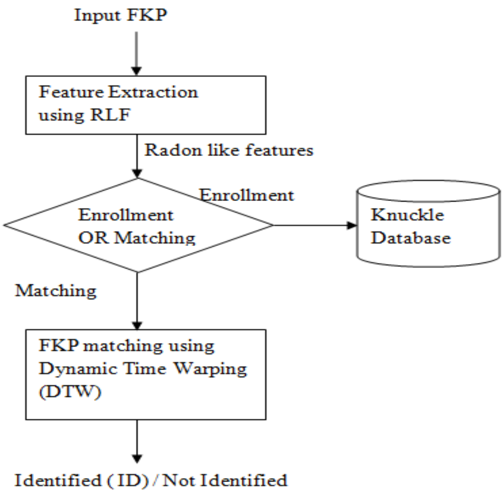

Fig. 5: Work Flow Diagram for FKP Identification Using Method III.

Method III is based on use of RLF for extracting knuckle features. This method found effective for enhancing lines and creases present on knuckle image. In proposed method thirty six lines are used to distribute desired information derived from pixel I(x,y) of an knuckle image . Set of principal points called knots along line l, are used to define line segments. (t_1,t_2……tn) represents set of principal points along line l. The value of Radon Like Feature at a point P along a line l between (x (ti) ,y(ti)) and (x (t $_{i+1}$) ,y (t $_{i+1}$)) is given by equation:

$$\psi(P, l, t_i, t_{i+1})[I(x,y)] = T(I, l(t)), \qquad t \in [t_i, t_{i+1}]$$

Where T is called extraction function. Each line has been associated with some direction. Here angle θ is used in association with each line where θ ϵ (θ, 2π) whose tangent gives its slop. In our method for edge enhancement, the principal points and the extraction function for Radon like features use the following transformation of the input image I(x,y)

$$R(x,y) = Max \Delta\, G(\sigma, \phi) * I(x,y)$$

Where σ *and* ϕ are scale and orientation of edge enhancing Gaussian second derivative (GCD) filter $\Delta\, G(\sigma, \phi)$, * denotes convolution. Principal points for Radon like features are defined using an edge map of R(x,y) and the extraction function T is given as

$$T(I, l(t)) = \frac{\int_{t_i}^{t_{i+1}} R(l(t))\, \partial t}{\|l(t_{i+1}) - l(t_i)\|2}, t \in [t_i, t_{i+1}]$$

Here l is a line along which features are obtained. Extraction function T assigns all the pixels between the principal points t_i *and* t_{i+1} along line l. The transformation function R(x, y) captures the response of the most dominant GSD filter at each pixel, across different values of σ *and* ϕ.

RLF is proposed to restructure the statistical input image in the dense feature descriptors and to improve the folds/lines occur in knuckle image. Enhanced knuckle image using Radon like Features is as shown in figure 5. It has been observed that edges are more noticeable as compared to original image.

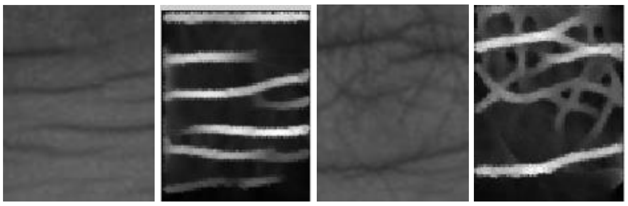

Fig. 5: Knukle Images and Corresponding Enhanced Knuckle Images Using RLF.

FKP Matching using Dynamic Time Warping
Let X and Y represent two FKP image then DTW-distance dist(X, Y) between two FKP.

$$X = (x_1, x_2, \ldots \ldots \ldots, x_M)$$

$$Y = (y_1, y_2, \ldots \ldots \ldots, y_N)$$

A matrix D of size M × N is constructed, where each entry D (i, j) where ($1 \le i \le M$, $1 \le j \le N$) is the cost of aligning the subsequences X1: i and Y1: j .To calculate the DTW distance D(X, Y), we can first construct an M×N matrix. Then, we find a path in the matrix which starts from cell (1:1) to cell (M: N) so that the average cumulative cost along the path can be reduced. Path indicates the optimal alignment.

Algorithm: Dynamic Time Warping

Input:
$X = (x_1, x_2, \ldots \ldots \ldots, x_M)$

$Y = (y_1, y_2, \ldots \ldots \ldots, y_N)$
W Window parameter
Output:
D DTW matrix
Distance DTW_distance

Begin
Step 1: Adapt window size
W= Maximum(W, abs(M – N))
Step 2:
for i= 1 to M+1 do
for j=1 to N+1 do
D(i ,j) = ∞
Step 3:
D(1,1)=0
Step 4:
for i=1 to M do
for j=Maximum (i-W,1) to Minimum (i+W,N) do

$$D(i,j) = min \begin{Bmatrix} D(i,j-1) \\ D(i-1,j) \\ D(i-1,j-1) \end{Bmatrix} + d(x_i, y_j)$$

Step 5: Distance =D(M+1 ,N+1)
End

Proposed work has been tested using IIT Delhi finger knuckle image database. Database consists of knuckle images obtained from more than 150 users. All the knuckle images are in the bitmap (*.bmp) format. All FKP samples in the database are of age group sixteen to fifty five years. Database contains 790 knuckle images, five images of knuckle of one person. Each image is numbered indicating user identification number. The resolution of image is 80×100 pixels. The entire database is made available for research.

4. Performance comparison

All three methods are compared based on performance metrics of biometric system. Figure shows the ROC curve comparison for proposed three methods. It has been observed that ROC curve of method II and method III is producing reduced EER as compared to method I. Performance of FKP identification methods can be compared based on EER, Decidability Index (Di) and Correct Recognition Rate. Decidability Index Di is another measure which assesses the overall quality of similarity measurement. Di is the ratio of the difference between genuine and impostor distribution means over the combined measure of their standard deviations. Di measures the amount of overlap between the matching score distributions. A smaller Di value signifies a larger overlap i.e. value of Di is expected to be maximum for better performance of the FKP identification. Di computation is done as shown in table. It has been observed from experiment that similarity measurement technique of method II and method III is producing promising results. Correct Recognition Rate (CRR) for genuine persons is also computed. CRR = (M / N) ×100 where M denotes the number of correct recognitions of FKP images and N is the total number of FKP images in the testing set. Table shows comparison of EER and CRR of our methods with other FKP related work.
From the experiment it has been observed that method II and method III is producing better results as compared to method I. From the comparison of ROC curves shown in figure 6.5 these two methods are producing reduced EER i.e. for method II EER is 0.03 and for method III EER is 0.17 whereas for method I EER is 0.20 (Refer table 1). Similarly if we compare decidability index Di for these three methods, it is maximum for method II (Di=3.427) and minimum for method I (Di=1.537) as shown in table 1. Detailed Di calculations are as shown in the table 1 . CRR is highest for method II (99.4%) whereas CRR of method I and method III is 95.6 & 98.2 respectively.

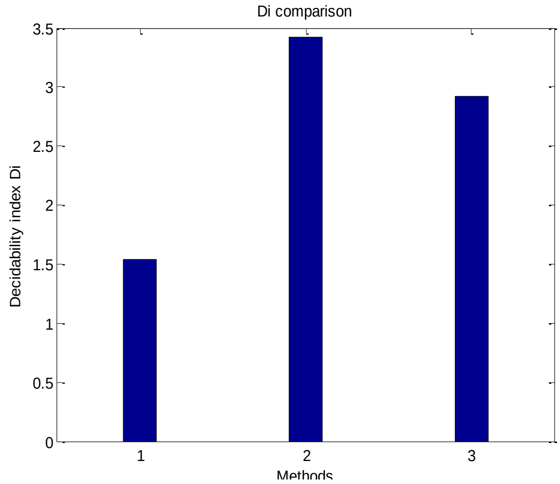

Fig. 6: Decidability Index (Di) Comparison.

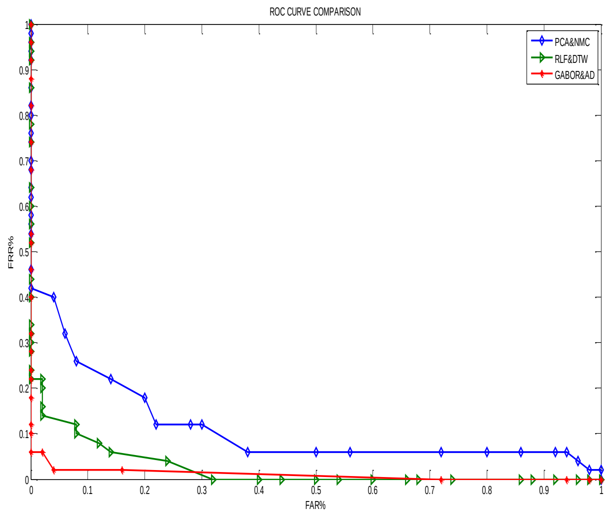

Fig. 7: ROC Curve Comparison.

Table 1: EER and Di of Proposed Methods

Method	EER	Decidability Index(Di)
Method I: PCA & Nearest mean classifier	0.2 0	1.537
Method II: Gabor coding &Angular distance	0.03	3.427
Method III: Radon like features & DTW	0.17	2.920

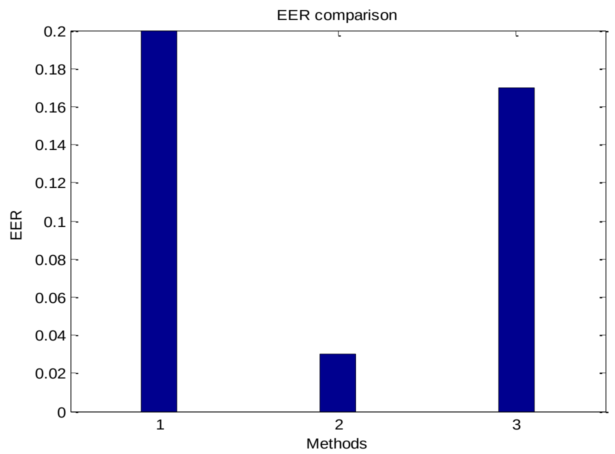

Fig. 8: EER Comparison.

Performance of our proposed work is also compared with the work of other researchers as shown in the table 2. Here we have compared performance measures EER, CRR and Di as shown in the table. As per the observation method III is producing optimal results.

Table 2: Comparison with Other FKP Related Work

Work done by Author	EER%	CRR%	Di
Woodland & Flynn	-	91%	-
Ribaric	0.76	-	-
Ajay Kumar Y. Zhou	1.14	98.6	-
Ajay Kumar Ch. Ravikanth	1.39	-	2.35
Lin Zhang LeiZhang DavidZhang HailongZhu	0.402	-	4.5356
Shoichiro Ayoma	0.556	-	-
Zhao Rui	-	96.62%	-
Badrinath Nigam	1.9 (SHIFT) 0.317(SURF)	99.9 99.1	-
Lin Zhang LeiZhang DavidZhang ZhenhuaGuo (2012)	1.274	-	4.3221
Our proposed work	Method I : 0.2 0 MethodII:0.03 Method III : 0.17	Method I : 95.6 Method II : 99.4 Method III : 98.2	Method I :1.537 MethodII :3.426 MethodIII : 2.920

As per the results discussed above it has been observed that our proposed methods are producing improved performance measures as compared to the other FKP related work.

5. Conclusion and future scope

In this work three different methods have been implemented for FKP feature extraction and matching. Principal Component Analysis (PCA), a statistical method, has been used to find Eigen knuckle space. Nearest mean classification is then used for the classification of FKP image. Secondly Gabor based coding scheme is also used for finding orientation knuckle features. Angular distance is then computed to find match between two FKP images namely enrolled FKP and test FKP images. Third method that we have used for identifying FKP is Radon like Features (RLF) and Dynamic Time Warping (DTW). Performance is measured by computing FAR, FRR and CRR. The number of false acceptance and false rejections are determined for different threshold values. Our proposed methods are producing improved performance measures as compared to the other FKP related work. Finger knuckle print has great potential to become promising biometric identifier. This work has many possibilities to explore the use of FKP based identification. Several directions could extend the current work and improve the efficiency and robustness of FKP identification. Performance of proposed methods is tested using FKP database of Indian people. FKP image database from other nation’s especially western countries needs further investigation. This work can also be incorporated to design multimodal biometric identifier.

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