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Research Article

Performance Evaluation of Texture Based Feature Extraction Techniques for personal Authentication using minor finger knuckle Matching

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Abstract

Personal Authentication using Finger Knuckle patterns has received substantial attention from researchers with prominent applications in biometrics and forensics. This paper explores the performance evaluation of texture based feature extraction techniques for personal authentication using minor finger knuckle patterns, which are formed on the finger surface joining distal phalanx and middle phalanx bones. The texture pattern produced by the finger knuckle blending is quite unique and has high capability to discriminate different individuals. Finger knuckle matching scheme is developed with key steps for region of interest segmentation, feature extraction and robust matching. Feature extraction techniques based on texture features, like Local binary patterns (LBP), Three patch local binary patterns (TLBP), 1-D log Gabor filter is evaluated and compared. The algorithms have been tested on database available from Hong Kong Polytechnic University of both male and female volunteers. The experimental results show that TLBP and 1-D log Gabor filter yields better accuracy with reduced computational time.

Keywords: *Texture, Feature Extraction, Segmentation, Finger Knuckle, Matching*

1. Introduction

Existing methods of human identification based on credentials (identification documents and PIN) are not able to meet the growing demands for strict security in applications. As a result biometrics, which is based on physiological and behavioral characteristics of a person, is being increasingly adopted and mapped to rapidly growing person identification applications. Automated identification of humans using their unique anatomical characteristics has been increasingly investigated for their applications in human surveillance and image forensics.

Finger knuckle biometrics has become apparent as a full proof method of automated personal authentication. The dermal patterns that are formed at birth will not change and these line features are consistent throughout the life of a person and they can serve as unique personal identifier. Moreover, these line textures are clearly visible on the hand's upper surface and they can be acquired using relatively inexpensive low resolution device. Accurate identification of finger knuckle patterns can be beneficial for several applications involving forensic and hole-and corner identification of suspects. The matching of finger knuckle patterns can help to identify the suspects and can deduce supportive scientific evidence from the photographs, especially in cases when no information regarding fingerprint or face is present in the available photographs.

Many different types of Biometrics are there such as Iris Identification, Retinal Identification, Face Recognition, Voice Recognition, Fingerprint, Hand or Finger Geometry, Signature verification, Keystroke Dynamics, and other cryptic biometrics. Hand-based biometrics, such as fingerprint and hand geometry, is the most ample biometric system but it suffers from a major drawback, which is its susceptibility to anti-security threats, such as the reproduction of fingerprints left on surfaces to misguide the system. On the other hand, the hand geometry features are not striking enough for identification when the number of users increases. Problem related to other identifiers are as human voice and signature can be copied, duplicates are available so face recognition will not be foolproof identifier. Palm print and finger print can be simultaneous extracted from the palm side which can give better performance improvement, but size of finger knuckle is very small as compared to palm print and offers more attractive alternative as it requires less processing as compared to palm print.

A normal human hand has four fingers each of which has 3 bone segments and 3 joints. The thumb has 2 bone segments and 2 joints. These segments are

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known as phalanges and are shown in figure 1 from a typical finger dorsal image

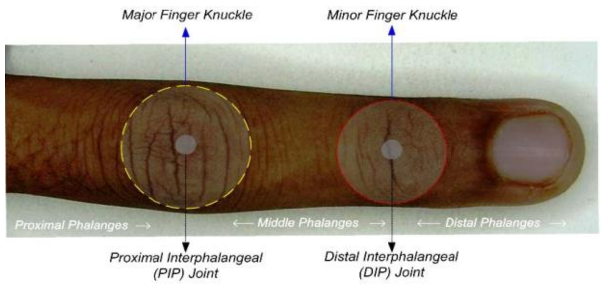

Fig.1 Finger Knuckle Anatomy

2. System Model

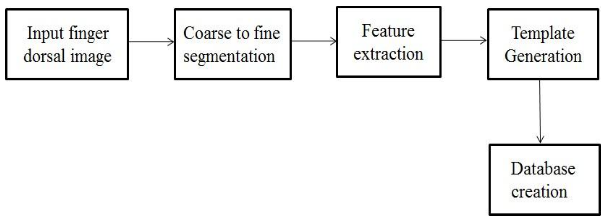

Fig.2 Database Creation

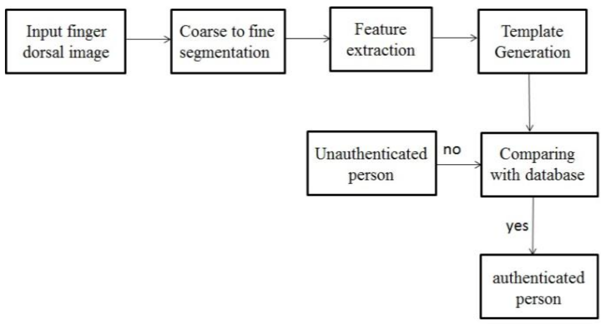

Fig.3 Matching

The system model is divided into Database creation and Matching. Coarse to fine segmentation is employed here. This idea aims to develop a completely automated scheme to simultaneously segment minor knuckle images of finger from finger dorsal images acquired using contactless imaging set up. Three Feature extraction techniques such as Local binary patterns, Three patch local binary pattern and 1-D log Gabor filter are employed for performance evaluation. Template matching using correlation algorithm is employed for matching.

3. Methodology and Design

3.1 Image Acquisition

The data used in the experiment was taken from the Hong Kong polytechnic university contactless finger knuckle images database, containing 100 middle finger dorsal images of 25 individuals (both male and female) in outdoor and indoor environment. Images are acquired using a contactless set up that simply uses a hand held camera.

3.2 Segmentation

The process of separating a digital image to multiple parts is known as segmentation. Using this technique a label is assigned to every pixel. The pixels having the same label have certain characteristics. Accurate personal identification using minor finger knuckle patterns will require accurate segmentation of region of interest images. The segmentation approach should be able to generate normalized and fixed size region of interest images from the finger dorsal images of subjects under varying age group. In this system coarse to fine segmentation strategy is performed for extracting the minor finger knuckle.

Coarse to Fine Segmentation: Fig 4 illustrates block diagram of preprocessing steps employed in image segmentation process. Each of the acquired image is first converted from RGB to grey. Then the gray scale image is subjected to Binarization using thresholding. The resulting images are cleaned (denoised) by automatically removing the isolated regions/pixels (≥100 pixels) so that the longest object representing finger is only retained. The fingertip estimation is done using sobel edge detector. The location of fingertip is utilized to eliminate the background image above the finger-tip. The orientation of fingers is then estimated using gradient field. The finger knuckle print image is divided into w*w blocks. For each block we estimate the gradient angle, also called as Orientation field angle. This gives the orientation field of the finger-knuckle-print. The direction of orientation field is calculated as follows:

$$\theta_w = \frac{1}{2} tan^{-1}(\sum_{i=1}^{w}\sum_{i=1}^{w} 2g_x(i,j)g_y(i,j) \,|\, \sum_{i=1}^{w}\sum_{i=1}^{w} g_x^2(i,j)g_y^2(i,j)) + \frac{\pi}{2} \quad (1)$$

The desired range of θ_w is between $[0,\pi]$. This is perpendicular to gradient direction and gives direction of ridge in that block.

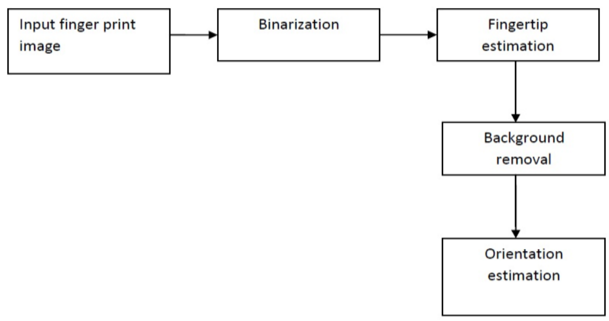

Fig. 4 Image Segmentation (Preprocessing)

Then coarse segmentation is done in which segments a small portion of acquired finger images that can include minor finger knuckle region while excluding the major knuckle region and major part of finger nail. Such segmentation strategy requires some assumptions for the maximum ratio of nail length to the finger length and assumption that the major finger knuckle region is located somewhere in the middle of the acquired finger dorsal image. Then nail check and removal steps are done with resulting image which consist of segmenting the image and locating the bonding box region for smaller parts and removing them. Then calculate the centroid of the connected components and segment a fixed size region that represents minor finger knuckle region for the finger dorsal image.

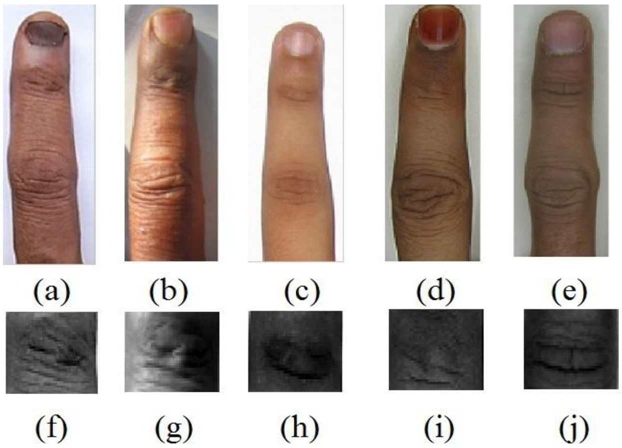

Fig. 5 Finger dorsal images in (a)-(e), segmented minor finger knuckle images in (f)-(j),

3.3 Feature Extraction

Feature extraction is a technique used to transform the input data into set of features and is a form of dimensionality reduction. The features set will extract the important information from the input data if the features are extracted correctly. The finger knuckle images typically represent some random texture pattern which appears to be quite unique in different fingers. Therefore a variety of spatial and spectral domain feature extraction strategies can be applied to ascertain the matching accuracy from the finger knuckle images. These approaches are local binary patterns, Three patch local binary patterns and 1 D log-Gabor filter.

3.3.1 Local Binary Patterns: The LBP operator can be seen as a consolidating approach to the traditionally disparate statistical and structural models of texture analysis. Texture is described in terms of micro-primitives (textons) and their statistical placement rules. The LBP operator is relatively invariant with respect to changes in illumination and image rotation. It can even resist changes in texture scale. The local binary patterns (LBP) encoding can acquire local knuckle patterns and also represent multi-scale texture appearances. The binary patterns for every pixel centered at z_c with neighbouring /surrounding pixels z_p, is computed as follows;

$$\mathrm{h}(Z_p - Z_c) = \begin{cases} 1, & Z_p - Z_c \geq 0 \\ 0, & Z_p - Z_c \leq 0 \end{cases} \quad (2)$$

LBP is created at a particular pixel location by thresholding the 3*3 neighborhood surrounding the pixel with the central pixels intensity value, and treating the subsequent pattern of 8 bits as a binary number. A histogram of these binary numbers in a predefined region is then used to encode the appearance of that region. Typically, a distinction is made between uniform binary patterns, which are those binary patterns that have at most 2 transition from 0 to 1, and the rest of the patterns.

3.3.2 Three-Patch LBP Code: Three-Patch LBP (TPLBP) code of a finger knuckle is produced by comparing the values of three patches to produce a single bit value in the code assigned to each pixel. For each pixel in the image, consider a $\omega * \omega$ patch centered on the pixel, and S additional patches distributed uniformly in a ring of radius r around it. For a parameter α, a pairs of patches are taken, i.e. α- patches apart along the circle, and compare their values with those of the central patch. The value of a single bit is set according to which of the two patches is more similar to the central patch. The resulting code has S bits per pixel. Specifically, we produce the Three-Patch LBP by applying the following formula to each pixel.

$$TLBP_{r,s,\omega,\alpha}(p) = \sum_i^s f(d(C_i, C_p) - d(C_{i+\alpha\, mods}, C_p))2^i \quad (3)$$

where C_i and $C_{i+\alpha\, mods}$ are two patches along the ring and C_p is the central patch. The function d(,)is any distance function between two patches (e.g., L2 norm of their gray level differences) and f is defined as:

$$f(x) = \begin{cases} 1, & x \geq \tau \\ 0, & x \leq \tau \end{cases} \quad (4)$$

3.3.3 1-D log Gabor filter: An alternative to the Gabor function is the Log-Gabor function proposed by Field [1987]. Log- Gabor filters can be constructed with arbitrary bandwidth and the bandwidth can be optimized to produce a filter with minimal spatial extent. 1-D log-Gabor filter based feature extraction approach that can exploit local phase information from the enhanced finger knuckle images. Each of the segmented knuckle images were filtered by 1-D Log-Gabor filter $\mathrm{H}(\omega)$ is defined as follows:

$$\mathrm{H}(\omega,\varphi) = e^{-\frac{(\ln(\omega/\omega_0)^2)}{2(\ln(2\pi\sigma f/\omega o)^2)}}\ e^{-\frac{(\varphi-\varphi_0)^2}{2\sigma\varphi^2}} \quad (5)$$

where ω_0 is the central frequency, φ_0 is the orientation, σ_f and σ_φ are the constants that respectively determine radial and angular bandwidth of the log-Gabor filter. The filtered knuckle images are employed to extract the local phase information. The log-Gabor function has the advantage of the symmetry on the log frequency axis. The Log-Gabor filters spread information equally across the channels. On the contrary, ordinary Gabor filters over-represent low frequencies. Filters are constructed in terms of two components.

1) Radial component, which controls the frequency band that the filter responds to
2) The angular component, which controls the orientation that the filter responds to.

The two components are multiplied together to construct the overall filter. Here are the parameters we have to decide on, several are interdependent.

- The minimum and maximum frequencies.
- The filter bandwidth to use.
- The scaling between Centre frequencies of successive filters.
- The number of filter scales.
- The number of filter orientations to use.
- The angular spread of each filter.

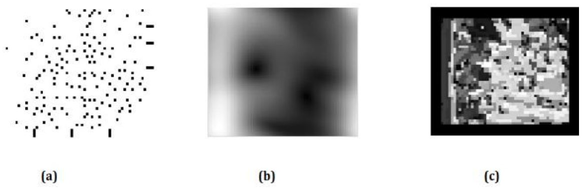

Fig.6 Feature extraction Results: (a) Local binary patterns (b) 1-D log Gabor filtered image (c)Three patch local binary patterns

3.4 Matching

For matching, the extracted features of finger knuckle images are stored as templates and are compared with the database images and results are displayed. The matching scores between the any two knuckle images were generated by using 2D correlation algorithm. In this algorithm, pixel by pixel value comparison is done. This is a classical task, and a numeric measure of image similarity is usually called image correlation. The correlation/ similarity between the pixel values are calculated. The correlation coefficient is a number representing the similarity between two images in relation with their respective pixel intensity. The correlations basically found using mean. The correlation coefficient always takes a value between -1 and 1, with 1 or -1 indicating perfect correlation. The formula for computing the correlation coefficient is given by

$$r = \frac{\sum m \sum n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum m \sum n (A_{mn} - \bar{A})^2)(\sum m \sum n (B_{mn} - \bar{B})^2)}} \quad (6)$$

Here A and B are the images that are comparing, whereas the subscript indices m and n refer to the pixel location in the image. $\bar{A}, \bar{B}$ denotes the difference between the intensity value at that pixel and the mean intensity of the whole image, for every pixel location in both images.

4. Experimental Results

Simulation is done using MATLAB. In this work a database of 100 middle fingers dorsal images are acquired from 25 individual (four middle fingers of each individual) where three images from each individual are used as training images and each one as testing image. The matching score between the knuckle images were generated using the correlation methodology. Both genuine and imposter matches are produced using this approach.

Table 1 Performance Evaluation of knuckle Matching

Feature extraction techniques	Correlation Accuracy
Local binary pattern	78%
1-D log Gabor filter	82%
Three patch LBP	88%

Conclusions

This paper has successfully investigated the possibility of employing minor finger knuckle images for the biometric identification. The coarse-to-fine segmentation strategy developed in this paper has been quite successful as it has been able to achieve higher matching accuracy. The experimental results in this paper have employed local binary patterns, Three patch local binary patterns, and 1D log-Gabor filter based matchers for the performance evaluation. Three patch local binary patterns using correlation matching show much better results than the others. The finger dorsal images employed this paper were acquired in single session and therefore conclusions on the accuracy points towards the uniqueness of minor finger knuckle patterns in the given database rather than on the stability of such patterns. The error is caused due to change in camera, background, different lightning conditions etc. with time. From the results, the efficiency and security associated using the finger knuckle pattern is still high to be comparable from those modalities like finger print, iris recognition, palm print etc.

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