Fingerprint verification using statistical descriptors

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1. Introduction

Fingerprint is probably the most widely used personal identification tool. Factors believed to be responsible for its widespread acceptance include individuality, uniqueness and reliability. A distinctive feature of fingerprint lies in the high degree of difficulty in terms of forgery, coupled with the fact that fingerprints are unique to each person. In fact, fingerprint provides an outstanding source of entropy, which makes it an excellent candidate for security applications. Users cannot pass their fingerprint characteristics to others as easily as they do with their cards or passwords [1–3].

The pattern of valleys and ridges on human fingertips forms the fingerprint image. Analyzing this pattern at different levels reveals different types of global and local features. A global feature normally provides a special pattern of ridges and valleys including singularities or singular point (SP). However, the important points of the 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 [4–6], fingerprint matching [7,8] and fingerprint alignment [9,10]. The local feature known as minutiae is also considered important for fingerprint matching.

The quality of fingerprint image is normally affected by three types of degradations; appearance of gaps on ridges, parallel ridges intercepts and natural effects such as cuts, wrinkles and injuries. The fingerprint enhancement is expected to improve the contrast between ridges and valleys as well as noise reduction on the fingerprint images. Much work has been conducted on fingerprint enhancement and a range of related approaches have been proposed. The most widely used method is based on contextual filters. O’Gonnan and Nickerson [11] proposed the first method which employed contextual filtering for fingerprint enhancement. Hong et al. [12], on the other hand, reported fingerprint enhancement based on the estimated local ridge orientation and frequency clarification of ridge and valley structures of input. The use of eight...
High quality fingerprint image is very important for fingerprint verification to function properly. In real life, the quality of the fingerprint image is affected by noise like smudgy area normally created by over-inking, breaks in ridges due to under-inking, changing positional characteristics of features mainly caused by skin resilient as well as fragmented and low contrast ridges which normally arise as a result of dry skin. Other factors affecting quality of fingerprint image include wounds and sweat with consequent ridge discontinuities and smudge marks respectively. While Fig. 2 shows original fingerprint images, Fig. 3 displays the corresponding enhanced fingerprint images.

The short time Fourier transform analysis (STFT) proposed by Refs. [28,29] is applied here for fingerprint image enhancement, STFT analysis and the enhancement method can be summarized as follows:

1. **Fingerprint Image Enhancement**
   - High quality fingerprint image is very important for fingerprint verification to function properly. In real life, the quality of the fingerprint image is affected by noise like smudgy area normally created by over-inking, breaks in ridges due to under-inking, changing positional characteristics of features mainly caused by skin resilient as well as fragmented and low contrast ridges which normally arise as a result of dry skin. Other factors affecting quality of fingerprint image include wounds and sweat with consequent ridge discontinuities and smudge marks respectively. While Fig. 2 shows original fingerprint images, Fig. 3 displays the corresponding enhanced fingerprint images.
   - The short time Fourier transform analysis (STFT) proposed by Refs. [28,29] is applied here for fingerprint image enhancement, STFT analysis and the enhancement method can be summarized as follows:
The fingerprint image is divided into overlapping windows.

Stage I: STFT analysis
1. For each overlapping window $B(x, y)$ in the image:
   a. Remove the DC component of $B$, using $B = B - \text{avg}(B)$.
   b. Multiply by spectral window $w$.
   c. Acquire the FFT of the window $F = \text{FFT}(B)$.
   d. Execute root filtering on $F$.
   e. Execute STFT analysis. The analysis outputs are ridge orientation image $O(x, y)$, energy image $E(x, y)$, and ridge frequency image $F(x, y)$.
2. Smooth the orientation image $O(x, y)$ using vector averaging to yield a smooth orientation image $O'(x, y)$, and using the smooth orientation image $O'(x, y)$ to generate the coherence image $C(x, y)$.
3. Generate region mask $R(x, y)$ by thresholding the energy image $E(x, y)$.

Stage II: Enhancement
4. For each overlapping window $B(x, y)$ in the image:
   a. Generate the angular filter $F_A$ centered on the orientation in the smooth orientation image $O(x, y)$ with a bandwidth inversely proportional to coherence image $C(x, y)$.
   b. Generate the radial filter $F_R$ centered around the ridge frequency image $F(x, y)$.
   c. Filter the window in the FFT domain, $F = F \ast F_R \ast F_A$.
   d. Generate the enhanced window by the inverse Fourier transform $B'(x, y) = \text{IFFT}(F)$.
5. Reconstruct the enhanced image by composing enhanced blocks $B'(x, y)$.

2.2. Singular point detection

The fingerprint image is made up of pattern of ridges and valleys which form replica of the human fingertips. The fingerprint image represents a system of oriented texture and has very rich structural information within its domain. The flow-like pattern is usually extracted from the style of the existing valleys and ridges. In the large part of fingerprint topologies, the orientation field is quite smooth. However, in some areas, the orientation appears in a discontinuous manner. These regions are called singularities or singular points. Core and delta are defined as the centers of those areas. In addition, the reference point is defined here as the point with maximum curvature on the convex ridge. The reliability of the orientation field describes the consistency of the local orientations in a neighborhood along the dominant part and is used to locate the unique singular point. The reliability can also be computed using the coherence proposed by Refs. [30] and [31]. Fig. 4 depicts the proposed method for detecting the singular point.

1. Orientation field.
   a. The image is divided into a non-overlapping blocks of size $W \times W$ and assigned a single orientation that corresponds to the most apparent or dominant orientation of the block. In this proposed method, $W$ is set to sixteen.
   b. Compute the horizontal and vertical gradients $G_x(x, y)$ as well as $G_y(x, y)$ at each pixel $(x, y)$ by using Sobel mask $[32]$. The mask is set to $3 \times 3$.
   c. Compute the ridge orientation of each pixel $(x, y)$ by averaging the squared gradients within a $W \times W$ window centered at $(x, y)$ as follows [33]:

\[
G_{xx} = \sum_{(x, y) \in W} G^2_x(x, y)
\]
Fig. 4. Proposed method for detecting singular point.

\[ G_{yy} = \sum_{(x,y) \in W} C_y^2(x, y) \]  
\[ G_{xy} = \sum_{(x,y) \in W} G_x(x, y) \cdot G_y(x, y) \]  
\[ \theta(x, y) = \frac{1}{2} \tan^{-1}\left( \frac{2G_{xy}}{G_{xx} - G_{yy}} \right) \]

d. Smooth the ridge orientation using Gaussian low-pass filter. However, to perform the low-pass filtering, the orientation image needs to be converted into a continuous vector field as follows:

\[ \Phi_x = \cos(2\theta(x, y)) \]

and

\[ \Phi_y = \sin(2\theta(x, y)) \]

where \( \Phi_x \) and \( \Phi_y \) are the \( x \) and \( y \) components of the vector field, respectively. With the resulting vector field, the Gaussian low-pass filter can be applied as follows:

\[ \Phi'_x(x, y) = \sum_{u=-1}^{1} \sum_{v=-1}^{1} w_{\Phi}(u, v) \Phi_x(x - uw_{\Phi}, y - vw_{\Phi}) \]  
\[ \Phi'_y(x, y) = \sum_{u=-1}^{1} \sum_{v=-1}^{1} w_{\Phi}(u, v) \Phi_y(x - uw_{\Phi}, y - vw_{\Phi}) \]

where \( W_{\Phi} \) is a two-dimensional low-pass filter with unit integral.

The result of the above method can be seen in Fig. 4(A).

2. Since the singular point has the maximum curvature. It can be located by measuring the strength of the peak using the following:

\[ \gamma_{\min} = \frac{G_{yy} + G_{xx} - (\Phi'_x G_{xx} - G_{yy}) - (\Phi'_y G_{xy})}{2} \]  
\[ \gamma_{\max} = \frac{G_{yy} + G_{xx} - \gamma_{\min}}{2} \]  
\[ \text{reliability} = 1 - \frac{\gamma_{\min}}{\gamma_{\max}} \]
Fig. 5. Singular points in fingerprint images.

Fig. 6. Rotated sub-image.

Fig. 4(B) shows the orientation field reliability map and the singular point can be seen inside its contour. After the computation of the orientation field reliability, the coordinate of the singular points is needed to be known in terms of $x$ and $y$ values. To achieve this, the following operations are applied.

3. The orientation field reliability map is segmented into two distinct regions one with a singular point region holding the reliability values greater than 0.1 and less than 0.5 and non-singular point region by applying a threshold $0.5 > t > 0.1$. Fig. 4(C) shows the result of the segmentation.

4. Thinning the segmented part is applied to the image which reduces the width of the contour line to one pixel. Fig. 4(D) shows the result after applying thinning.

5. Morphological opening and closing is then applied on singular point contour with eventual reduction to a single point. Fig. 4(E) shows the closing and opening to the image and Fig. 4(F) shows the location of the singular point in the original image.

In Fig. 5 the singular points can be seen clearly.

2.3. Extracting the singular point sub-image and normalization

Fingerprint images do not come in the same sizes. Different acquisition for the same finger may result in different size or orientation of fingerprint image. Since the area near the singular point contains correct and efficient information about the fingerprint, making the singular point as the center, a sub-image of $129 \times 129$ is extracted from the original fingerprint image. In addition, this will reduce the computation time and the storage size. For this method, the images have to be aligned properly to ensure an overlap of the common region in the two fingerprint images. This is done by rotating the image to zero orientation at the singular point using the method describes in Ref. [32]. This process is performed in order to avoid the time-consuming translation alignments of previous algorithms. Fig. 6 shows the extracted fingerprint sub-images and its rotation.

2.4. Feature extraction

In this case, the sub-image is analyzed as a texture. The importance of texture for human visual system is to provide information for recognition and interpretation necessary for identifying objects or regions of interest in an image. Texture is a region descriptor that provides a quantifying measure of the property such as smoothness, coarseness and regularity. There are three main approaches to describe texture: statistical, structural and spectral. Statistical techniques describe texture by the statistical properties of the gray levels of points comprising a surface such as smooth, coarse or grainy. In general, these properties are computed from the statistical moments of the intensity histogram or gray level co-occurrence matrix.

of an image or region. To incorporate this type of information into the texture-analysis process is to consider not only the distribution of intensities, but also the relative positions of pixels in an image. The use of co-occurrence matrix produces this type of information. Structural techniques characterize texture as being composed of simple “texture primitive”, which are regularly arranged on a surface according to some rules. These rules limit the number of possible arrangement of the primitives. Spectral techniques are based on properties of the Fourier spectrum and describe the directionality period of the gray levels of a surface by identifying high-energy peaks in the spectrum.

The gray-level co-occurrence matrix (GLCM) is a statistical approach that can describe second-order statistics of a textured image. GLCM is basically a two-dimensional histogram in which the \((i, j)\)th element is the frequency that event \(i\) co-occurs with event \(j\). A co-occurrence matrix is specified by the relative frequencies \(P(i, j, d, \theta)\) in which two pixels, separated by distance \(d\), occur in a direction specified by angle \(\theta\), one with gray level \(i\) and the other with gray level \(j\). A co-occurrence matrix is therefore a function of distance \(r\), angle \(\theta\) as well as grayscales \(i\) and \(j\) [34].

A single GLCM might not be enough to describe the textural features of an input fingerprint. For example, a single horizontal spatial relationship might not be sensitive to texture with a vertical orientation. For this reason, multiple GLCMs are computed for values of \(\theta\) at 0\(^\circ\), 45\(^\circ\), 90\(^\circ\), and 135\(^\circ\). And the relative distance is one pixel. Fig. 7 shows the direction and position of other pixels with respect to pixel of interest, which results in four co-occurrence matrices. Based on each computed GLCM, four features that can successfully characterize the statistical behavior of a co-occurrence matrix are extracted. These are as follows [32]:

\[
\begin{align*}
(i) \quad \text{Correlation} & = \frac{\sum_{i=1}^{k} \sum_{j=1}^{k} (i - m_r)(j - m_c)P_{ij}}{\sigma_r \sigma_c} \\
(ii) \quad \text{Contrast} & = \sum_{i=1}^{k} \sum_{j=1}^{k} (i - j)^2 P_{ij} \\
(iii) \quad \text{Energy} & = \sum_{i=1}^{k} \sum_{j=1}^{k} P_{ij}^2 \\
(iv) \quad \text{Homogeneity} & = \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{P_{ij}}{1 + |i - j|}
\end{align*}
\]

where \(m_r, m_c\) are ‘means’ and \(\sigma_r, \sigma_c\) are the ‘standard deviations’ computed along the rows and columns respectively, and \(P_{ij}\) is the number of times that pixel occurred.

3. Experiment

The proposed algorithm has been evaluated using the fingerprint datasets Db1_a, Db2_a, Db3_a and Db4_a from the public databases of FVC2002 [35]. In order to achieve maximum performance, the relative distance has been set to be four pixels, which results in sixteen co-occurrence matrices. Overall, 800 fingerprints are included from 100 different fingers with 8 images from each finger. These images were captured using a low-cost capacitive sensor, which give rise to poor-quality images.

Series of experiments were conducted for each dataset. The data were divided into training and testing sets. Six out of eight fingerprints from each person were chosen for training and the remaining two were set aside for testing. Therefore, 600 patterns were used for training and 200 for testing. The same experiments were repeated two times by selecting different fingerprints for training and testing; the average of the two experimental results was then calculated as the final performance.
The false acceptance rate (FAR) is computed by the following equation:

\[
FAR = \frac{\text{Number of accepted imposter claims}}{\text{Total number of imposter accesses}} \times 100
\]  

(16)

the false rejection rate (FRR) is computed by:

\[
FRR = \frac{\text{Number of rejected genuine claims}}{\text{Total number of genuine accesses}} \times 100
\]  

(17)

and the equal error rate (EER) is calculated by:

\[
EER = \frac{\text{FAR} + \text{FRR}}{2}
\]  

(18)

The genuine match and impostor match tests were performed on the four datasets comprising the FVC2002 database. While assessment for the genuine match test was conducted by comparing fingerprint for each person with other fingerprints of the same person, impostor match test was carried out by comparing fingerprint of each person with fingerprints belonging to other persons respectively.

Table 1 shows the result of the experiment, with the average FAR and FRR at 0.35% and 0.21% respectively.

The Euclidean distance is used for evaluating the similarity between the input and the template in the database. The comparison of the proposed method with the methods proposed by Yang et al. [10] using tessellated invariant moment feature, Ross et al. [23] using minutiae and ridge feature map features, Jin et al. [25] using integrated wavelet and Fourier–Mellin invariant framework with four multiple training WFMT feature as well as Amornraksa et al. [36] using DCT feature proves that the proposed method is more accurate. Table 2 shows that this method has an average EER of 0.28% with a minimum difference of 3.29% between the other methods and the proposed.

Furthermore, the results have been analyzed using the Program for Rate Estimation and Statistical Summaries (PRESS) [37]. Table 3 shows clearly the results obtained by PRESS method is almost the same as that obtained by FVC2002 protocol. Fig. 8 shows the ROC graph for each database, and Fig. 9 for the result of the four datasets Db1_a, Db2_a, Db3_a, and Db4_a.

The experimental analysis was performed in MATLAB 7.4.0 and run using a HP Compaq Intel core2 duo CPU E4400 with 2.00 GHz and 1.96 GB RAM.

4. Conclusion

This paper proposes a novel method to verify enhanced fingerprint images using 16 co-occurrence matrices to compute four statistical descriptors. In reality, the quality of the fingerprint images is low, thus for this reason, the short time Fourier transform analysis is applied to enhance the images. Given that the singular point is important for image alignment a new reliable method has been introduced which uses the fingerprint orientation field reliability. The experimental results were analyzed twice, first using FVC testing protocol, then using the Program for Rate Estimation and Statistical Summaries (PRESS). The results of both analyses were almost the same. The experimental results were also compared with the methods proposed by Yang et al. using tessellated invariant moment feature, Ross et al. using minutiae and ridge feature map features, Jin et al. using integrated wavelet and Fourier–Mellin invariant framework with four multiple training WFMT feature, and
Amornraksa et al. using DCT feature. The experimental results have demonstrated that the proposed algorithm exhibits encouraging performance for verifying the enhanced fingerprint images. Further works need to be investigated for different input conditions and different relative pixel positions.

References


[35] B.S. Lab, Pattern Recognition and Image Processing Laboratory, Biometric Test Center, 2002.
[37] CFTR, Program for Rate Estimation and Statistical Summaries (PRESS), 2009.

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