Finger-Knuckle-Print ROI Extraction using Curvature Gabor Filter for Human Authentication

Aditya Nigam[1] and Phalguni Gupta[2]

[1]School of Computer Science and Electrical Engineering, Indian Institute of Technology Mandi (IIT Mandi), Mandi, India

[2]National Institute of Technical Teacher's & Research (NITTTR), Salt Lake, Kolkata, India

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Abstract: Biometric based human recognition is a most obvious method for automatically resolving personal identity with high reliability. In this paper we present a novel finger-knuckle-print ROI extraction algorithm. The basic Gabor filter is modified to Curvature Gabor Filter (*CGF*) to obtain central knuckle line and central knuckle point which are further used to extract FKP ROI image. Largest public FKP database is used for testing which consists of $7,920$ images collected from 660 different fingers. The results has been compared with the only other existing Convex Direction Coding (*CDC*) ROI extraction algorithm. It has been observed that the proposed algorithm achieves better performance with *EER* drop percentage more than 20% in all experiments. This suggests that the proposed *CGF* algorithm has been extracting ROI more consistently then *CDC* and hence can facilitates any finger-knuckle-print based biometric systems.

1 INTRODUCTION

Biometric based authentication system has been used widely in commercial and law enforcement applications. The use of various biometric traits such as fingerprint, face, iris, ear, palmprint, hand geometry and voice has been well studied (Jain et al., 2007). Recently some multimodal systems has also been reported in (Nigam and Gupta, 2015a; Nigam and Gupta, 2014a; Nigam and Gupta, 2013a) fusing various combinations of palmprint, knuckleprint and iris images in pursuit of superior performance. The quality estimation of any biometric trait is also a very important and difficult task because quality is directly proportional to system performance. Good amount of work has been done to estimate the quality of face and fingerprint images due to the presence of some very specific texture. But limited work is done so far for iris (Nigam et al., 2013), knuckleprint (Nigam and Gupta, 2013b) and palmprint quality estimation as its lacks any such specific texture and structure. Some more work on knuckleprint and palmprint recognition is reported in (Badrinath et al., 2011; Nigam and Gupta, 2011; Nigam and Gupta, 2014b) using SIFT and SURF fusion and $LK-$tracking of corner features.

It is reported that the skin pattern on the finger-knuckle is highly rich in texture due to skin folds and creases, and hence, can be considered as a biometric identifier (Woodard and Flynn, 2005).

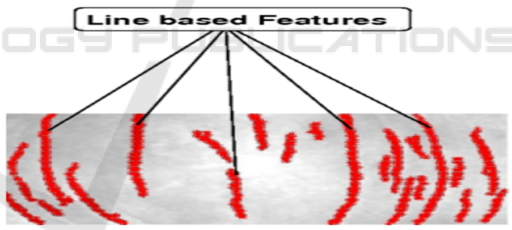

Figure 1: Finger-Knuckle-Print Anatomy.

1.1 Motivation

The line like (*i.e.* knuckle lines) rich pattern structures in vertical as well as horizontal directions exist over finger-knuckle-print, as shown in Fig. 1. These horizontal and vertical pattern formations are believed to be very discriminative (Zhang et al., 2011a). The finger-knuckle-print texture is developed very early and last very long because it occurs on the outer side of the hand and no one can use them for almost any work except boxers. Negligible wear and tear as well as print quality degradation with time and age are observed. Its failure to enrollment rate is also expected to be very low as compared to the fingerprint and it does not require much user cooperation. Further, ad-

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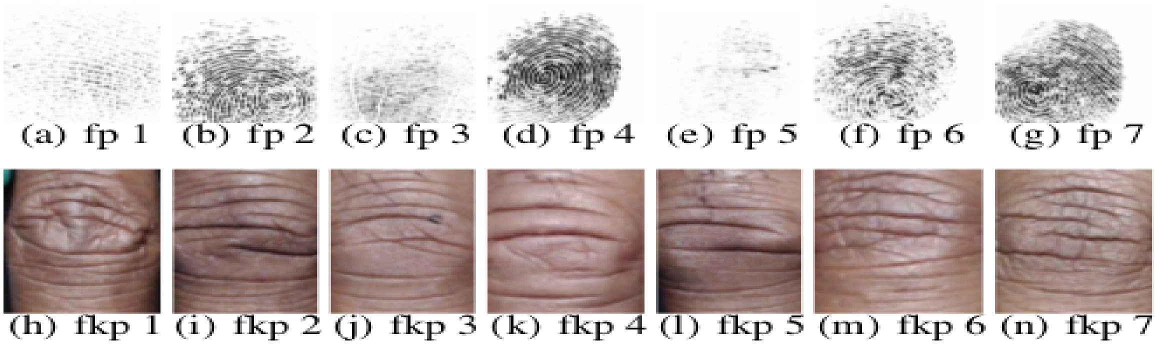


Figure 2: Fingerprint Vs FKP (Row 1 shows fingerprints while second row shows the corresponding knuckleprints).

vantages of using FKP include rich in texture features (ChorasÂt' and and Kozik, 2010), easily accessible, contact-less image acquisition, invariant to emotions and other behavioral aspects such as tiredness, stable features (Zhang et al., 2011b) and acceptability in the society (Kumar and Zhou, 2009).

1.2 FKP Vs Fingerprint

In this work we have considered knuckleprint over fingerprint mainly because it is observed that in rural areas the fingerprint quality is very poor. The cultivators and hard workers use their hands very roughly, causing sever damage to their fingerprints permanently. But still there knuckleprint quality is very good because no one can use them for any work. Hence it can be inferred that rural knuckleprint quality is better than rural fingerprint as one can also observe from Fig. 2. In such a scenario it has low failure to enroll rate FTE as compared to fingerprint and can be easily acquired using an inexpensive setup with lesser user cooperation. Also user acceptance favors knuckleprint as unlike fingerprint it has never being associated to any criminal investigations in the past.

1.3 Literature Review

Despite of these characteristics and advantages of using FKP as biometric identifier, limited work has been reported in the literature (Jungbluth, 1989) as it is a relatively new biometric trait. Systems reported in literature have used global features, local features and their combinations (Zhang et al., 2011b) to represent FKP images. In (Kumar and Ravikanth, 2009), FKP features are extracted using principle component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA). In (Zhang et al., 2009b), FKP is transformed using Fourier transform and band-limited phase only correlation (BLPOC) is employed to match the FKP images.

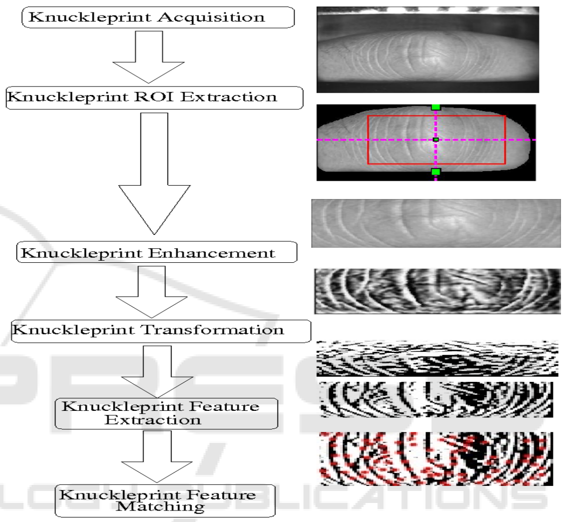
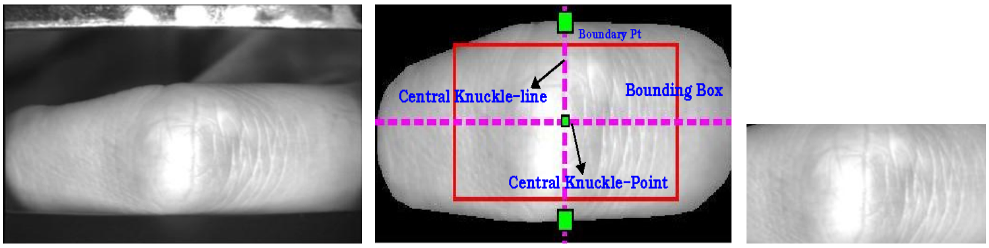


Figure 3: Overall architecture of FKP recognition system.

In (Zhang et al., 2009a), Zhang *et.al* extracted *ROI* using convex direction coding and used *BLPOC* for matching. In (Morales et al., 2011a), knuckleprints are enhanced using *CLAHE* and *SIFT* keypoints are used for matching. In (Xiong et al., 2011), features are extracted using local gabor binary patterns and a discriminating local pattern is extracted to represent that pixel. In (Zhang et al., 2011a), local *gabor* and global *BLPOC* features are fused to achieve better performance. Both local and global scores are fused to get the better result. In (Zhang et al., 2010b), a bank of six gabor filters at an angle of $\frac{\pi}{6}$ is applied to extract features for those pixels that are having varying gabor responses. In (Zhang et al., 2012), three local features *viz.* phase congruency, local orientation and local phase are fused at score level.

Global feature can extract the general appearance (holistic characteristics) of FKP which is suitable for coarse level representation, while local feature provides more detailed information for any specific local region which is appropriate for finer representa-



(a) Raw finger-knuckle-print (b) Annotated FKP (c) FKP ROI

Figure 4: Finger-knuckle-print ROI Annotation.

tion (Zhang et al., 2011b). There exist systems where local features of FKP are extracted using the Gabor filter based competitive code (CompCode) (Zhang and Zhang, 2009) and magnitude information (ImCompCode&MagCode) (Zhang et al., 2010c). Further, in (Kumar and Zhou, 2009), orientation of random knuckle lines and crease points (KnuckleCodes) of FKP which are determined using radon transform are used as features. In (Woodard and Flynn, 2005), FKP is represented by curvature based shape index. Morales et. al., (Morales et al., 2011b) have proposed an FKP based authentication system (OE-SIFT) using scale invariant feature transform (SIFT) from orientation enhanced FKP. In (ChorasÂt' and and Kozik, 2010), an hierarchical verification system using probabilistic hough transform (PHT) for coarse level classification and the speeded up robust features (SURF) for finer classification has been proposed. SIFT and SURF features of FKP are matched using similarity threshold (Morales et al., 2011b). In (Zhang et al., 2010a), features are extracted using Hilbert transform (MonogenicCode). Further, Zhang *et.al* (Zhang et al., 2011b) have proposed a verification system which is designed by fusing the global information extracted by BLPOC (Zhang et al., 2009b) and the local information obtained by Compcode (Zhang and Zhang, 2009). However, there does not exist any system which is robust to scale and rotation.

The ROI extraction is an initial phase and is very crucial because all other modules has been using its output. Incorrect ROI extraction render all other steps meaningless. This paper deals with the problem of designing an efficient finger-knuckle-print ROI extraction system. It is compared with the only other available algorithm Convex Direction Coding (CDC) (Zhang et al., 2011a; Zhang et al., 2010c). The finger-knuckle-print ROI is extracted by applying a modified version of gabor filter to estimate the central knuckle line and point as shown in Fig. 4(b). The central knuckle point is used to extract consistently the finger-knuckle-print ROI from any image.

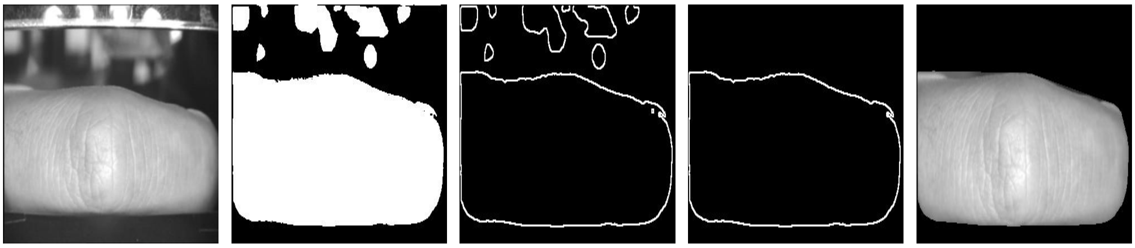
Any FKP system consists of five major tasks, *viz*. ROI extraction, quality estimation, ROI preprocessing, feature extraction and matching. The overall architecture of any finger-knuckle-print based recognition system is shown in Fig. 3. The publicly available finger-knuckle-print PolyU database (PolyU, 2010) is used to test the proposed system that contains both the raw sensor images (that are used to segment) as well as extracted ROI (that are used to compared performance). The PolyU database contains images that are acquired using normal web-cam of resolution 384×288 using their indigenous capturing device. The device allows the user to place only one finger at a time and acquires images that are horizontally aligned. Therefore, at the time of ROI extraction, raw finger-knuckle-print images are assumed to be horizontal and contain single finger knuckle.

2 PROPOSED FKP ROI EXTRACTION

This section proposes an efficient finger-knuckle-print ROI extraction technique. The prime objective of any ROI extraction technique is to segment same region of interest consistently from all images. The central knuckle point as shown in Figure 4(b) can be used to segment any finger-knuckle-print consistently. Since finger-knuckle-print is aligned horizontally, one can now easily extract the central region of interest from any finger-knuckle-print that contains rich and discriminative texture using this point. The proposed ROI extraction algorithm performs in three steps; detection of knuckle area, central knuckle-line and central knuckle-point defined as follows.

2.1 Knuckle Area Detection

In this step, the whole knuckle area is segmented from the background in order to discard background region. The acquired finger-knuckle-print may be of poor quality. Hence, each finger-knuckle-print is enhanced using contrast limited adaptive histogram equalization (Pizer et al., 1987) (CLAHE) to obtain better



(a) Raw (b) Binary (c) Canny (d) Boundary (e) FKP Area

Figure 5: Steps involved in Knuckle Area Detection.

edge representation which helps to detect the knuckle area more robustly. CLAHE divides the whole image into blocks of size 8×8 and applies histogram equalization over each block. The enhanced image is binarized using Otsu thresholding that segments the image into two clusters (knuckle region and background region) based on their gray values. Such a binary image is shown in Fig. 5(b). It can be observed that the knuckle region may not be accurate because of sensor noise and background clutter. This can be obtained by using canny edge detection. A resultant image is shown in Fig. 5(c) and the largest connected component is considered as the required knuckle boundary. The detected boundary is eroded to smooth it and remove any discontinuity as shown in Fig. 5(d). Finally all pixels within the convex hull of the knuckle boundary are considered as the knuckle area. Figure 5(e) shows a segmented knuckle area. Some top and bottom rows are assumed to be background and are discarded from the raw image.

2.2 Central Knuckle-Line Detection

The central knuckle line is defined as that column of the image with respect to which the knuckle can be considered as symmetric as observed from Figure 4(b). This line is used to extract the finger-knuckle-print ROI. A very specific and symmetric texture is observed around the central knuckle line which is used for its detection. To perceive such a specific texture, a knuckle filter is created by modifying the conventional gabor filter which is defined as follows.

[A] Knuckle Filter: The conventional gabor filter is created when a complex sinusoid is multiplied with a Gaussian envelope as defined in Eq .(1) and is shown in Figure 6(f).

$$G(x,y;\gamma,\theta,\psi,\lambda,\sigma) = \underbrace{e^{-\left(\frac{X^2+Y^2\cdot\gamma^2}{2\cdot\sigma^2}\right)}}_{\text{Gaussian Envelope}} \times \underbrace{e^{i\left(\frac{2\pi X}{\lambda}+\psi\right)}}_{\text{Complex Sinusoid}} \tag{1}$$

where x and y are the spatial co-ordinates of the filter and X, Y are obtained by rotating x, y by an angle θ using the following equations:

$$X = x * cos(\theta) + y * sin(\theta) \tag{2}$$

$$Y = -x * sin(\theta) + y * cos(\theta) \tag{3}$$

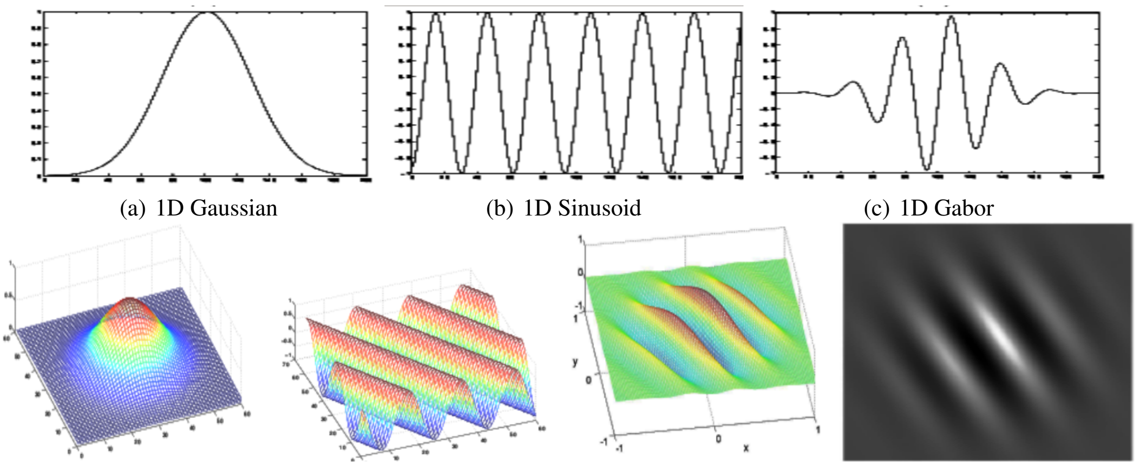
In order to model the curved convex knuckle lines, a knuckle filter is obtained by introducing curvature parameter in the conventional gabor filter. The basic gabor filter equation remains to be the same (as in Eq. (1)). Only X and Y co-ordinates are modified as follows:

$$X = x * cos(\theta) + y * sin(\theta) + c * (-x * sin(\theta) + y * cos(\theta))^2 \tag{4}$$

$$Y = -x * sin(\theta) + y * cos(\theta) \tag{5}$$

The curvature of the gabor filter can be modulated by the curvature parameter. This curved gabor filter with parameters ($\gamma = 1, \theta = \pi, \psi = 1, \lambda = 20, \sigma = 20$) can be used for knuckle filter creation. The value of curvature parameter is varied as shown in Fig. 8 and its optimal value for our database is selected heuristically. The proposed knuckle filter is obtained by concatenating two such curved gabor filters (f_1, f_2) ensuring the distance between them as d. The first filter (f_1) is obtained using the above mentioned parameters while the second filter ($f_2 = f_1^{flip}$) is just the vertically flipped version of the first filter because finger-knuckle-prints are vertically symmetric. In Figure 8, several knuckle filters are shown with varying curvature and distance parameters. One can observe that increasing curvature parameter c introduces more and more curvature in the filter. Finally $c = 0.01$ and $d = 30$ are considered for selected knuckle filter ($F_{kp}^{0.01,30}$).

[B] Knuckle Line Extraction: All pixels belonging to knuckle area are convolved with the knuckle filter $F_{kp}^{0.01,30}$. Pixels over the central knuckle line must be having higher response as compared to others because of filter's shape and construction. The filter response for each pixel is binarized using threshold as $f * max$ where max is the maximum knuckle filter response and $f \in 0\ to\ 1$ is a fractional value. The

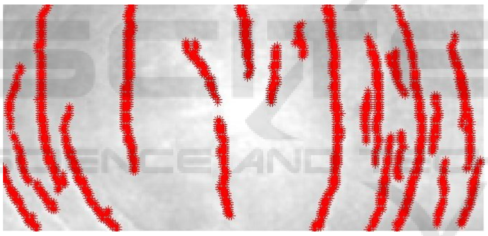


(a) 1D Gaussian (b) 1D Sinusoid (c) 1D Gabor

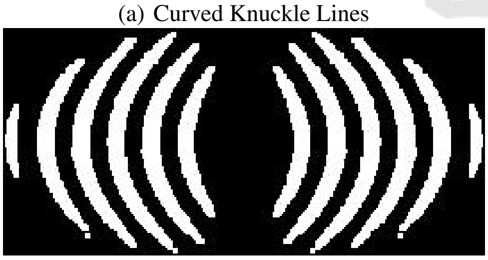
(d) 2D Gaussian (e) 2D Sinusoid (f) 2D Gabor (g) 2D Gabor Filter

Figure 6: Conventional 1 and 2 Dimensional Gabor Filter (Prasad and Domke, 2007).

binarized filter response is shown in Fig. 9(a) where it is super imposed over knuckle area with blue color. The column-wise sum of the filter response for each column is computed. The central knuckle line is considered as, that column which is having the maximum knuckle filter response as shown in Fig. 9(b).



(a) Curved Knuckle Lines

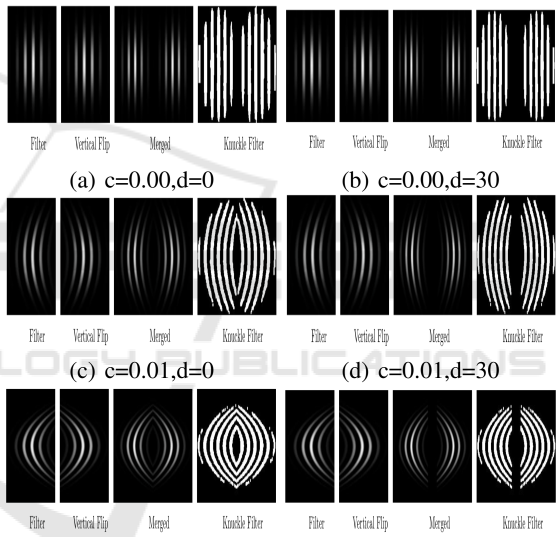


(b) Curvature Knuckle Filter

Figure 7: Curvature Knuckle Filter.

2.3 Central Knuckle-Point Detection

The central knuckle point is required to crop the knuckle-print ROI that must lie over central knuckle line. Hence the top and the bottom point over central knuckle line, belonging to the knuckle area, are computed and their mid-point is considered as the central knuckle point. It is shown in Figure 9(b). The required finger-knuckle-print ROI is extracted as a region of size $(2*w+1)\times(2*h+1)$ considering central knuckle point as the center. It is shown in Fig. 9(c).



(a) c=0.00,d=0 (b) c=0.00,d=30

(c) c=0.01,d=0 (d) c=0.01,d=30

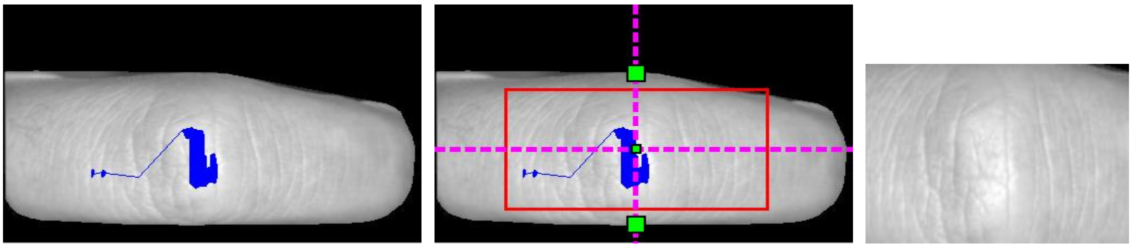
(e) c=0.04,d=0 (f) c=0.04,d=30

Figure 8: Various Knuckle Filter Arrangements.

Given a raw finger-knuckle-print image I, Algorithm 1 can be used to extract the finger-knuckle-print ROI (FKP_{ROI}) from it.

3 EXPERIMENTAL ANALYSIS

The proposed ROI extraction algorithm is tested over largest publicly available finger-knuckle-print database (PolyU, 2010). Some of the segmented PolyU finger-knuckle-print database images are shown in Fig. 10. One can observe that the proposed algorithm can extract consistently the ROI of images



(a) Knuckle Filter Response (b) Annotated (c) FKP ROI

Figure 9: Finger-knuckle-print ROI detection. (a) Knuckle filter response is super impose over the knuckle area with blue color, (b) Full Annotated and (c) FKP (FKP_{ROI}).

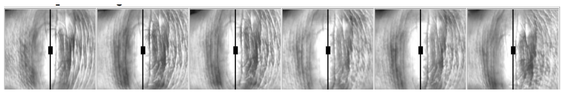
in the database. The correct segmentation accuracy of the proposed algorithm is observed as $95.15\% = \frac{7536}{7920}$ over the PolyU finger-knuckle-print (PolyU, 2010) database that contains images acquired from 660 subjects. Some images for which the proposed algorithm failed to segment are shown in Fig. 11. The algorithm fails mainly due to poor image quality. Finally such subjects are segmented manually.

Algorithm 1: Finger-knuckle-print ROI Detection.

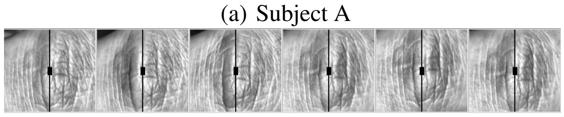
Require:
Raw finger-knuckle-print image I of size $m \times n$.
Ensure:
The finger-knuckle-print ROI FKP_{ROI}, of size $(2*w+1) \times (2*h+1)$.

1: Enhance the FKP image I to I_e using CLAHE;
2: Binarize I_e to I_b using Otsu thresholding;
3: Apply Canny edge detection over I_b to get I_{cedges};
4: Extract the largest connected component in I_{cedges} as FKP raw boundary, (FKP^{raw}_{Bound});
5: Erode the detected boundary FKP^{raw}_{Bound} to obtain continuous and smooth FKP boundary, FKP^{smooth}_{Bound};
6: Extract the knuckle area K_a = All pixels in image $I \in$ the $ConvexHull(FKP^{smooth}_{Bound})$;
7: Apply the knuckle filter $F^{0.01,30}_{kp}$ over all pixels $\in K_a$;
8: Binarize the filter response using $f * max$ as the threshold;
9: The central knuckle line (c_{kl}), is assigned as that column which is having the maximum knuckle filter response;
10: The mid-point of top and bottom boundary points over $c_{kl} \in K_a$, is defined as the central knuckle point (c_{kp}).
11: The knuckle ROI (FKP_{ROI}) is extracted as the region of size $(2*w+1) \times (2*h+1)$ from raw finger-knuckle-print image I, considering c_{kp} as its center point.

The only other available ROI extraction algorithm is based on Convex Direction Coding (CDC) (Zhang et al., 2011a). The proposed Curvature Gabor Filter (CGF) based algorithm is compared with *CDC* as shown in Fig 12 and Table 1. The images are cropped using both methods and are matched using algorithm as proposed in (Nigam and Gupta, 2015b). Exactly same testing protocol is used in order to make a fair comparison. One can clearly observe that all performance parameters are improved for all finger categories as well as over full FKP database. In all cases *EER* drop [1] percentage was more than 20% suggesting that the proposed *CGF* algorithm has been extracting ROI more consistently.



(a) Subject A



(b) Subject B

Figure 10: Some Correctly Segmented finger-knuckle-prints.

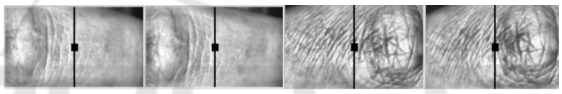


Figure 11: Failed Knuckle ROI detection.

4 CONCLUSION

The ROI extraction can be considered as the most crucial stage in any recognition system. In this paper a novel finger-knuckle-print ROI extraction algorithm is presented and compared with the only other available algorithm Convex Direction Coding (CDC) (Zhang et al., 2011a; Zhang et al., 2010c) over PolyU FKP database. The finger-knuckle-print ROI is extracted by applying a modified version of gabor filter

[1] % drop is calculated with respect to *CDC*

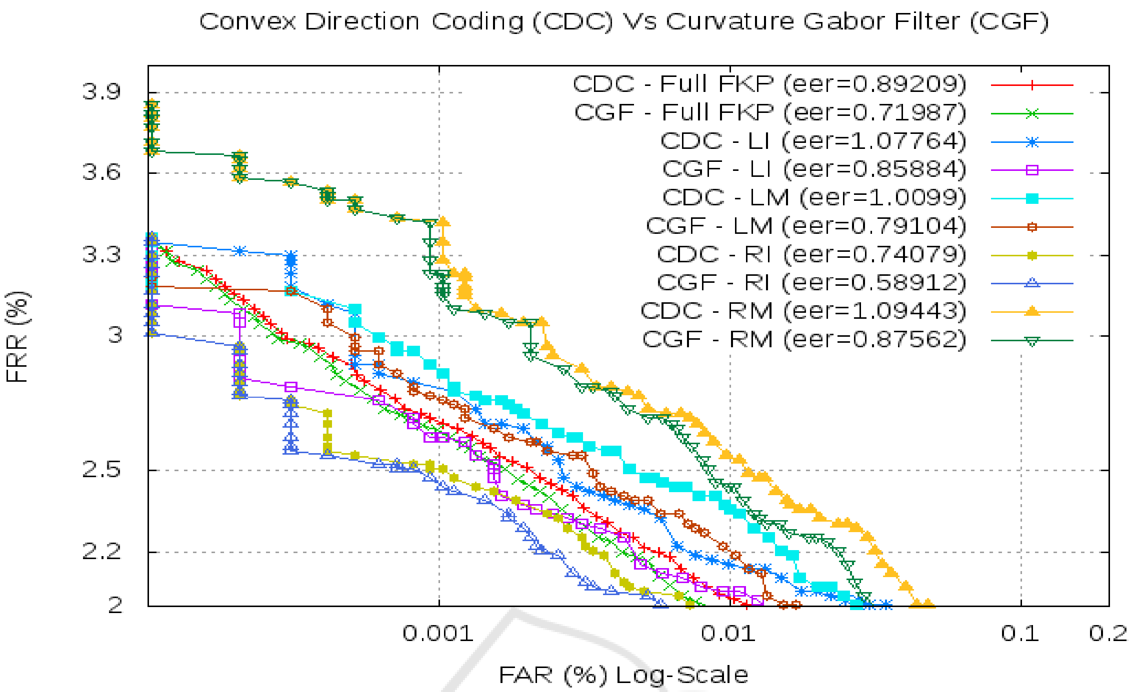


Figure 12: Comparative Analysis using same matching algorithm based on *CIOF* (Nigam and Gupta, 2015b), while ROI segmentation is done using *CDC* and *CGF*.

Table 1: Comparative Analysis : Curvature Gabor Filter (*CGF*) Vs Convex Direction Coding (*CDC*) (Zhang et al., 2011a).

Db	DI		EER			Accuracy		EUC		CRR	
	CGF	CDC	CGF	CDC	Drop(%)	CGF	CDC	CGF	CDC	CGF	CDC
FKP	1.65	1.63	0.71	0.89	20.22	99.38	99.28	0.165	0.201	99.97	99.94
LI	1.63	1.63	0.858	1.077	20.33	99.25	99.15	0.228	0.302	100	99.79
LM	1.68	1.68	0.791	1.009	21.6	99.32	99.19	0.298	0.356	100	100
RI	1.61	1.61	0.58	0.740	21.6	99.46	99.37	0.068	0.086	100	100
RM	1.67	1.66	0.875	1.094	20.01	99.25	99.2	0.213	0.265	100	100

to estimate the central knuckle line and point. It is observed that in all experiments *EER* drop percentage was more than 20% suggesting that the proposed *CGF* algorithm has been extracting ROI more consistently then *CDC*.

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