An Effective Fingerprint Verification System

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Abstract— Fingerprints are widely used in biometric techniques for automatic personal identification. It remains a reliable, efficient and commonly accepted biometric. In this paper, a fingerprint recognition system for identifying the low quality fingerprint on inked-printed paper is developed. In proposed system, ridge feature-based approach for fingerprint recognition is developed. Firstly, the Core Point (CP) of the input fingerprint is detected. Keeping the CP in the center, the image of size w x w is cropped and further processing is done with the cropped portion of the image. The orientation fields of the fingerprint are detected from the cropped image. In addition to orientation feature, we also use extended feature, including skeleton image. The features of the input fingerprint and template fingerprint are extracted by using the proposed system and matched. If it is over a certain threshold the result of the matching process is positive otherwise negative. We tested our system by matching 300 inked images with live scan fingerprints of same identities. The experimental results indicate that orientation fields and skeleton features are the most effective features in improving the matching accuracy.

Keywords— Biometric, Fingerprint, Fingerprint Recognition

I. INTRODUCTION

Recently, biometric technologies have shown more and more importance in various applications. In recent years, this technology has received increasingly more attention. Biometrics is a rapidly evolving technology that has been widely used in forensics, such as criminal identification and prison security, and has the potential to be widely adopted in a very broad range of civilian applications such as Banking security, Physical access control, Information system security, customs and immigration. Among them, fingerprint recognition is considered one of the most reliable technologies and has been extensively used in personal identification. Fingerprints have been routinely used as a method for person identification for more than a century [1].

Fingerprints of any individual are unique (even in the case of identical twins), remain the same over lifetime, and are easy to collect. A pattern of ridges, valleys and minutiae can be extracted from the fingerprint image. A fingerprint pattern is composed of a sequence of ridges and valleys which generally run parallel to each other in fingerprint. The ridges are dark lines while the valleys are the light areas between the ridges. The underlying ridge structure pattern can be analyzed on a global and local level. These are the features of fingerprint.

The global features mainly give an overall characteristic of the finger. A global feature normally provides a special pattern of ridges and valleys including singularities or singular point (SP). The most used singularities are core and delta. While the core is usually defined as a point on the inner most ridge, the delta is known as the center point where three different flows meet. The SP provides important information used for fingerprint classification, fingerprint matching and fingerprint alignment. Generally, fingerprints can be classified into five classes: left loop, right loop, whorl, arch and tented arch. Major concept used in local representations of fingerprints is finger ridges. Minutiae are minute details of the fingerprint. The minutiae are ridge endings or bifurcations on the fingerprints. They, including their coordinates and direction, are most distinctive features to represent the fingerprint.

In forensics, fingerprint images can be classified in two categories: fingerprint impressions and latent fingerprints. Fingerprint impressions are obtained either by scanning the inked impressions on paper or by using scanning devices. Latent fingerprints are obtained from crime scenes and usually come from small portion of friction ridge skins. The qualities of fingerprint images are mainly depend on the acquisition devices.

The different kinds of fingerprint images are described in Fig. 1. The high quality images acquired by live-scan device, fingerprint inked impression on paper and fingerprint image from FVC2002 database are shown.

![Fingerprint images](image)

(a) Live-scan fingerprint (b) Inked fingerprint on paper (c) Fingerprint from FVC 2002

A fingerprint recognition system can be used for both verification and identification. In verification, the system compares an input fingerprint to the “enrolled” fingerprint of a specific user to determine if they are from the same finger (1:1 match). In identification, the system compares an input fingerprint with the prints of all enrolled users in the database to determine if the person is already known under a duplicate or false identity (1:N match).

Fingerprint matching means matching of two fingerprint images with respect to certain features like minutiae, ridges, etc of two images. The feature based matching is an...
appropriate method of matching and provides better results for majority of fingerprints, but there are a number of fingerprints of low quality which could not be identified easily by these methods [2]. Several methods of automatic fingerprint identification have been proposed in the literature. Minutiae based approach often gives satisfactory results for good quality images. But if, the quality of the image is poor, then minutiae extraction is a very difficult task and often gives incorrect results that are not acceptable for real time authentication applications. The minutiae sets may suffer from false, missed, and displaced minutiae, caused by poor fingerprint image quality and imperfections in the minutiae extraction stage [3].

Another class of fingerprint matching algorithms doesn’t use the minutiae features of the fingerprint. These methods usually match features extracted from the image by means of certain filtering or transform operations; hence they are named ridge feature-based methods. In [4], the 2D wavelet decomposition on J octaves of the image is used as the features for recognition. These approaches require less preprocessing or post processing effort than minutiae-based methods. While minutiae-based methods normally require a minutiae location process [5], image-based methods match two fingerprint images directly, based on their texture features.

In this paper, we propose the ridge feature-based approach towards fingerprint recognition. The fingerprints are matched based on the skeleton image and orientation image. A skeleton is a one-pixel-wide ridge, which is traced in the thinned image and represented as a list of points. Ridge orientation map is obtained by dividing the image into non overlapping blocks of size 16 × 16 and assigning a single orientation, wavelength, and quality value to each block. The proposed system can recognize not only the fingerprint acquired from device but also the low quality fingerprint image from inked-printed images on paper.

The rest of the paper is organized as follows: section 2 reports the overview of the proposed system. In section 3 the preprocessing step is described. Section 4 and 5 present feature extraction and matching. Section 6 is experimental results. Finally, in section 7, the concluding remarks are given.

II. SYSTEM OVERVIEW

In proposed system, the fingerprint image acquired from inked printed papers is preprocessed and features are extracted. The fingerprint on printed paper is a low quality, sometime is complex with fabric background. Therefore, in order to be the narrow area with good ridge features around the center area, the center point or core point of the fingerprint is manually selected and cropping is done around the center point. To improve the clarity of the ridge lines, the enhancement of fingerprint is performed. The orientation fields and skeleton image of the two fingerprints are extracted and matched and then determine the matching scores of the two images.

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image. The cropped image and enhanced image are shown in Fig. 4.

(a) Cropped Image (b) After histogram equalization

C. Enhancement

Fingerprint image enhancement is to make the image clearer for easy further operations. Since the fingerprint images are not assured with perfect quality, enhancement methods, for increasing the contrast between ridges and furrows and for connecting the false broken points of ridges due to insufficient amount of ink, are very useful to keep a higher accuracy to fingerprint recognition.

In the frequency domain, the image was divided into small processing blocks (32×32 pixels) and the Fast Fourier transform (FFT) was applied in the following way –

\[
F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \exp \left\{ -j2\pi \frac{ux}{M} + \frac{vy}{N} \right\}
\]

(1)

where \( u = 0, 1, 2, ..., 31 \) and \( v = 0, 1, 2, ..., 31 \).

In order to enhance a specific block by its dominant frequencies, the FFT of the block as multiplied by its magnitude for a number of times. Here, the magnitude of the original FFT = \(|F(u,v)|\).

\[
g(x,y) = F^{-1} \left[ |F(u,v)| \cdot F(u,v) \right]^k
\]

(2)

where \( F^{-1} (F(u,v)) \) is done by:

\[
F(x,y) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(u,v) \exp \left\{ -j2\pi \frac{ux}{M} + \frac{vy}{N} \right\}
\]

(3)

for \( x = 0, 1, 2, ..., 31 \) and \( y = 0, 1, 2, ..., 31 \). The value of \( k \) in equation (2) is an experimentally determined constant, however based on our experimentation a better result was found for \( k = 0.5 \). So with an appropriate selection of \( k \) value, the ridges and the overall appearance of the image can be improved, which is useful for proper feature extraction and classification. Enhanced image is shown in Fig 5.

IV. FEATURE EXTRACTION

Feature extraction is concerned with the quantification of ridge line characteristics. The proposed system utilizes the orientation features and the skeleton image of the fingerprint.

A. Ridge Orientation Detection

The term orientation image often refers to the determination of local ridge orientation in the fingerprint image. Gradient-based method was introduced in [6] and has been utilized by some researchers. In proposed system, gradient-based approach is used to detect fingerprint orientation.

The orientation of a pixel in an image can be expressed as a vector \([ G_x(x,y), G_y(x,y) ]\), which is defined as [6]:

\[
\begin{bmatrix}
G_x(x,y) \\
G_y(x,y)
\end{bmatrix} = \nabla I(x,y) = \begin{bmatrix}
\frac{\partial I(x,y)}{\partial x} \\
\frac{\partial I(x,y)}{\partial y}
\end{bmatrix}
\]

(4)

where \( I(x,y) \) is the gray-scale fingerprint image. Commonly, a main orientation in a block can be decided by the gradient vector of most pixels. So the gradient vector of all pixels in a local area can be used to estimate the local ridge orientation. However, gradients cannot directly be accumulated in local area since opposite gradient vectors will cancel each other, although they denote the same ridge orientation. Method in [6, 7] uses a method to double the angles of the gradient vectors before averaging, in this way opposite gradient vectors will point to the same direction. In [8], not only the angle is doubled, but also the length of the gradient vectors is squared.

In this paper, a convenient way to estimate the local ridge orientation is proposed. We first adjust equation (5) as follows:

\[
\begin{bmatrix}
G_x(x,y) \\
G_y(x,y)
\end{bmatrix} = \text{sign}(\frac{\partial I(x,y)}{\partial x}) \begin{bmatrix}
\frac{\partial I(x,y)}{\partial x} \\
\frac{\partial I(x,y)}{\partial y}
\end{bmatrix}
\]

(5)

It is confirmed that the first element in gradient vector is positive in equation (5). The opposite gradient vector will reinforce each other while averaging. The local ridge orientation can be obtained in the following steps:

1. Accumulate the gradient of \( x \) and \( y \) axis using equations (6) and (7):

\[
G_x = \sum_W G_x(x,y)
\]

(6)

\[
G_y = \sum_W G_y(x,y)
\]

(7)

2. Mutative orientation between ridges and valleys, which is perpendicular to ridge orientation, can be computed as equation (8):

\[
\psi(i,j) = \arctan(G_y / G_x)
\]

(8)

3. Using equation (9), local ridge orientation is obtained.

\[
\theta(i,j) = \begin{cases} 
\psi(i,j) + 0.5\pi & \psi(i,j) \leq 0, \\
\psi(i,j) - 0.5\pi & \psi(i,j) > 0.
\end{cases}
\]

(9)

where \( (i,j) \) is the block number in fingerprint image, \( \theta(i,j) \) \( (\theta \in (-0.5\pi, 0.5\pi)) \) is the corresponding ridge orientation, and \( W \) denotes the range of block.
Ridge frequency is another intrinsic property of the fingerprint. The most commonly used method for computing ridge frequency is based on the projection sum taken. Oriented fingerprint image is shown in Fig 6.

Fig 6. Orientation Image

B. Thinning

The skeleton image is one-pixel-wide ridge, which is traced in the thinned image. In our system, we have used the Single pass thinning algorithm presented in [9] for obtaining skeleton fingerprint.

Single pass thinning algorithm uses both flag map and smoothing templates for boundary pixel deletion [10]. The skeleton produced by this algorithm is not only one-pixel thick, perfectly connected, well-defined, but also has the desired property of handling boundary noise. In thinning algorithm, the image and the flag map are used together to decide on which pixel to delete. When examining a pixel and its neighbours to decide if it is to be flagged as a boundary pixel, both the flag and the results from the last iteration are used in the decision-making process.

The symbols $P_0$, $P_1$, $P_2$, $P_3$, $P_4$, $P_5$, $P_6$, $P_7$ and $P_8$, shown in Fig 7(a), represent the pixel $P[i][j]$ in the bitmap and its neighbours. The flag map is used for flagging those pixels that will eventually be deleted. The size of the flag map is the same as that of the image. For an $n \times m$ image, the size of the flag map will also be $n \times m$. The symbols $Q_0$, $Q_1$, $Q_2$, $Q_3$, $Q_4$, $Q_5$, $Q_6$, $Q_7$ and $Q_8$, as shown in Fig 7(b), correspond to $P_0$, $P_1$, $P_2$, $P_3$, $P_4$, $P_5$, $P_6$, $P_7$ and $P_8$ respectively. Initially, all pixels in the flag map are set to 1. The value will be changed to 0 as soon as that pixel is flagged.

Fig. 7 (a) Local pixel notation of bitmap (b) Local pixel notation of flag map

Three functions are used in single pass thinning. They are the previous neighbourhood function $PN$, the current neighbourhood function $CN$ and the “0→1” transition function $Trans$. The previous neighbourhood function $PN$ is defined as follows:

$$PN(P_0) = \sum_{i=1}^{8} P_i$$  \hspace{1cm} (10)

It counts the number of previous neighbours of pixel $P_0$, that is the number of its neighbours in the bitmap from the last iteration. Previous neighbourhood function $PN$ is used to detect whether a foreground pixel $P_0$, whose pixel value in the bitmap is one, is a boundary point. If $PN(P_0)$ is equal to 8, then pixel $P_0$ is not a boundary point since there is no background pixel, whose pixel value is zero, in its neighbourhood. The current neighbourhood function $CN$ is defined as follows,

$$CN(P_0) = \sum_{i=1}^{8} (P_i \times Q_i)$$ \hspace{1cm} (11)

It counts the number of current neighbours of pixel $P_0$. If one foreground pixel in the neighbourhood of $P_0$ has been flagged then it can no longer be considered to exist. The operator “\times” in the function $CN$ is the logical “and’ and the operator “+” is the logical “or”.

The “0→1” transition function, $Trans$, is defined as follows,

$$Trans(P_i) = \sum_{i=1}^{8} count(P_i)$$ \hspace{1cm} (12)

where

$$count(P_i) = \begin{cases} 1, & \text{if } ((P_i \times Q_i) = 0) \& \& (P_{i+1} \times Q_{i+1}) = 1) \\ 0, & \text{otherwise} \end{cases}$$

and

$$P_9 = P_1, \hspace{0.2cm} Q_9 = Q_1$$

It gives the number of “0→1” transitions when traversing across the 8-neighbours $P_1, P_2, \ldots, P_8$. The function $Trans$ is used to measure the connectivity within the immediate neighbourhood of the pixel. If the condition ($Trans(P_0) = 1$) and ($CN(P_0) > 1$) are true, then there exists only one connected component within the perimeter of the $3 \times 3$ sub-image. It is safe to remove the central pixel that has the value 1, since its removal will not affect the connectivity of the rest of the pixels in the local window. If the condition ($Trans(P_0) = \min CN(P_0), \ 8-(CN(P_0))$) is true, that means the central pixel P is a break point. The removal of the break point will damage the connectivity of the image and hence it must be preserved. Fig 8 shows the thinned image.

Fig 8. Thinned Image

V. FINGERPRINT MATCHING

For the verification process, the input image is preprocessed and thinned to one pixel thick image and the ridge orientation is detected.

To compare two fingerprint orientation fields, the first step is alignment of these two fingerprints. It can be done by using the core point or reference point to align the fingerprints.

In the matching step, the correlation between two aligned orientation fields, $A$ and $B$, is computed as below. Let $\Omega$ denotes the intersection of the two effective regions after alignment, and $N$ is the total number of points in $\Omega$. The matching score between two orientation fields is defined as
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\[ s(A,B) = \frac{1}{N} \sum_{(i,j) \in \Omega} \delta(i,j) \]  

(13)

In (13), \( \delta(i,j) \) is the difference between the orientation values at the point \((i,j)\) in image \(A\) and \(B\), which is formulated as follows:

\[ \delta(i,j) = \begin{cases} 
\delta_0(i,j), & \text{if } \delta_0(i,j) \leq \frac{\pi}{2} \\
\pi - \delta_0(i,j), & \text{otherwise} 
\end{cases} \]

(14)

and \( \delta_0(i,j) \) is defined as

\[ \delta_0(i,j) = |\theta_A(i,j) - \theta_B(i,j)| \]

(15)

where \( \theta_A(i,j) \) and \( \theta_B(i,j) \) are the direction of point \((i,j)\) in image \(A\) and \(B\). If the matching score \( s(A,B) \) is higher than a certain threshold, we say the two orientation fields are “matched”.

From the thinned image, the features points are extracted and matched with the source image. Distance matching has been used in the proposed system for the purpose of recognition. Relative distances of each feature point are compared with the stored feature points. The feature point as well as the skeleton image which best matches with the source image and distance value is below the maximum threshold, is recognized as a genuine attempt, else an imposter.

VI. EXPERIMENTAL RESULTS

In this research work, the proposed matching technique was tested on the database of 300 images. Each fingerprint image is manually cropped around the center point and enhanced. The skeleton image is extracted and the orientation image is detected. The experimental results show that the cropping area is very important. Cropping around the center area that can have important ridge line information is done for image alignment. If the cropped areas of the registered image and input image are different, this can lead to a few error rates. Therefore, the center area around the core point is cropped with the size of 200×200.

To verify the system, the receiver operating characteristic (ROC) curve and equal error rate (EER) are used to evaluate the performance of the proposed method. The ROC curve is a false acceptance rate (FAR) versus false rejection rate (FRR) curve. For a given distance threshold, FRR and FAR can be calculated.

Different thresholds are taken to perform tests according to the proposed method and multiple sets of FRR and FAR values are obtained; the FRR and FAR graph of relation is drawn. Fig 10 represents the ROC results, which measures the accuracy of fingerprint matching process and shows the overall performance of an algorithm. The EER is the point where a false acceptance rate and the false rejection rate are equal in value. The smaller the EER is, the better the algorithm. From Fig 9, we can see that the performance of our algorithm is good and the EER is 2.80%. The overall performance of the proposed system is up to 97%.

REFERENCES


