Finger Knuckleprint based Recognition System using Feature Tracking

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Abstract. This paper makes use of finger knuckleprints to propose an efficient biometrics system. Edge based local binary pattern (ELBP) is used to enhance the knuckleprint images. Highly distinctive texture patterns from the enhanced knuckleprint images are extracted for better classification. It has proposed a distance measure between two knuckleprint images. This system has been tested on the largest publicly available Hong Kong Polytechnic University (PolyU) finger knuckleprint database consisting 7920 knuckleprint images of 165 distinct subjects. It has achieved CRR of more than 99.1% for the top best match, in case of identification and ERR of 3.6%, in case of verification.

Keywords: Biometrics,Knuckleprint, Local Binary Pattern, Lukas Kanade Tracking, Edge-map

1 Introduction

Biometrics authentication is extensively applied in law enforcement, computer security, banking etc. Exponential increase in the computational power and the requirement of the society lead researchers to develop fast, efficient and low cost authentication systems to meet the real time challenges.

Recently a significant amount of research has been carried out to design efficient biometric systems. Several traits such as face, fingerprint, iris, palmprint, ear, signature *etc* are investigated exhaustively. Every trait has its own pros and cons. There exist various challenges depending on the trait such as pose and illumination for face, occlusion and cooperative acquisition for iris *etc*.

Biometric recognition systems based on hand (*e.g.* palm print and fingerprint) have gathered attraction over past few years because of their good performance and inexpensive sophisticated acquisition sensors. Pattern formation at finger knuckle bending are unique [1–3] and hence can be considered as a discriminative biometrics trait. Factors favoring knuckleprint include higher user acceptance and less expected user cooperation.

Patterns extracted from finger knuckle surface have high discriminative power [4] and can be useful for personal identification. Surface curvatures of knuckleprints have been considered for matching. But it has not performed well because of its large size and costly as well as time consuming acquisition system. 2D finger knuckle surface has been used in [5] for authentication by combining several global feature extraction methods such as ICA, PCA and LDA. But these methods do not extract features based on knuckle lines well. Hence, these methods have achieved limited performance. Local features such as robust line orientation code (RLOC) [6] and modified finite radon transform (MFRAT) [3] have been proposed to extract the local pixel orientation and stored as *knucklecode*.

Zhang *et. al* [7] have designed a low cost CCD based finger knuckle data acquisition system and extracted the region of interest using convex direction coding for knuckleprint verification. It calculates the correlation between two knuckleprint images using band limited phase only correlation (BLPOC) where high frequencies are not considered as they are prone to noise. In [8] bank of gabor filters has been used to extract the features. It considers pixels that have varying gabor response and fused orientation and magnitude information to get much better performance. In [2] local and global features are fused to get better performance.

In [9], SIFT features which are invariant to rotation and scaling are considered as key-points. Real part of orthogonal gabor filter with contrast limited adaptive histogram equalization (CLAHE) has been used to enhance knuckleprint images to compensate non-uniform reflection. Knuckleprint based recognition system using local gabor binary patterns (LGBP) has been proposed in [10]. Eight gabor filters are applied on a knuckleprint image and histogram features are extracted by 8-neighborhood LBP within blocks. Classification of test samples is done using chi-squared distance statistics.

This paper proposes a measure to compare finger knuckleprint images which is robust against slight amount of local non-rigid distortions. Its performance has been studied on the largest publicly available Hong Kong Polytechnic University (PolyU) finger knuckleprint database [11].

The paper is organized as follows. Section 2 discusses mathematical basis of the proposed system. Section 3 proposes an efficient knuckleprint based recognition system. The system has been analyzed in Section 4. Conclusions are given in the last section.

2 Mathematical Basis

2.1 LBP based Image Enhancement

In [12] a transformation, very similar to LBP [13] has been introduced to preserve the distribution of gray level intensities in iris images. It helps to address the problems like robustness against illumination variation and local non-rigid distortions. It is observed that a pixel's relative gray value with respect to its 8-neighborhood pixels can be more stable than its own gray value. But this transformation fails when gray values of 8-neighbors are very similar to each other. In [14, 15] gt-transformation providing more tolerance to variations in illumination and local non-rigid distortions is proposed. It is observed that gray level intensities are indistinguishable within a small range.

2.2 Lukas Kanade Tracking

LK tracking algorithm [16] estimates the sparse optical flow between two frames. Let there be a feature at location (x, y) at time instant t with intensity $I(x, y, t)$ and this feature has moved to the location $(x + \delta x, y + \delta y)$ at time instant $t + \delta t$. Three basic assumptions used by LK Tracking [16] are:

– **Brightness Consistency**: Features on a frame do not change much fo small value of δt, *i.e*

$$I(x, y, t) \approx I(x + \delta x, y + \delta y, t + \delta t) \tag{1}$$

– **Temporal Persistence**: Features on a frame moves only within a small neighborhood. It is assumed that features have only small movement for small value of δt. Using the Taylor series and neglecting the high order terms, one can estimate $I(x + \delta x, y + \delta y, t + \delta t)$ as

$$\frac{\delta I}{\delta x}\delta x + \frac{\delta I}{\delta y}\delta y + \frac{\delta I}{\delta t}\delta t = 0 \tag{2}$$

Dividing both sides of Eq 2 by δt one gets

$$I_x V_x + I_y V_y = -I_t \tag{3}$$

where V_x, V_y are the respective components of the optical flow velocity for pixel $I(x, y, t)$ and I_x, I_y and I_t are the derivatives in the corresponding directions.

– **Spatial Coherency**: In Eq 3, there are two unknown variables for every feature point (*i.e* V_x and V_y). Hence finding unique V_x and V_y for every feature point is an ill-posed problem. Spatial coherency assumption is used to solve this problem. It assumes that a local mask of pixels moves coherently. Hence one can estimate the motion of central pixel by assuming the local constant flow. LK gives a non-iterative method by considering flow vector (V_x, V_y) as constant within 5×5 neighborhood (*i.e* 25 neighboring pixels, $P_1, P_2 \dots P_{25}$) around the current feature point (center pixel) to estimate its optical flow. The above assumption is reasonable and fair as all pixels on a mask of 5×5 can have coherent movement. Hence, one can obtain an overdetermined linear system of 25 equations which can be solved using least square method as

$$\underbrace{\begin{pmatrix} I_x(P_1) & I_y(P_1) \\ \vdots & \vdots \\ I_x(P_{25}) & I_y(P_{25}) \end{pmatrix}}_{\text{C}} \times \underbrace{\begin{pmatrix} V_x \\ V_y \end{pmatrix}}_{\text{V}} = - \underbrace{\begin{pmatrix} I_t(P_1) \\ \vdots \\ I_t(P_{25}) \end{pmatrix}}_{\text{D}} \tag{4}$$

where rows of the matrix C represent the derivatives of image I in x, y directions and those of D are the temporal derivative at 25 neighboring pixels. The 2×1 matrix $\widehat{\mathbf{V}}$ is the estimated flow of the current feature point determined as

$$\widehat{\mathbf{V}} = (C^T C)^{-1} C^T (-D) \tag{5}$$

The final location $\widehat{\mathbf{F}}$ of any feature point can be estimated using its initial position vector $\widehat{\mathbf{I}}$ and estimated flow vector $\widehat{\mathbf{V}}$ as

$$\widehat{\mathbf{F}} = \widehat{\mathbf{I}} + \widehat{\mathbf{V}} \tag{6}$$

3 Proposed System

The proposed system consists of three components: image enhancement, feature extraction and matching. Image enhancement is performed using edge based local binary pattern (ELBP). Corner features are extracted using the method proposed in [17] while LK tracking [16] is used for matching. Details of each task are discussed in the following subsections.

3.1 Image Enhancement

Knuckleprint images have strong vertical edges that can be useful for recognition purposes. Proposed transformation calculates *edge based local binary pattern* (ELBP) for each pixel in the image. A knuckleprint image is transformed into an *edgecode* (as shown in Fig. 1) that is robust to illumination and local non-rigid distortions. Knuckleprint image A is preprocessed by applying the sobel edge operator in horizontal direction to obtain vertical edge map. To obtain the *edgecode*, ELBP value for every pixel $A_{j,k}$ in the vertical edge map is defined as a 8 bit binary number S whose i^{th} bit is

$$S_i = \begin{cases} 0 & \textbf{if } (Neigh[i] < threshold) \\ 1 & \textbf{otherwise} \end{cases} \tag{7}$$

where $Neigh[i], i = 1, 2, ...8$ are the horizontal gradient of 8 neighboring pixels centered at pixel $A_{j,k}$. The value of *threshold* is evaluated experimentally.

In *edgecode* (as shown in Fig. 1), every pixel is represented by its $ELBP$ value which is an encoding of strong edge pixels in its 8-neighborhood. It can be noted that any change caused due to sudden change in the illumination can affect the gray values but $ELBP$ value is not affected much because the strong edge pattern near the pixel remains to be more or less same. This property has been used in knuckleprint images as it contains lot of illumination variation.

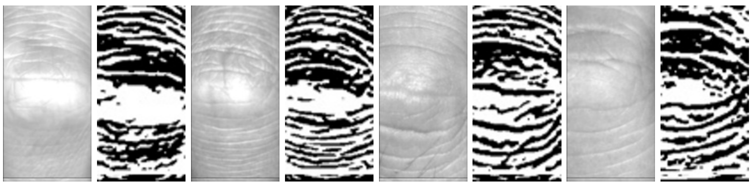

Fig. 1. Original and Transformed (*edgecodes*) knuckleprint Images

3.2 Feature Extraction

Strong derivative points except corner ones in the $edgecode$ cannot be considered as features because they look alike along the edge. But corners have strong derivative in two orthogonal directions and can provide enough information for tracking. The autocorrelation matrix M can be used to calculate good features from $edgecode$ having strong orthogonal derivatives. Matrix M can be defined for any pixel at i^{th} row and j^{th} column of $edgecode$ as:

$$M(i,j) = \begin{pmatrix} A & B \\ C & D \end{pmatrix} \tag{8}$$

such that

$$\begin{aligned}
A &= \sum_{-K \leq a,b \leq K} w(a,b).I_x^2(i+a,j+b) \\
B &= \sum_{-K \leq a,b \leq K} w(a,b).I_x(i+a,j+b).I_y(i+a,j+b) \\
C &= \sum_{-K \leq a,b \leq K} w(a,b).I_y(i+a,j+b).I_x(i+a,j+b) \\
D &= \sum_{-K \leq a,b \leq K} w(a,b).I_y^2(i+a,j+b)
\end{aligned}$$

where $w(a,b)$ is the weight given to the neighborhood, $I_x(i+a,j+b)$ and $I_y(i+a,j+b)$ are the partial derivatives sampled within the $(2K+1) \times (2K+1)$ window centered at each selected pixel.

The matrix M can have two eigen values λ_1 and λ_2 such that $\lambda_1 \geq \lambda_2$ with e_1 and e_2 as the corresponding eigenvectors. Like [17], all pixels having $\lambda_2 \geq T$ (smaller eigen value greater than a threshold) are considered as corner feature points. Let $a = \{i,j\}$ be a 2-tuple array to indicate that $(i,j)^{th}$ pixel of the knuckleprint image A, $A_{i,j}$ is a corner point.

3.3 Matching

Let A and B be two knuckleprint images that are to be compared. Let a and b be the 2-tuple arrays containing the corner information of knuckleprint images A and B respectively. In order to make the decision on matching between A and B, LK Tracking, discussed in Section 2, has been used to determine the average number of features tracked successfully in one knuckleprint image against all corner points of another image. Let $a(i,j)$ be a corner point of knuckleprint image A. LK Tracking calculates its estimated location in $edgecode$ of B, say $edgecode_B(k,l)$. For every $a(i,j)$ of a, we tell that a pixel $a(i,j)$ is tracked successfully if the euclidean distance between $a(i,j)$ and $edgecode_B(k,l)$ is less than or equal to a preassigned threshold, TH_d and the sum of the absolute difference between every neighboring pixel of $a(i,j)$ and $edgecode_B(k,l)$, termed as tracking error, is less than or equal to a preassigned threshold, TH_e. Thus,we can define $Tracked(a(i,j), edgecode_B)$ for successful/unsuccessful tracking as

$$Tracked(a(i,j), edgecode_B) = \begin{cases} 1 \textbf{ if } ||a(i,j), b(k,l)|| \leq TH_d \\ \quad \textbf{and } T_{Error} \leq TH_e \\ \\ 0 \textbf{ otherwise} \end{cases} \tag{9}$$

where T_{Error} is the tracking error. For every point in a, one can determine whether it can successfully tracks a pixel in $edgecode_B$. Features Tracked Successfully (fts) for a to $edgecode_B$ can be defined by

$$fts(a, edgecode_B) = \sum_{\forall a(i,j) \in a} Tracked(a(i,j), edgecode_B)) \tag{10}$$

Thus,the average number of features tracked successfully (FTS) for a to $edgecode_B$ and b to $edgecode_A$ is defined by

$$FTS(A, B) = \frac{1}{2} \times [fts(a, edgecode_B) + fts(b, edgecode_A)] \tag{11}$$

4 Experimental Results

This section analyses the performance of the proposed system. It has been evaluated on the publicly available largest FKP database from the Hong Kong Polytechnic University (PolyU) [11]. This database contains 7920 FKP images obtained from 165 subjects. Images are acquired in two sessions. At each session, 6 images of 4 fingers (distinct index and middle fingers of both hands) are collected. Subjects comprise of 125 males and 40 females. The age distribution of users are as follows: 143 subjects are having age lying between 20 and 30 while remaining are between 30 and 50. Like [1–3, 7–10] images collected in first session are considered for training and those collected in the second session are used for query.

Performance of the system is measured using correct recognition rate (CRR) in case of identification and equal error rate (EER) for verification. CRR of the system is defined by

$$CRR = \frac{N_1}{N_2} \tag{12}$$

where N_1 denotes the number of correct (Non-False) top best match of FKP images and N_2 is the total number of FKP images in the query set.

At a given threshold, the probability of accepting the impostor, known as false acceptance rate (FAR) and probability of rejecting the genuine user known as false rejection rate (FRR) are obtained. Equal error rate (EER) is the value of FAR for which FAR and FRR are equal.

$$EER = \{FAR | FAR = FRR\} \tag{13}$$

The proposed FTS measure is parametrized by two parameters TH_d and TH_e. TH_d depends on the amount of expected motion and TH_e is the pixel-wise patch absolute difference around the initial and estimated feature. Both of these parameters are calculated empirically. These values are chosen in such a way that CRR is maximum.

The proposed system has been compared with all well known knuckleprint based systems reported in [10]. It is found that the CRR of the proposed system which is more than 99.1% for all 4 fingers is better. $CRRs$ of various systems obtained from various fingers of the PolyU database are shown in Table 1. Further, EER of the proposed verification system is 3.6%. For each finger, Receiver Operating Characteristics

Table 1. Identification Performance (compared as reported by [10])

	CRR % Left Index	CRR % Left Middle	CRR % Right Index	CRR % Right Middle
PCA [10]	0.5638	0.5364	0.6051	0.6010
LDA[10]	0.7283	0.7030	0.7606	0.7525
Gabor+PCA[10]	0.9253	0.9101	0.9586	0.9293
Gabor+LDA[10]	0.9485	0.9263	0.9626	0.9323
LBP[10]	0.9010	0.8909	0.9556	0.9121
LGBP[10]	0.9414	0.9424	0.9727	0.9475
Proposed	**0.9910**	**0.9926**	**0.9936**	**0.9922**

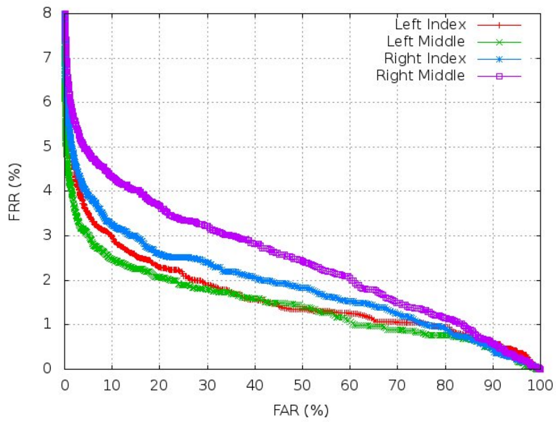

Fig. 2. Fingerwise ROC Curves

(ROC) curves which plots FAR against FRR is shown in Fig. 2. It is observed that the performance of left hand fingers is better than right hand fingers. It can be noted here that previously known systems have not reported their respective EER and hence the proposed system could not be compared.

5 Conclusion

This paper has proposed a measure termed as Features Tracked Successfully (FTS) to compare shapes in gray scale images. Further, this measure is used to design a finger knuckleprint based biometric system. This system works on edge-maps to compensate the effect of illumination variations.

It works on the features obtained from gray images and uses FTS measure to achieve the appearance based comparison on knuckleprint images. FTS measure has experimentally shown tolerance to slight variation in translation, illumination and rotation. The system has been tested on publicly available PolyU database of knuckleprint images. It has considered knuckleprints of 4 fingers (index and middle fingers of both hands) of 165 subjects to measure its performance. It has achieved CRR of more than 99.1% for the top best match, in case of identification and EER of 3.6% in case of verification. The proposed system has been compared with all well known knuckleprint based systems and is found to perform better.

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