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Personal Identification using Finger Knuckle Orientation Features

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This paper proposes a novel approach for personal identification using finger images which exploits the orientation features from the random knuckle lines using finite Radon transform. The feasibility of this approach is rigorously evaluated on a publically available finger knuckle database from 158 subjects and achieves highly promising results.

Introduction: The hand-based biometrics exploits several internal and external features that are quite distinct in an individual. The finger-back surface, also known as the dorsum of hand, can be highly useful in user identification but has attracted very little attention (please refer to review in [1]-[2]) from the researchers. In particular, the image pattern formation from the finger-knuckle bending are highly unique and makes this surface a distinctive biometric identifier. The user acceptance for the outer finger surface imaging can be very high as, unlike popular fingerprints, there is no stigma of criminal investigation associated with finger knuckle surface imaging. The peg-free imaging of the finger knuckle surface is highly convenient to users and offers very high potential for reliable personal identification.

The appearance based approach recently investigated in [2] for the finger knuckle identification cannot exploit line-based features and therefore achieves moderate performance. The finger knuckle surface is highly rich in lines and creases which are rather curved but highly unique in individuals. Therefore the exploitation of localized information, rather than the global appearance based information employed in [2], can generate more reliable performance and is proposed in this work. In the proposed method, fixed size knuckle sub-images are automatically segmented and then pre-processed. The pre-processing step accentuates texture features and also helps to cope with the illumination variations. The local orientation of random knuckle lines and creases are exploited to generate a unique *KnuckleCode* using finite Radon transform. The similarity between two *KnuckleCodes* is ascertained from their normalized Hamming distance. We also investigate the *KnuckleCodes* generated using even Gabor filters. Since there is no publically available finger knuckle database, the middle finger knuckle database developed and employed in this work is made publically available [6] for further research. The experimental results are presented on a peg-free database of 790 finger images from the 158 subjects and achieve highly promising results. A comparison of the proposed approach with the *eigenknuckle* approach [2] is also presented.

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Methodology: The finger surface represents highly curved surface and results in non-uniform reflections. Therefore, the extracted finger knuckle images often have non-uniform brightness and low contrast. The enhancement of knuckle images is achieved by firstly dividing the image into 10×10 pixels sub-blocks. The mean gray-level in each of these blocks is computed which represents estimated reflection of the block. The estimated coarse reflection is expanded into original size knuckle image using bi-cubic interpolation. This estimated reflection (figure 1c) is subtracted from the original image which results in the uniform illumination of the image. The resulting image is histogram equalized to improve the contrast and smoothen the boundaries between adjacent blocks.

The finite Radon transform (FRT) can be effectively employed to detect random lines and creases by integrating gray-level pixels in a small neighbourhood. The FRT exhibits *wrap around* effect due to the inherent 'modulo operation' [4], which can be eliminated for the effective detection of knuckle lines and creases. The modified FRT or MFRAT for a discrete image *g*[*m*,*n*] on a finite grid R_q^2 is defined as:

$$s[X_p] = \mathrm{M}_i(p) = \sum_{(x,y)\in X_p} g[x,y] \tag{1}$$

where $R_q = \{0, 1, \ldots, q-1\}$, q is a positive integer, and R_q^2 is centred at (x_0, y_0). The X_p represents set of points on R_q^2 such that

$$X_p = \{(x,y): y = p(x - x_0) + y_0, x \in R_q\} \tag{2}$$

where *p* denotes the slope of X_p, *i.e*. slope of line passing through the centre (x_0, y_0) of R_q^2. The MFRAT, unlike FRAT, is not an invertible transform but useful to represent line and crease like features. The line width of X_p can be empirically selected corresponding to the width of the observed knuckle lines in the acquired finger images. In this work, this line width is therefore empirically selected as two pixels.

The key objective of employing MFRAT in this work is to *efficiently* and *effectively* ascertain the orientation *p* of knuckle lines/creases in a finite/local neighbourhood region. Therefore we compute the direction of every pixel centred at (x_0, y_0) on R_q^2 from the summation of pixels along the line of given slope *p*. The index of the dominant direction at every pixel forms the feature and is computed as follows:

$$\theta_p(x_0, y_0) = \arg(min_p(s[\mathrm{X}_p]))\,,\ p = 1, 2, \ldots, W \tag{3}$$

where the $\theta_p(x_0, y_0)$ represents the line direction or the dominant index of pixel $g[x_0, y_0]$. This operation is repeated as the centre of lattice R_q^2 moves over all the pixels in the image. The dominant direction θ_p at every pixel is binary coded using *b* binary bits and is referred to as *KnuckleCode*. The generation of matching distance between two *KnuckleCodes* T_b and Q_b , extracted from two *M* × *N* size knuckle images, is achieved as follows:

$$D(T_b, Q_b) = \min_{\forall\, u,v} \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\phi\left(T_b^{u,v}, Q_b\right)}{M\times N}, \text{ where}$$

$$\phi(J_b, K_b) = \begin{cases} 0 & if\;\; J_b = K_b \;\forall\; b \\ 1 & otherwise \end{cases} \tag{4}$$

$T_b^{u,v}$ represents the translated template in u × v neighbourhood, and *b* = 1, 2, ..*Z* which denotes bits for the Z bit binary code. The equation (4) effectively compares two Z bit *KnuckleCodes* and generates the best (minimum) matching score from all the translated versions templates.

Experiments*:* The performance from the proposed approach is evaluated on a publically available [6] finger knuckle image database from 158 subjects. This database was acquired over a period of 11 months and each subject/volunteer contributed five image samples which resulted in total of 790 images. These images were acquired using a digital camera in an indoor environment using unconstrained (peg-free) setup as detailed in [2]. The middle finger images from each of the subjects are employed to automatically extract 80 x 100 pixel knuckle region using the segmentation method detailed in [2]. Figure 1(a) shows a sample of acquired middle finger image and correspondingly segmented knuckle image in figure 1(b). The segmented images have low contrast and may suffer from non-uniform illumination. Therefore enhancement of knuckle images is required and the sample of enhanced knuckle image is shown in figure 1(d). It can be easily seen from the enhanced image sample that the knuckle features are much more prominent in the enhanced image as compared to the original image.

Each of the enhanced knuckle images is subjected to the feature extraction, using MFRAT, as detailed in previous section. The total number of candidate directions (W) for every pixel is empirically fixed to 12. The performance evaluation is achieved by 5-fold cross validation and the average of experimental results is presented. This represents a more realistic experiments, similar to as in [7], as the knuckle images have large variations within the same class resulting from shadows, illumination and pose changes. The receiver operating characteristics (ROC) using 790 (158×5) genuine and imposter 124030 ($158 \times 157 \times 5$) matching scores is shown in figure 2(a). The comparison of experimental results from our approach, with the appearance based approach, *i.e.*, *eigenknuckles* employed in [2], on the database employed in this work is also shown in figure 2. Table 1 summarizes the average equal error rate from the experiments. We also performed experiments for the recognition and the corresponding comparative cumulative match characteristics (CMC) are shown in figure 2(b). Another possible approach for extracting orientation features is to employ real part of Gabor functions and ascertain the orientation at every pixel using the maximum filtered response. Such an approach has been investigated on the palmprint data in [5] and achieves promising results. Therefore the generation of *KnuckleCode* using such Gabor filters is also investigated and the comparative results are shown in figure 2 (a)-(b). The twelve real Gabor filters, with 17 $\times$ 17 mask size, centred at frequency of $1/(2\sqrt{2})$ were employed to achieve the best performance. The experimental results in figure 1 and figure 2 suggests that the performance from the *KnuckleCodes* generated using MFRAT, *i.e., KnuckleCodes* (Radon), is far superior as compared to those from real Gabor filter based encoding.

It may also be noted that the generation of *KnuckleCodes* using Gabor filters is highly computationally demanding as it requires convolution operation at every pixel and orientation as compared to simple sum in MFRAT. Therefore, the *KnuckleCodes* generated from MFRAT are also favourably suitable for online user identification. It should be noted that reference [2] simultaneously employs hand geometry features while reference [3] [5] employed palmside finger/palm features. Therefore any direct comparison of our results, that employed only middle finger knuckle images, with [2]-[3] [5] is difficult. The accuracy of segmenting knuckle images from the presented fingers highly influences the matching scores between the corresponding *KnuckleCodes*. In order to handle the rotational and translational variations in the segmented knuckle images, we employed minimum of matching score (6) generated from the translation of respective templates in the region that extended to one third of length and width of the templates. The database employed in this work is now made freely available [6] for further research efforts.

***Conclusion*:** In summary, the proposed approach for the finger knuckle identification using *orientation features* from the finite Radon transform achieves highly promising results, *i.e.*, average rank-one recognition rate of 98.6% and equal error rate of 1.14% on the database of 158 persons. These results can be attributed to (i) effective characterization of orientation features using *KnuckleCodes*, (ii) usage of robust image enhancement technique, and (iii) usage of reliable matching distances that can account for translation of finger knuckles. These experimental results suggest that the orientation based *KnuckleCodes* offer a promising and computationally simpler alternative for the automated personal identification.

References

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Table 1: Comparative Performance for verification experiments

	Equal Error Rate		
EER (%)	KnuckleCodes (Radon)	KnuckleCodes (Gabor)	EigenKnuckles
Mean	1.14	2.66	12.6%
Std deviation	1.37	1.81	1.27

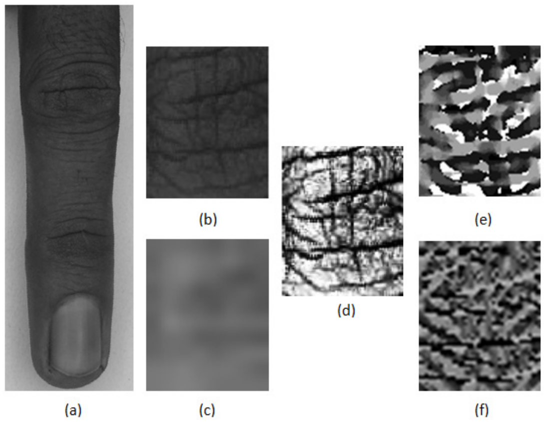

Fig. 1 (a) Middle finger image, (b) Segmented knuckle image, (c) mean bi-cubic image, (d) enhanced knuckle image; gray level representation of *KnuckleCodes* generated using even Gabor filters in (e), and using finite Radon transfom in (f)

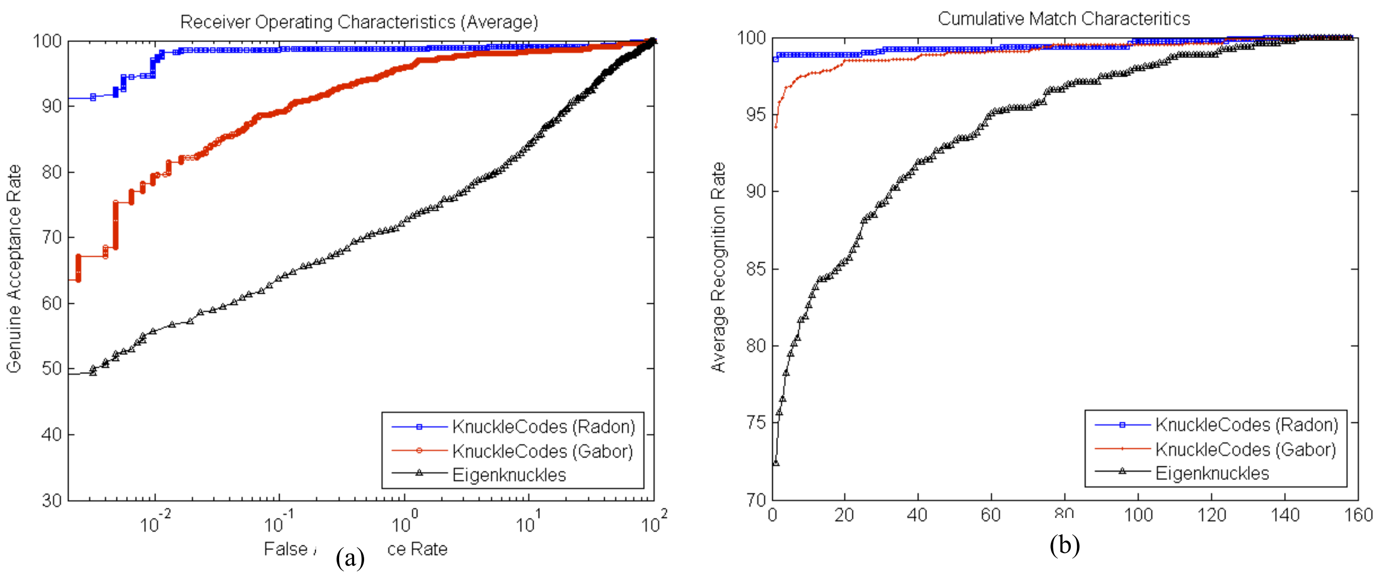

Fig. 2 The ROC curve in (a) and the CMC curve in (b) from experiments