A Hough Transform Based Feature Extraction Algorithm for Finger Knuckle Biometric Recognition System

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Abstract. Finger Knuckle Print is an emerging biometric trait to recognize one's identity. In this paper, we have developed a novel method for finger knuckle feature extraction and its representation using Hough transform. Hough transform plays a significant role in locating features like lines, curves etc., present in the digital images by quantifying its collinear points. This paper formulates the Elliptical Hough Transform for feature extraction from the captured digital image of finger knuckle print (FKP). The primary pixel points present in the texture patterns of FKP are transformed into a five dimensional parametric space defined by the parametric representation in order to describe ellipse. The discrete coordinate of the five dimensional coordinate spaces along with its rotational angle are determined and characterized as the parameters of elliptical representation. These parametric representations are the unique feature information obtained from the captured FKP images. Further, this feature information can be used for matching various FKP images in order to identify the individuals. Extensive experimental analysis was carried out to evaluate the performance of the proposed system in terms of accuracy. The obtained results shows the lowest error rate of EER = 0.78%, which is found to be remarkable when compared to the results of existing systems presented in the literature.

1 Introduction

Finger knuckle print of a person has inherent structure patterns present in the outer surface of the finger back region which is found to be highly unique and stable birth feature (invariant throughout the lifetime). These patterns have greater potentiality towards the unique identification of individuals which in turn contributes a high precision and rapid personal authentication system [1].

The various other hand based biometric modalities are fingerprints, palmprints, finger geometry, hand geometry and hand vein structures etc., Fingerprints have greater vulnerability towards tapping of finger patterns when it is left on the surface of the image acquiring device. On the other hand, the feature information extracted from finger geometry and hand geometry are found to have less discriminatory power when size of the data sets grows exponentially [2]. In palm prints, the region of interest captured for feature extraction is large in size which may result in computational overhead. The hand vein structures biometric modality has the main drawback of complex capturing system to conquer the vein patterns of the hand dorsum surface.

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Unlike fingerprints, finger knuckle prints are very difficult to scrap because it is captured by means of contact less capturing devices and patterns captured are present in the inner surface of the finger knuckle. Moreover, the presence of phalangeal joint in the finger knuckle surface creates flexion shrinks which has rich texture patterns like lines, creases and wrinkles and size of the captured finger knuckle print is very small when compared to palm prints, which reduces the computational overhead.

In general, the recognition methods for finger knuckle print matching are categorized into two broad categories viz., Geometric based methods and Texture based methods [3]. In texture analysis methods, the feature information is extracted by means of analyzing the spatial variations present in the image. In this analysis, the mathematical models are used to characterize spatial variation in terms of feature information. The spatial quantifiers of an image can be derived by analyzing the different spectral values that is regularly repeated in a region of large spectral scale. Texture analysis on the digital image results in a quantification of the image the texture properties.

Kumar and Ravikanth [4] were the first to explore texture analysis method for finger knuckle biometrics. In their work, the feature information of captured finger knuckle print is extracted by means of statistical algorithms viz, principal component analysis, linear discriminant analysis and Independent component analysis. Further, Zhang *et al.* [5] derives a band limited phase only correlation method (BPLOC) for matching finger knuckle prints based on texture analysis. Linlin shen *et al.* [6] used two dimensional Gabor filters to extract feature information from the finger knuckle print image texture and uses hamming distance metric to identify the similarities and the differences between the reference and input images of finger knuckle print. Furthermore, Chao lan *et al.* [7] proposes a new model based texture analysis methods known as complex locality preserving projection approach for discriminating the finger knuckle surface images. Lin Zhang *et al.* [8] used ridgelet transform method to extract the feature information from the captured FKP images. A.Merounica *et al.*, [9] have shown the implementation of Fourier transform functions for deriving the feature information from the finger knuckle region and palm region.

From the study conducted, it has been found that texture methods provides high accuracy rate when the captured image is of high quality images. But, in the case of any missing information in the input image and also in the case of low quality images like noisy images, these methods fail to work. This paper addresses this problem by proposing new methodology for feature extraction from finger knuckle print based on Elliptical Hough Transform. This feature extraction process is robust towards missing information and well tolerant to noise when the FKP images are captured partially and by using low quality sensors respectively.

2 The Proposed System Design

The following Fig.1 illustrates the design of the proposed biometric recognition system based on finger knuckle print. The proposed biometric system gets the images of

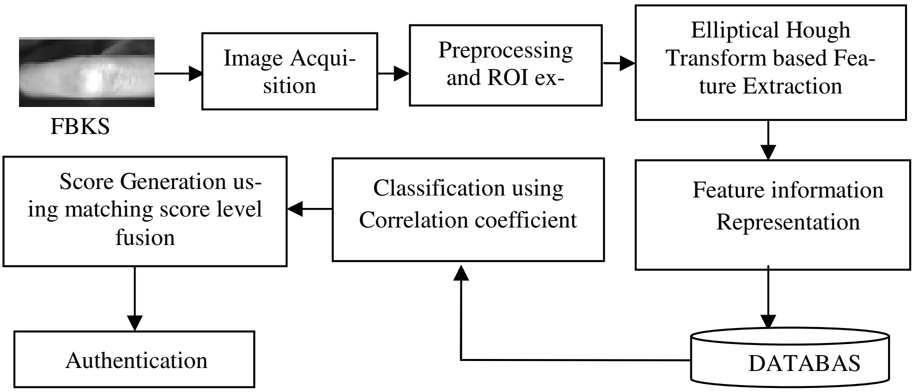

Fig. 1. Block diagram of proposed biometric authentication system based on finger knuckle print

right index finger knuckle, left index finger knuckle, right middle finger knuckle and left middle finger knuckle are given as input to the proposed model.

Initially, preprocessing and extraction of region of interest of the finger knuckle print is done based on edge detection method. Secondly, Elliptical Hough Transform based feature extraction process is done to derive the feature information from the finger knuckle print. Thirdly, the extracted feature information is represented to form the feature vector. This vector information is passed to the matching module which implemented using correlation coefficient. Finally, matching scores generated from different fingers are fused based on matching score level fusion to make the final decision on identification.

2.1 Preprocessing and ROI Extraction

The preprocessing and ROI extraction is done on the captured FKP in order to extract a portion of the image which is rich in texture patterns. These processes enable to extract highly discriminative feature information from the captured FKP image even though it varies according to their scaling and rotational characteristics. The preprocessing of the captured FKP image is done by incorporating the coordinate system [10]. This is achieved by defining the x- axis and y-axis for the captured image. The base line of the finger is taken as x-axis. The y-axis for the knuckle patterns in the finger is defined by means of convex curves determined from the edge record of the canny edge detection algorithm [11]. The curvature convexities of the obtained convex curves are determined for finger knuckle patterns. The Y axis of the finger knuckle print is derived by means of the curvature complexity which is nearly equal to zero at the center point. By this method, ROI is extracted from the FKP which of 110x180 pixel size.

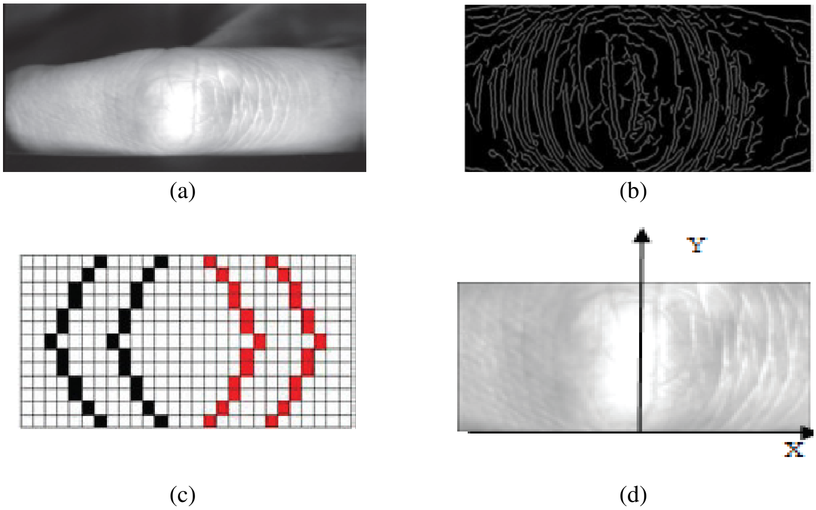

Fig. 2. (a) Captured finger knuckle print,(**b**) FKP image subjected to canny edge detection algorithm,(**c**) Convex Curves of FKP image,(d) Coordinated system for the FKP image

The above Fig. 2 (a), (b),(c), and (d) illustrates the captured finger knuckle print, edge image of the FKP detected using canny edge detection algorithm, convex curves detected from FKP image and coordinated system constructed for FKP image.

2.2 Elliptical Hough Transform Based Feature Extraction Method

Elliptical Hough Transform (EHT) [12] is used to isolate an elliptical structure from the knuckle part based on the primary pixel points obtained from the FKP image patterns. An elliptical structure posses a unique property which states that, the summation of distance obtained from the every point on the curved line to the two specific points (termed as foci points) located horizontally inside the curved line remains constant. From the FKP image, the foci points and a point on a curved line can be derived from the convex curves obtained through the preprocessing of the captured image. The following figure 3 shows the convex curves representing the foci points and base points on the curve. The convex curve obtained through preprocessing of the FKP, curves both left wards and rightwards from the phalangeal joint point. While preprocessing any number of curves are obtained according to the patterns of the captured finger knuckle print. The obtained curves can be classified as innermost curve and outer most curves of finger knuckle print. From this, the edge points of the innermost curve on either side of the phalangeal joint is considered as foci points and the base point of the outer most right side convex curve is considered as the point on the curved line. Here, the foci points are $(f_{x1}, f_{y1}), (f_{x2}, f_{y2})$ and the base points on the curves termed as(b_x, b_y).

In Cartesian coordinates the elliptical structure can be using the foci points and curve base points using the following Eq. 1,

$$\mathbf{S_d} = \sqrt{(\mathbf{b_x} - \mathbf{f_{x1}})^2 + (\mathbf{b_y} - \mathbf{f_{y1}})^2} + \sqrt{(\mathbf{b_x} - \mathbf{f_{x2}})^2 + (\mathbf{b_y} - \mathbf{f_{y2}})^2} \quad (1)$$

Where S_d is the sum of the distances from the two foci points to the base point of the curve.

The set of curve points can be defined by the relation shown in Eq. 2.

$$f(f_{x1}, f_{y1}, f_{x2}, f_{y2}, S_d), (b_x, b_y) = \sqrt{(\boldsymbol{b_x} - \boldsymbol{f_{x1}})^2 + (\boldsymbol{b_y} - \boldsymbol{f_{y1}})^2} + \sqrt{(\boldsymbol{b_x} - \boldsymbol{f_{x2}})^2 + (\boldsymbol{b_y} - \boldsymbol{f_{y2}})^2} \quad (2)$$

The set of curve points with the forms the ellipse using the curve tracing algorithm [15] , with following Eq. 3.

$$f(f_{x1}, f_{y1}, f_{x2}, f_{y2}, S_d), (b_x, b_y) = \sqrt{(\boldsymbol{b_x} - \boldsymbol{f_{x1}})^2 + (\boldsymbol{b_y} - \boldsymbol{f_{y1}})^2} + \sqrt{(\boldsymbol{b_x} - \boldsymbol{f_{x2}})^2 + (\boldsymbol{b_y} - \boldsymbol{f_{y2}})^2} - \boldsymbol{S_d} = \mathbf{0} \quad (3)$$

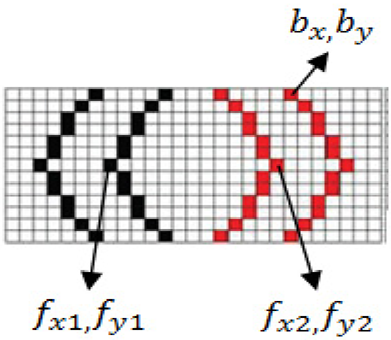

Fig. 3. Representation of knuckle foci points and base points

Hence the knuckle pixel points are identified from the pattern generated from the captured finger knuckle prints, which are transformed in to a parametric representation to derive in the form of elliptical structure. The knuckle feature information can be obtained by analyzing the elliptical structure.

2.3 Feature Information Representation

The knuckle feature information is obtained by examining the elliptical structure derived from the finger knuckle patterns. The feature vector represents the parameters of the knuckle elliptical structure which can be derived from the following equations.

The distance from the center to the focus point defined as knuckle foci distance K_f and given by Eq. 4.

$$K_f = \frac{\sqrt{(b_x - f_{x1})^2 + (b_y - f_{y1})^2}}{2} \tag{4}$$

The primary and secondary axes of the knuckle elliptical structure, which can be defined as primary knuckle axis (K_p) and secondary knuckle axis (K_s),are given by Eq. 5 and Eq. 6.

$$K_p = \frac{S_d}{2} \tag{5}$$

$$K_s = \sqrt{\left(\frac{S_d}{2}\right) - {K_f}^2} \tag{6}$$

Further, knuckle base point angle (K_a), can be derived from the knuckle elliptical structure as given by Eq. 7.

$$K_a = \tan^{-1}\left(\frac{f_{y2} - f_{y1}}{f_{x2} - f_{x1}}\right) \tag{7}$$

The obtained finger knuckle feature information is stored in the vector named as $V_{ref} and V_{inp}$, V_{ref} represents the vector obtained from the registered finger knuckle image and V_{inp} represents the vector obtained from the input image of the finger knuckle image.

2.4 Classification

The feature information from the finger knuckle print image were derived for four different fingers belonging to the same individual and stored in the corresponding feature vector. The matching process of different finger knuckle prints is done by means of finding the correlation between reference and input vectors. The derivation of correlation coefficient [13] for the classification process is done by means of the following Eq.8.

$$\rho = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \tag{8}$$

where $x \text{ and } y$ are values taken from reference and input vectors respectively.

If the value of ρ is close to 1, then high degree of similarity is identified, when the value of ρ diminishes to 0 indicates the dissimilarity.

2.5 Matching Score Level Fusion

Matching Score level fusion scheme is adopted to consolidate the matching scores produced by the knuckle surfaces of the four different fingers [14]. In the Matching score level, different rules can be used to combine scores obtained by from each of the finger knuckle. In this paper, sum rule is used. In the sum rule, say that $S_1, S_2, S_3, and\ S_4$ represent score values obtained from finger knuckle surface of left index finger, right index finger, left middle finger and right middle finger respectively. The final score S_f is computed using the following Eq. 9.

$$\boldsymbol{S_f = S_1 + S_2 + S_3 + S_4} \tag{9}$$

From the obtained final score the authentication decision is taken.

3 Experimental Analysis and Results Discussion

The evaluation of the finger knuckle biometric recognition system based on Hough transform is done by using PolyU database [15]. In this, finger knuckle print is captured using automated low cost contactless method using low resolution camera and in peg free environment. The knuckle images were collected from 165 persons. Extensive experiments were conducted and performance analysis was done based on the parameters viz., genuine acceptance rate and equal error rate.

Table 1. Performance of the Proposed System based on Genuine Acceptance Rate

Finger Knuckle Print	**Genuine Acceptance Rate %**		
	FAR = 0.5%	**FAR=1%**	**FAR=2%**
Left Index (LI)	78.34	84.78	88.26
Left Middle (LM)	79.89	85.9	90.27
Right Index (RI)	77.69	84.31	89.52
Right Middle (RM)	79.8	85.79	92.98
LI +LM	81.56	87.62	90.75
LI+RI	82.9	88.78	93.25
LI+RM	80.67	89.45	91.56
LM+RI	81.45	88.6	91.98
LM+RM	82.49	89.98	92.01
RM+RI	80.69	87.89	92.78
LI + RI+RM	83.89	92.56	93.56
LI+LM+RI	84.54	93.78	94.79
LI+LM+RM	83.76	94.89	94.68
RI+RM+LM	85.78	95.34	95.85
All the four fingers	90.65	95.98	97.62

The genuine acceptance rate is computed by manipulating the number of genuine matches and imposter matches corresponding to the total number of matches done with the system. Equal error rate is a point at which false acceptance rate and false rejection rate becomes equal. The above shown Table 1 illustrates the values of the genuine acceptance for the different combination of fusion.

From the above tabulated results, it is obvious that the finger knuckle print can be considered as one of the reliable biometric identifier. The following graphical illustration in Fig.4 depicts the some of the tabulated results. From the results obtained, it is clear that the accuracy of the system is considerably better when the single sample of finger knuckle surface is used. Further, the accuracy gets increases as when fusion of two, three finger knuckle regions was done. The best part of the accuracy can be accomplished by fusing the entire four fingers knuckle regions.

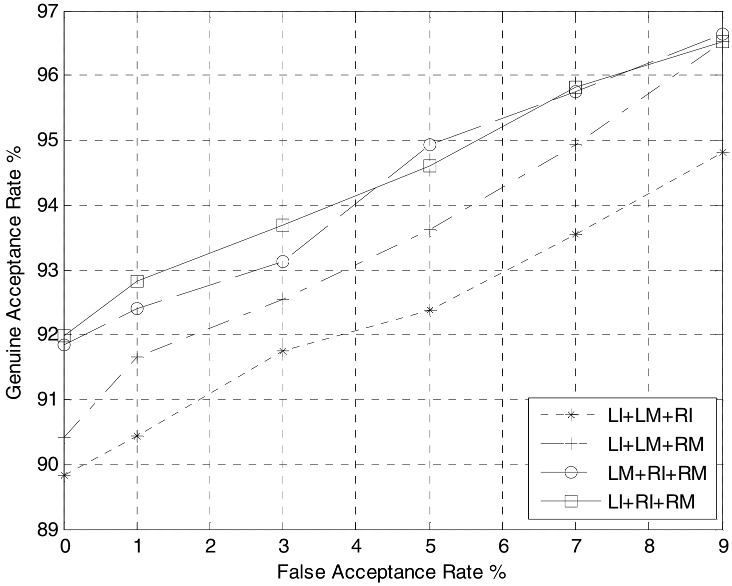

Fig. 4. Recognition rates obtained using EHT based feature extraction

The proposed Hough transform based feature extraction method for finger knuckle biometric recognition system is compared with the other geometric and texture based methods of feature extraction. The following Table 2 illustrates comparative analysis of the existing methods with the proposed methodology.

From the comparative analysis chart shown, it is obvious that the proposed Elliptical Hough transform based feature extraction method outperforms the existing methodology with high accuracy of Recognition rate = 98.26% and lowest error rate of EER = 0.78%.

Table 2. Comparative analysis of the Performance of the Proposed System

References	Dataset	Recognition Methods	Results
A. Kumar *et al.* [4]	Newly created database – 105 users with 630 Images	Principal Component Analysis, Linear Discriminant Analysis, Independent Component Analysis	EER – 1.39%
Zhang *et al.* [5]	PolyU database for Knuckle database.	Band Limited Phase only correlation method	EER - 1.68%
Chao lan *et al.* [7]	PolyU database for Knuckle database.	Complex locality preserving approach	EER - 4.28%
Lin Zhang *et al.* [8]	PolyU database for Knuckle database.	Ridgelet Transform	EER - 1.26%
A.Merounica *et al.*[9]	PolyU database for Knuckle database.	Fourier Transform	EER-1.72%
This paper	PolyU database for Knuckle database	Elliptical Hough Transform based Feature Extraction	EER = 0.78%

4 Conclusion

This paper presents a novel method for feature extraction based on Elliptical Hough Transform for the implementation of personal recognition system using finger knuckle prints. In this, EHT is formulated to isolate the elliptical structures present in the finger knuckle print and feature information obtained from those structures was represented to identify the individuals. The rigorous experiments were conducted and well promising results were achieved.

References

1. Hand-based Biometrics. Biometric Technology Today 11(7), 9–11 (2000)
2. Kumar, A., Zhang, D.: Combining fingerprint, palm print and hand shape for user authentication. In: Proceedings of International Conference on Pattern Recognition, pp. 549–552 (2006)

3. Rowe, R.K., Uludag, U., Demirkus, M., Parthasaradhi, S., Jain, A.K.: A multispectral whole-hand biometric authentication system. In: Biometric Symposium (2007)
4. Kumar, A., Ravikanth, C.: Personal Authentication Using Finger Knuckle Surface. IEEE Transactions on Information Forensics and Security 4(1), 98–110 (2009)
5. Zhang, L., Zhang, L., Zhang, D.: Finger-Knuckle-Print Verification Based on Band-Limited Phase-Only Correlation. In: Jiang, X., Petkov, N. (eds.) CAIP 2009. LNCS, vol. 5702, pp. 141–148. Springer, Heidelberg (2009)
6. Shen, L., Bai, L., Zhen, J.: Hand-based biometrics fusing palm print and finger-knuckle-print. In: 2010 International Workshop on Emerging Techniques and Challenges for Hand-Based Biometrics (2010)
7. Jing, X., Li, W., Lan, C., Yao, Y., Cheng, X., Han, L.: Orthogonal Complex Locality Preserving Projections Based on Image Space Metric for Finger-Knuckle-Print Recognition. In: 2011 International Conference on Hand-based Biometrics (ICHB), pp. 1–6 (2011)
8. Zhang, L., Li, H., Shen, Y.: A Novel Riesz Transforms based Coding Scheme for Finger-Knuckle-Print Recognition. In: 2011 International Conference on Hand-based Biometrics (2011)
9. Meraoumia, A., Chitroub, S., Bouridane, A.: Fusion of Finger-Knuckle-Print and Palmprint for an Efficient Multi-biometric System of Person Recognition. In: 2011 IEEE International Conference on Communications (2011)
10. Bao, P., Zhang, L., Wu, X.: Canny Edge Detection Enhancement by Scale Multiplication. IEEE Transactions on Pattern Analysis and Machine Intelligence 27(9), 1485–1490 (2005)
11. Zhanga, L., Zhanga, L., Zhanga, D., Zhub, H.: Online Finger-Knuckle-Print Verification for Personal Authentication, vol. 1, pp. 67–78 (2009)
12. Olson, C.F.: Constrained Hough Transforms for Curve Detection. Computer Vision and Image Understanding 73(3), 329–345 (1999)
13. Shen, D., Lu, Z.: Computation of Correlation Coefficient and Its Confidence Interval in SAS, vol. 31, pp. 170–131 (2005)
14. Hanmandlu, M., Grover, J., Krishanaadsu, V., Vasirkala, S.: Score level fusion of hand based Biometrics using T-Norms. In: 2010 IEEE International Conference on Technologies for Homeland Security, pp. 70–76 (2010)
15. Alen, J.V., Novak, M.: Curve Drawing Algorithms for Raster displays. ACM Transactions on Graphic 4(2), 147–169 (1985)