Robust Fingerprint Recognition System using Orientation and Texture features

Zin Mar Win and Myint Myint Sein

Abstract— Fingerprint recognition is one of the most well-known and publicized biometrics for personal identification. Fingerprints exhibit oriented texture-like patterns. The texture information of the fingerprint can be used for fingerprint matching. Gabor filters can optimally capture global and local texture information even from poor-quality or incomplete images. But Gabor filterbank-based approach use only texture information and it is not robust to image distortion and rotation. In this paper, a hybrid fingerprint matching algorithm is developed by combining orientation features and the local texture pattern obtained using a bank of Gabor filters. Extensive experiments have been conducted on four different fingerprint databases: FVC2000 DB, live-scan fingerprint database acquired by Hamster Eye-D, inked fingerprint database and fingerprints from Myanmar National Registration Cards (NRC). The proposed matching approach is compared with the filterbank-based approach, and the proposed system produces a much improved matching performance by combining the orientation features to the filterbank-based features.

Keywords— Biometrics, fingerprint, fingerprint recognition, Gabor filters

I. INTRODUCTION

BIOMETRIC system is an imperative area of research in recent years. Biometrics refers to the use of distinct physiological and behavioral characteristics to identify individuals automatically and has the ability to distinguish between an authorized person and imposter. Physiological characteristics include fingerprint, face, retina iris etc. and these characteristics are unique to every person [3]. Among all biometrics (e.g., face, fingerprint, hand geometry, iris, retina, signature, voice print, facial thermo gram, hand vein, gait, ear, odor, keystroke dynamics, etc.), fingerprint-based identification is one of the most mature and proven technique. The pattern of ridges and furrows on the surface of a fingertip are formed by accumulation of dead cells that constantly slough as scales from the exposed surface. Its formation is determined during the first seven months of fetal development [4].

Fingerprints of any individual are unique (even in the case of identical twins), remain the same over lifetime, and are easy to collect. A fingerprint pattern is composed of a sequence of ridges and valleys [1] 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. 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 innermost 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. Minutiae are the locations where a ridge becomes discontinuous.

The different kinds of fingerprint images are described in Fig.1. The fingerprint from FVC200 database and the high quality images acquired by digital device (Hamster Eye-D) and low quality ink image from paper are shown in Fig.1(a), Fig.1(b), and Fig.1(c), respectively. Fig.1(d) shows the poor quality fingerprint image. This image is scanned from NRC card and its quality is poor than the ink image. The background pattern of image is very complex and can’t be seen clearly the ridge of the fingerprint. Several methods of automatic fingerprint identification have been proposed in the literature. They considered for first two types of the fingerprint images. In our research, not only the high quality fingerprints but also the inked fingerprints and the poor quality images of NRC card are considered for recognition.

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 [2].

Another class of fingerprint matching algorithms doesn’t use the minutiae features of the fingerprint. The texture features of the fingerprints are used for fingerprint matching.

In this paper, a hybrid fingerprint matching approach is proposed that combines orientation feature representation of the fingerprint with a Gabor-filter (texture-based) representation for matching purposes. The proposed system combines orientation feature matching to texture-based matching described in [7]. According to the experimental results, the proposed hybrid fingerprint matching algorithm is effective and efficient for both high and low quality fingerprints.

The rest of the paper is organized as follows: section 2 reports related works. In section 3, the overview of the proposed system is described. In section 4 to 7, preprocessing, feature extraction, feature matching, score level fusion are described. Section 8 is experimental results. Finally, in section 9, the concluding remarks are given.

II. RELATED WORKS

There has been a lot of work in various types of fingerprint identification.

With the development of fingerprint identification, the state of the art application use the fingerprint ridge line features such as minutiae point and texture feature in order to obtain the improved fingerprint recognition system. Zhou Weina et al., [5] described an algorithm combining wavelet transform with prewitt edge detection for fingerprint verification. The fingerprint verification system is based on wavelet’s supply of detail information and prewitt edge detection’s stable characteristics in translation, scaling and rotation. Leon et al., [6] developed two algorithms for image enhancement and also, the invariant moments in verification phase. Fingerprint verification is considered using a combination of Fast Fourier Transform (FFT) and Gabor filters by image enhancement. In [9], we proposed combined approach of orientation and skeleton features extraction for fingerprint matching. A skeleton is a one-pixel-wide ridge, which is traced in the thinned image and represented as a list of points. The texture feature-based approach [10] using Discrete Wavelet Transform (DWT) is proposed to identify the low quality fingerprint from inked-printed images on paper.

III. OVERVIEW OF THE PROPOSED SYSTEM

The overview of the proposed fingerprint identification system is shown in Fig. 2. The four different types of fingerprints are used for recognition.

In the enrollment stage, the input fingerprint image is preprocessed and enhanced. After enhancing the fingerprint, core point detection, cropping is done. Finally, texture and orientation features are extracted and stored in the database.

For the identification stage, the input fingerprint is preprocessed to remove noise. The core point of the fingerprint is detected from orientation image and keeping the core point as the center point, the image of size w×w is cropped. The orientation features of the fingerprint are extracted and compared with all the fingerprints in the database. The minimum matching score is calculated which is further used in calculating final matching score.

For texture feature matching, gabor texture features of the cropped fingerprint are extracted and compared with the fingerprints in the database. A feature vector, which we call FingerCode, is the collection of all the features (for every sector) in each filtered image. These features capture both the global pattern of ridges and valleys and the local characteristics. Matching is based on the Euclidean distance between the FingerCodes.

Matching scores obtained by two matching algorithms are fused using sum rule to give a final matching score. If the final matching score is higher than a certain threshold, the input fingerprint is recognized as a genuine attempt, else an imposter.

IV. PREPROCESSING

A fingerprint image is one of the noisiest of image types. This is due predominantly to the fact that fingers are our direct form of contact for most of the manual tasks we perform: finger tips become dirty, cut, scarred, creased, dry, wet, worn, etc. The image enhancement step is designed to reduce this noise and to enhance the definition of ridges against valleys.

Image preprocessing includes gray scale converting, segmentation. Segmentation is done to obtain Region of
Interest (ROI) from background. In Fig. 4(b), enhanced result image is shown.

V. FEATURE EXTRACTION

Feature extraction is concerned with the quantification of texture characteristics in terms of a collection of descriptors or quantitative feature measurements, often referred to as a feature vector. In this paper, the orientation features and the texture features derived by using the Gabor filters based algorithm proposed in [7] are used for fingerprint matching.

It is desirable to obtain representations for fingerprints which are scale, translation, and rotation invariant. Scale invariance is not a significant problem since most fingerprint images could be scaled as per the dpi specification of the sensors. In the proposed feature extraction scheme, translation is handled by a single reference point location during the feature extraction stage. The present implementation of feature extraction assumes that the fingerprints are vertically oriented. In reality, the fingerprints in our database are not exactly vertically oriented; the fingerprints may be oriented up to away from the assumed vertical orientation. This image rotation is partially handled by a cyclic rotation of the feature values in the FingerCode in the matching stage.

Fingerprint can be uniquely represented by its frequency content and orientation. Gabor filters can be used to extract this unique frequency and orientation information. Therefore, an input fingerprint image is filtered using this set of Gabor filters. A square tessellation, is then applied to each filtered image to examine the local response to the filter; a feature vector measuring average absolute deviation from mean (AAD), in the filtered images is next obtained. A collection of these feature vectors (over the tessellation) constitutes the Gabor texture pattern that is used to represent the fingerprint. Additional features, orientation features are stored as feature vector for fingerprint matching.

The five main steps in our feature extraction algorithm are

1) detect the orientation features of the fingerprint
2) determine a core or reference point and region of interest for the fingerprint image;
3) tessellate the region of interest around the reference point;
4) filter the region of interest in eight different directions using a bank of Gabor filters;
5) compute the average absolute deviation from the mean (AAD) of gray values in individual sectors in filtered images to define the feature vector or the FingerCode.

A. Ridge Orientation Detection

The term orientation image often refers to the determination of local ridge orientation in the fingerprint image. Reliable orientation extraction in low-quality regions is still an open problem and new approaches are often proposed in the literature. In proposed system, gradient based approach is used for extraction of ridge direction. The following steps are applied for finding orientations (Hong et al., 1998).

Let θ be defined as the orientation field of a fingerprint image. θ(x,y) is the least square estimate of the local ridge orientation at the block centered at pixel (x,y). Firstly, divide the fingerprint image into non-overlapping blocks of size w×w:

Compute the gradients \( \partial_x \) and \( \partial_y \) of each pixel (x,y) corresponding to the horizontal and vertical directions. The Sobel operator is employed in this work.

The local orientation of the (x,y) centered w×w sized block is calculated by:

\[
\begin{align*}
V_x(x, y) &= \sum_{u=-W/2}^{W/2} \sum_{v=-W/2}^{W/2} 2\partial_x(u,v)\partial_x(u,v) \\
V_y(x, y) &= \sum_{u=-W/2}^{W/2} \sum_{v=-W/2}^{W/2} \partial_y(u,v) - \partial_y(u,v) \\
\theta(x, y) &= \frac{1}{2} \tan^{-1} \left( \frac{V_y(x, y)}{V_x(x, y)} \right)
\end{align*}
\]

Fig. 3 (a)Original inked image (b) Enhanced image (c)Orientation image

B. Core Point Detection

Fingerprints have many conspicuous landmark structures and a combination of them could be used for establishing a reference point. We define the reference point of a fingerprint as the point of maximum curvature of the concave ridges in the fingerprint image.

In this paper, the core point of the fingerprint image is detected by calculating the Poincare Index value and then, the area near the centre point is extracted to be the ROI of the feature extraction. This method is the most classical, intuitive and simple algorithm to detect singular points. It is based on the mathematical model of the fingerprint and detects the centre point of the fingerprint by calculating the Poincare Index value in the fingerprint orientation field.

1) Orientation field O is defined as an M×N image, where O(i,j) represents the local ridge orientation at pixel (i,j).

An image is divided into a set of w×w non-overlapping blocks and a single orientation is defined for each block.

2) Initialize A, a label image used to indicate the core point.

3) For each pixel (i,j) in O, compute Poincare index and assign the corresponding pixels in A the value of one if Poincare index is between 0.45 and 0.51. The Poincare index at pixel (i,j) enclosed by a digital curve N, which consists of sequence of pixels that are on or within a distance of one pixel apart from the corresponding curve, is computed as follows:

\[
\text{Poincare Index} = \frac{1}{N^2} \sum_{p \in N} (d(p, (i,j))^n - d(p, (i,j))^m)
\]
Poincaré index (4)

\[ Poincare(x, y) = \frac{1}{2\pi} \sum_{k=0}^{N-1} \Delta(k) \]

\[ \Delta(k) = \begin{cases} 
\delta(k) & \text{if } |\delta(k)| < \frac{\pi}{2} \\
\pi + \delta(k) & \text{if } |\delta(k)| \leq \frac{\pi}{2} \\
\pi - \delta(k) & \text{otherwise} 
\end{cases} \]

\[ \delta(k) = \theta(x_{(k+1)\mod N}, y_{(k+1)\mod N}) - \theta(x_k, y_k) \]

where \( \theta \) is the orientation field, and \( x_{(k+1)} \) and \( y_{(k+1)} \) denote coordinates of the \( k \)th point on the arc length parameterized closed curve \( N \).

4) The center of block with the value of one is considered to be the center of fingerprint. Poincaré index is computed by summing up the difference in the direction surrounding the block \( P \). For each block \( P_j \), we compute the angle difference from 8 neighboring blocks along counter-clockwise direction. If the sum of difference is \( 180^\circ \), it is the core point. If more than one block has value of one, then calculate the average of coordinates of these blocks.

C. Gabor filter-based texture extraction

Gabor filters have both frequency-selective and orientation-selective properties and have optimal joint resolution in both spatial and frequency domains.

Different steps in texture extraction are as follows:

1) ROI extraction: Tessellate the region of interest centered at the reference point. The region of interest is divided into a series of \( B \) concentric bands and each band is sub-divided into \( k \) sectors (\( B = 5 \), \( k = 16 \)). Thus, a total of \( 16 \times 5 = 80 \) sectors (\( S0 \) through \( S79 \)).

2) Normalization: The region of interest in each sector is normalized separately to a constant mean and variance before filtering. Normalization is done to remove the effects of sensor noise and finger pressure differences. Let \( I(x, y) \) denote the gray intensity value of the pixel at position \( (x, y) \), \( M_i \), and \( V_i \) be the estimated mean and variance of the sector block \( S_i \) respectively and \( N_i (x, y) \), the normalized gray-level value at pixel \( (x, y) \). For all the pixels in sector \( S_i \), where \( MO \) and \( VO \) are the desired mean and variance values, respectively, the normalized image is given by following formula:

\[ N_i(x, y) = \begin{cases} 
M_o + \sqrt{\frac{V_o \times (I(x, y) - M_i)^2}{V_i}}, & \text{if } I(x, y) > M_i \\
M_o - \sqrt{\frac{V_o \times (I(x, y) - M_i)^2}{V_i}}, & \text{otherwise} 
\end{cases} \]

3) Image Filtering: A 2-D Gabor filter can be viewed as a complex plane wave modulated by a 2-D Gaussian envelope. These filters can be used for extracting local frequency and orientation information. By tuning a Gabor filter to a specific frequency and direction, the local frequency and orientation information can be obtained. Thus, they are useful for extracting texture from fingerprint images. An even symmetric Gabor filter has following general form in the spatial domain [7].

\[ \begin{align*}
G_{f, \theta}(x, y) &= \exp \left\{ -\frac{1}{2} \left[ \frac{x^2}{\delta_x^2} + \frac{y^2}{\delta_y^2} \right] \right\} \cos(2\pi f x') \\
x' &= x \sin \theta + y \cos \theta \\
y' &= x \cos \theta - y \sin \theta 
\end{align*} \]

where \( f \) is the frequency of the sinusoidal plane wave at an angle \( \theta \) with the \( x \) axis, and \( \delta_x, \delta_y \) are the standard deviations of the Gaussian envelope along the \( x \) and \( y \) axes, respectively. The normalized region of interest in a fingerprint image is convolved with each of these eight filters to produce a set of eight filtered images. For extracting texture information at various orientations of the Gabor filter, the parameters \((f, \delta_x, \delta_y, \theta)\) are set to following values:

a) The frequency, \( f \), corresponds to the inter-ridge distance in a fingerprint image. For the 500 dpi images, the average inter-ridge distance is approximately 10 pixels. Hence, \( f = 0.1 \) [7].

b) The bandwidth of the Gabor filter is determined by standard deviation values \( \delta_x \) and \( \delta_y \). Based on empirical data, both these values are set as 4 [7].

c) Eight different orientations are examined. These correspond to \( \theta \) values of \( 0^\circ, 22.5^\circ, 45^\circ, 67.5^\circ, 90^\circ, 112.5^\circ, 135^\circ \) and \( 157.5^\circ \) respectively.

D. Gabor Feature Vector

Let \( F_{i\theta}(x,y) \) be the \( \theta \)-direction filtered image for sector \( S_i \). Now for \( \forall \ i \in \{0, 2, 3, ..., 79\} \) and \( \theta \in \{0^\circ, 22.5^\circ, 45^\circ, 67.5^\circ, 90^\circ, 112.5^\circ, 135^\circ, 157.5^\circ\} \), the feature values are the average absolute deviations from the mean defined as:

\[ F_{i\theta} = \frac{1}{n_i} \left( \sum_{n_i} |F_{i\theta}(x,y) - P_{i\theta}| \right) \]

where \( n_i \) is the number of pixels in \( S_i \) and \( P_{i\theta} \) is the mean of pixel values of \( F_{i\theta}(x,y) \) in sector \( S_i \).

Thus, the average absolute deviation of each sector is calculated for all eight filtered images. The feature vector (FingerCode) of the size \((80 \times 8)\) thus obtained, called as ‘Gabor texture pattern’ is used to find normalized Gabor matching. The proposed feature extraction algorithm is shown in Fig. 4.
VI. MATCHING

A. Orientation Matching

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 Ω denotes the intersection of the two effective regions after alignment, and N is the total number of points in Ω. The matching score between two orientation fields is defined as

\[ s(A,B) = \frac{1}{N} \sum_{(i,j) \in \Omega} \delta(i,j) \]  

In Eq.(8), \( \delta(i,j) \) is the difference between the orientation values at the point \((i,j)\) in image A and B, which is formulated as follows:

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

(9)

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

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

(10)

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”.

B. FingerCode Matching

Fingerprint matching is based on finding the Euclidean distance between the corresponding FingerCodes. The final matching distance score is taken as the minimum of the scores, i.e., matching of the input FingerCode with each of the fingerprint templates in the database. The minimum distance corresponds to the two fingerprints being matched.

Matching scores of FingerCode and orientation algorithms are fused using sum rule to give a final matching score. The minimum score corresponds to the best alignment of the two fingerprints being matched.

VII. SCORE LEVEL FUSION

The matching scores generated by comparing the Gabor feature sets and orientation features are combined in order to generate a single matching score. While a variety of strategies may be used to fuse these scores, here following sum rule is used [8]. Let Gabor Matching Score (GMS) and Orientation Matching Score (OMS) indicate the matching scores obtained using Gabor feature matching and orientation feature matching, respectively. Then, the final matching score (FMS), is computed as

\[ FMS = \alpha \times GMS + (1 - \alpha) \times OMS \]  

(11)

where, \( \alpha \in [0,1] \). Here, \( \alpha \) is set as 0.5.

VIII. EXPERIMENTAL RESULTS

The proposed system is tested on four different databases: FVC2000, live-scan fingerprint database acquired from Hamster Eye-D device, inked fingerprint database and NRC fingerprint database. Each database consists of 300 fingerprint images. The performance of the proposed hybrid fingerprint matching system is compared with the filterbank-based fingerprint matching algorithm proposed in [7] that utilizes only texture information for representing the fingerprint.

To test the performance of the proposed system, we first implement the filterbank-based fingerprint matching system that uses only texture features. The database is then processed using the implemented system. We then add the orientation features with the new algorithm to compute the oriented FingerCode. The same database is again processed. Each test fingerprint image is matched with all the other fingerprints in the database.

The filterbank-based matching algorithm is not robust to identify the low quality fingerprints such as fingerprints from NRC cards and it is not rotation-invariant. In addition, the orientation features of the fingerprints are utilized in this system that is rotation-invariant. More importantly, the orientation features can be extracted from NRC fingerprints
and inked fingerprints of poor quality. The proposed system is efficient for low quality images with low computation time.

The performance of a biometric system can be shown as a Receiver Operating Characteristic (ROC) curve that plots the Genuine Accept Rate against the False Accept Rate (FAR) at different thresholds on the matching score. The Receiver Operating Characteristic (ROC) curves for Filterbank-based and the proposed system matchers are shown in Fig. 6.

The proposed approach outperforms the filterbank-based approach over a wide range of FAR values. The fingerprints on NRC cards and ink-printed papers are low quality images, sometimes is complex with fabric background. It is difficult to extract the ridge lines clearly. Because of the low textural contents, it reduces the accuracy of the filterbank-based approach. This shows that the filterbank-based approach is not robust with respect to image quality.

![Fig. 6 The ROC curves comparing the performance of the proposed approach with the FilterBank based approach on four different databases](image)

**IX. CONCLUSION**

The hybrid fingerprint matching scheme that utilizes both orientation and texture information available in the fingerprint have presented. A bank of Gabor filters is used to extract features from the tessellated cells of the template and input images. Additional features such as the orientation of the fingerprints is detected and matched. According to the experimental results, additional orientation matching improved the accuracy of the fingerprint recognition system and is robust to image distortion and rotation. The proposed matching algorithm is effective and efficient for low quality and rotated images.

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