Fingerprint Image Enhancement Techniques and Performance Evaluation of the SDG and FFT fingerprint enhancement techniques

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Abstract—This paper is a study of various techniques of fingerprint enhancement and the performance evaluation of fingerprint enhancement by using SDG and FFT. Due to the poor quality fingerprint image the extraction of features is most challenging problem faced in fingerprint image identification. To make the performance of an automatic fingerprint identification system (AFIS) will be robust with respect to the quality of input fingerprint images, it is essential to incorporate a fingerprint enhancement module in the AFIS system. An enhancement method improves the performance of the fingerprint verification system and makes it more robust with respect to the quality of input fingerprint image.

Index Terms—fingerprint enhancement; gabor filter, Gaussian filter; Fourier Transform.

I. INTRODUCTION

Characteristics are used for human identification on the basis of their universality, uniqueness, permanence and collectability. Fingerprint is the most interesting and oldest human identity used for recognition of individual.

Basically there are two types of fingerprint Recognition System [9]:

1).AFAS (Automatic Fingerprint Authentication System)
2).AFIS (Automatic Fingerprint Identification/Verification System)

The methods for constructing enhancement image for fingerprint images [1]:

- normalization,
- orientation estimation,
- ridge frequency estimation,
- filtering,
- segmentation,
- binarisation, and
- thinning

The first step in this approach involves the normalisation of the fingerprint image so that it has a pre-specified mean and variance. An orientation image is then calculated, which is a matrix of direction vectors representing the ridge orientation at each location in the image. The Ridge frequency image defines the local frequency of the ridges contained in the fingerprint. The filtering increases the contrast between the foreground ridges and the background, whilst effectively reducing noise. Segmentation is the process of separating the foreground regions in the image from the background regions. The foreground regions correspond to the clear fingerprint area containing the ridges and valleys, which is the area of interest. The background corresponds to the regions outside the borders of the fingerprint area, which do not contain any valid fingerprint information. Most minutiae extraction algorithms operate on binary images where there are only two levels of interest: the black pixels that represent ridges, and the white pixels that represent valleys. Binarisation is the process that converts a grey level image into a binary image. This improves the contrast between the ridges and valleys in a fingerprint image, and consequently facilitates the extraction of minutiae. The final image enhancement step typically performed prior to minutiae extraction is thinning. Thinning is a morphological operation that successively erodes away the foreground pixels until they are one pixel wide. [1]

II. ENHANCEMENT TECHNIQUES

A fingerprint is the pattern of ridges and valleys on the surface of a finger. Minutiae are local discontinuities in the fingerprint pattern. The most important ones are ridge ending and ridge bifurcation. Spurious ridge structure may change the individuality of input fingerprints. Ridges and valleys in a local neighborhood form a sinusoidal-shaped plane wave, which has a well-defined frequency and orientation. The individuality feature of a fingerprint is then desirable and widely utilized in the personal identification process. The success of the identification (or matching) process is very much relied on the image quality. In many cases algorithm fail because fingerprints are with numerous discontinuous ridges. The main difficulty for feature extraction is that fingerprint quality is often too low, thus noise and contrast deficiency can produce false minutiae or hide valid ones. Even high quality images can also yield false minutiae, for example, when the person has cuts or scars in his/her fingers.
Various methods of fingerprint image enhancement methods

2. Wiener Filtering [2]
3. Isotropic and Anisotropic Filtering[2]
4. Use of Gabor filters as bandpass filters to remove the noise and preserve true ridge/valley structures [3]
5. Fingerprint Enhancement by Fourier Transform [4]
6. Fingerprint image enhancement using STFT analysis (Short Time Fourier Transform )[4]
7. Fingerprint enhancement by mean of wavelet transform and directional filtering [5]
8. Fingerprint enhancement with dyadic-scale-space [15]
9. Image Enhancement Based on Genetic Algorithm: It uses the genetic algorithm to find those filters for superior performance of singularity extraction.
11. Second Derivative Gaussian Filter (SDG) [5]

The main purpose of an enhancement algorithm is to improve the clarity of ridge structures of fingerprint images in recoverable regions.

A. Local Histogram

Histogram equalization defines a mapping of gray levels \( p \) into gray levels \( q \) such that the distribution of gray level \( q \) is uniform. This mapping stretches contrast for gray levels near the histogram maxima i.e. expands the range of gray levels near the histogram maxima. Since contrast is expanded for most of the image pixels, the transformation improves the detectability of many image features. The probability density function of a pixel intensity level \( r_k \) is given by:

\[
P_r(r_k) = \frac{n_k}{n} \tag{1}
\]

where: \( r_k \) is a range of intensity levels, \( k = 0, 1, \ldots, 255 \), \( n_k \) is the number of pixels at intensity level \( r_k \) and \( n \) is the total number of pixels. The histogram is derived by plotting \( P_r(r_k) \) against \( r_k \). A new intensity \( s_k \) of level \( k \) is defined as:

\[
s_k = \sum_{i=0}^{k} \sum_{j=0}^{n} s_{ij} = \sum_{i=0}^{k} P_r(r_j) \tag{2}
\]

Applying the histogram equalization locally by using a local windows of 11x11 pixels. This results in expanding the contrast locally, and changing the intensity of each pixel according to its local neighborhood. Fig. 1 (right) presents the improvement in the image contrast obtained by applying the local histogram equalization.

B. Wiener filtering noise reduction

It uses a pixel-wise adaptive Wiener method for noise reduction. The filter is based on local statistics estimated from a local neighborhood \( \eta \) of size 3x3 of each pixel, and is given by:

\[
w(n_1, n_2) = \mu + \frac{v^2}{\sigma^2} (f(n_1, n_2) - \mu) \tag{3}
\]

where \( v^2 \) is noise variance, \( \mu \) and \( \sigma^2 \) are local mean and variance, \( f \) represents the gray level intensity in \( n_1, n_2 \in \eta \). The result of the wiener filtering is shown in Fig. 2 (left).

C. Anisotropic Filter

A structure adaptive anisotropic filtering technique is proposed by Yang [7] for image filtering. Instead of using local gradients as a means of controlling the anisotropism of filters, it uses both a local intensity orientation and an anisotropic measure to control the shape of the filter. The modified anisotropic filter by shaping the filter kernel and applied it to fingerprint images [8]. The kernel is allowed to be shaped or scaled according to local features within a given neighborhood. The filter kernel applied at each point \( x_0 \) is defined as follows [7]:

![Figure 1. Histogram equalization: original image and its histogram (left) and after equalization (right)](image1)

![Figure 2 (left) Wiener filtering result using local neighborhood of 3x3 pixels and (right) Binary image](image2)
where \( n \) and \( n_\perp \) are mutually normal unit vectors, and \( n \) is in parallel with the ridge direction. The shape of the kernel is controlled through \( \sigma_1^2(x_0) \) and \( \sigma_2^2(x_0) \), \( \rho \) satisfies the condition \( \rho(x) = 1 \) when \( |x| < r \), and \( r \) is the maximum support radius. The modified filter to a band pass filter in order to adapt it to a fingerprint image [8]:

\[
h(x_0, x) = -2 + 10 \cdot k(x_0, x) \tag{5}\]

when a ridgeline edge is encountered the kernel is deformed into an ellipse with a major axis aligned in parallel with the edge (Fig. 3). Therefore, smoothing is performed along but not across the ridgeline.

\[
k(x_0, x) = \rho(x - x_0) \exp \left\{ -\left[ \frac{(x - x_0, n)^2}{\sigma_1^2(x_0)} + \frac{(x - x_0, n_\perp)^2}{\sigma_2^2(x_0)} \right] \right\}
\]

\( (x_0, y_0) \) are selected as the coordinates of the center of the kernel.

**Figure 3 Controlling the shape of anisotropic filter.**

D. **Gabor Filter**

Gabor filters optimally capture both local orientation and frequency information from a fingerprint image. By tuning a Gabor filter [3] to specific frequency and direction, the local frequency and orientation information can be obtained as shown in Figure 4.

An even symmetric Gabor filter has the following general form in the spatial domain:

\[
h(x, y; \psi, f) = \exp \left\{ -\frac{1}{2} \left( \frac{x^2}{\delta_x^2} + \frac{y^2}{\delta_y^2} \right) \right\} \cos(2\pi f x_0)
\]

Where

\[x_0 = x \cos \theta - y \sin \theta \quad \text{and} \quad y_0 = x \sin \theta + y \cos \theta\]

where \( f \) is the frequency of the sinusoidal plane wave along the direction \( \theta \) from the x-axis, and \( \delta_x \) and \( \delta_y \) are the space constants of the Gaussian envelope along x and y axes, respectively.

The filtering is performed in the spatial domain with a mask size of 17x17. The frequency \( f \) is the average ridge frequency (1/K), where K is the average inter ridge distance. The average inter ridge distance is approximately 10 pixels in a 500 dpi fingerprint image. Hence, \( f = 1/10 \). Sixteen different orientations are examined. These correspond to \( \theta \) values of 0, 11.25, 22.5, 33.75, 45, 56.25, 67.5, 78.75, 90, 101.25, 112.5, 123.75, 135, 146.25, 157.5 and 168.75 degrees. The values for \( \delta_x \) and \( \delta_y \) were empirically determined and each is set to 4 (about half the average inter ridge distance).

**E. Fast Fourier Transform**

In this method the image is divided into small processing blocks (32 x 32 pixels) and perform the Fourier transform according to equation:

\[
f(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) X e^{i \frac{2\pi}{M} x (u + \frac{u'}{M})} e^{i \frac{2\pi}{N} y (v + \frac{v'}{N})}
\]

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

In order to enhance a specific block by its dominant frequencies, we multiply the FFT of the block by its magnitude a set of times. Where the magnitude of the original FFT = abs \( F(u, v) = |F(u, v)| \).

So we get the enhanced block according to the equation:

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

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

\[
f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} f(u, v) X e^{i \frac{2\pi}{M} x (u + \frac{u'}{M})} e^{i \frac{2\pi}{N} y (v + \frac{v'}{N})}
\]

For \( x = 0, 1, 2, ..., 31 \) and \( y = 0, 1, 2, ..., 31 \).

The \( k \) in formula (8) is an experimentally determined constant, which we choose \( k=0.45 \) to calculate. A high value of \( k \) improves the appearance of the ridges by filling up small holes in ridges, but too high value of \( k \) can result in false joining of ridges which might lead to a termination become a bifurcation.

**Figure 4: Filtered images and their corresponding feature vectors for orientations 0°, 22.5°, and 45° are shown.**

**Figure 5(a) Enhanced Image after FFT, (b) Image before FFT**
The enhanced image after FFT has the improvements as some falsely broken points on ridges get connected and some spurious connections between ridges get removed.

F. Short time Fourier Transform (STFT)

During STFT [4] analysis, the image is divided into overlapping windows. It is assumed that the image is stationary within this small window and can be modeled approximately as a surface wave. The Fourier spectrum of this small region is analyzed and probabilistic estimates of the ridge frequency and ridge orientation are obtained. The STFT analysis also yields an energy map that may be used as a region mask to distinguish between the fingerprint and the background regions. The orientation image is then used to compute the angular coherence. The coherence image is used to adapt the angular bandwidth. The resulting contextual information is used to filter each window in the Fourier domain. The enhanced image is obtained by tilting the result of each analysis window.

Short Time Fourier analysis: To resolve the properties of the image both in space and also in frequency it uses two dimensional image signals to perform short (time/space)-frequency analysis. [4]

When analyzing a non-stationary 1D signal \( x(t) \) it is assumed that it is approximately stationary in the span of a temporal window \( w(t) \) with finite support. The STFT of \( x(t) \) is now represented by time frequency atoms \( X(T,w) \) given by,

\[
X(T, \omega) = \int_{-\infty}^{\infty} x(t) W^*(t-T)e^{-j\omega t} dt
\]

In the case of 2D signals such as a fingerprint image, the space-frequency atoms is given by,

\[
X(T_{1},T_{2},\omega_{1},\omega_{2}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} I(x,y) W^*(x - T_{1}, y - T_{2})e^{-j(\omega_{1}x + \omega_{2}y)} dx dy
\]

Here \( T_{1}, T_{2} \) represent the spatial position of the two dimensional window \( W(x,y) \). \( w_{1}, w_{2} \) represents the spatial frequency parameters. A local region of the image can be modeled as a surface wave according to

\[
I(x,y) = A \{ \cos(2\pi f \{ x\cos(\theta) + y\sin(\theta) \}) \}
\]

III. DIRECTIONAL WAVELET TRANSFORM

In the fingerprint image, the pattern is related to the ridge direction. In principle, the enhancement can help visualizing the ridges. A directional wavelet transform is applied to decompose the image into its orientation representation. Directional filtering is applied to each direction before image reconstruction. This is shown in Fig. 5 below.

Wavelet transform is suited for the analysis of transient and time varying signals. In two dimensions, a scaling function \( \phi(x,y) \) , and three directional wavelets \( \psi_{h}^{j}(x,y), \psi_{v}^{j}(x,y) \) and \( \psi_{d}^{j}(x,y) \) are necessary. Each scaling function or wavelet is the product of the one dimensional scaling function \( \phi \) and corresponding wavelet \( \psi \). The four two-dimensional products produce the scaling function (13) and separable directional sensitive wavelets (14), (15) and (16).

\[
\phi(x,y) = \phi(x)\phi(y)
\]

\[
\psi_{h}^{j}(x,y) = \psi(x)\phi(y)
\]

\[
\psi_{v}^{j}(x,y) = \phi(x)\psi(y)
\]

\[
\psi_{d}^{j}(x,y) = \phi(x)\psi(y)
\]

These wavelets measure the gray level variations for images along three directions, where \( \psi_{h}(x,y) \) measures variations along columns (horizontal), \( \psi_{v}(x,y) \) responds to variations along rows (vertical) and \( \psi_{d}(x,y) \) corresponds to variations along diagonals.

In a two dimensional discrete wavelet transform, the scaled and translated basis functions are defined by:

\[
\varphi_{j,m,n}(x,y) = 2^{j/2} \varphi(2^{j} x - m, 2^{j} y - n)
\]

\[
\psi_{i,j,m,n}(x,y) = 2^{j/2} \psi_{i}(2^{j} x - m, 2^{j} y - n)
\]

where index \( i \) identifies the directional wavelets according to equation (11), (12) and (13). The discrete wavelet transform of function \( f(x,y) \) of size \( M \times N \) is formulated as:

\[
W_{\varphi}(j_{0},m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \varphi_{j_{0},m,n}(x,y)
\]

\[
W_{\psi_{i}}(j_{0},m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \psi_{i,j_{0},m,n}(x,y)
\]

where \( i = \{ H, V, D \} \), \( j_{0} \) is the starting scale, the \( W_{\varphi}(j_{0},m,n) \) coefficients define the approximation of \( f(x,y) \) at scale \( j_{0} \).

The \( W_{\psi_{i}}(j_{0},m,n) \) coefficients represent the horizontal, vertical and diagonal details for scales \( j > j_{0} \) . Here \( j_{0} = 0 \) and select \( M + N = 2^{s} \) so that \( j = 0,1,2,...,J-1 \) and \( m, n = 0,1,2,...,2^{J-1} \). Then \( f(x,y) \) is obtained via the inverse discrete wavelet transform.

\[
f(x,y) = \frac{1}{\sqrt{2^{J}}} \sum_{j=0}^{J} \sum_{m=0}^{2^{J-1}} \sum_{n=0}^{2^{J-1}} W_{\varphi}(j,m,n) \varphi_{j,m,n}(x,y) + \frac{1}{\sqrt{2^{J}}} \sum_{i=H,V,D} \sum_{j=0}^{J} \sum_{m=0}^{2^{J-1}} \sum_{n=0}^{2^{J-1}} W_{\psi_{i}}(j,m,n) \psi_{i,j,m,n}(x,y)
\]

Now the wavelets are defined by both the scaling function \( \varphi(x,y) \) (Father Wavelet) and wavelet functions \( \psi(x,y) \) (mother wavelet) in the discrete time domain. The wavelet function acts as a bandpass filter whose bandwidth is reduced to half after each scaling.

**Figure 6:** Fingerprint enhancement by mean of wavelet transformation and directional filtering.
IV. DYADIC SCALE-SPACE

Here first decompose the fingerprint image into a series of images at different scales, then analyze and organize whole characters and details, at last combine the creditable information to enhance the fingerprint image.

Scale-space theory provided a canonical framework for modeling visual operations at multiple scales. The scale-space representation L: R²xR→R of a two-dimensional image f is defined as the one-parameter family of functions obtained by convolving f with Gaussian kernel:

\[ L(\ldots) = f(\ldots) * g_t(\ldots) \]

Where

\[ g_t(x,y, \theta) = \frac{1}{2\pi \sigma^2} e^{-\frac{(x^2 + y^2)}{2\sigma^2}} \]

and the parameter t is called scale parameter. \( \theta \) is the direction of the pixel (x, y). Although fingerprint images are non-isotropic, we use the linear scale-space to detect the feature because in local region, the ridge is a line. And the convolution is along the ridge direction, as we adapt the filter to ridge direction.

In scale-space, with the increase of the scale, the number of the details decreases and the noise is successively suppressed gradually. The feature of the image in large scale exists in the image of small scale, while weak signal will disappear in the large scale space. Those existing in the image of large scale are global structure.

Using a series of scale \( \sigma_1, \sigma_2, \ldots, \sigma_n \) to filter the image f, note the scale-space representation as \( L\sigma_k \), \( k = 1, 2, \ldots, n \) with scale \( \sigma_k \). We define the details between two scales as following:

\[ D_k = L\sigma_k - L\sigma_{k+1} \]

Let:

\[ D_0 = f - L\sigma_1 \]

When we get the scale-space representation and its details, construct the image f:

\[ f = \sum_{k=0}^{n-1} D_k + L\sigma_n \]

We get the smoothed image of the fingerprint image f using dyadic scale-space:

\[ \hat{L}_k = f * g_{2k}(x, y, \theta) \quad \text{where} \quad k=1,2,\ldots,n_0 \]

V. SECOND DERIVATIVE GAUSSIAN FILTER

A 2D Gaussian filtering is widely used in the area of image processing. Generally it performs low pass filtering. Its plot is shown in Fig. 6(a). However, for directive filtering a plan cosine wave can be multiplied to the Gaussian function. Its first and second derivatives are also widely used. For example, the line detection technique proposed by [11]. It appears in several slight different forms. However, the one we are interesting is taken from [12]. Its appearance is shown in Fig. 6b. Gabor filter is another well known filter in fingerprint enhancement. Its appearance is shown in Fig. 6c.

The 2D circular Gaussian filter \( \sigma_x = \sigma_y \) is mostly adopted as an image preprocessing step for image smoothing and denoising, while the 2D elliptical Gaussian filter can be used for enhancement of lines since \( \sigma_x \) and \( \sigma_y \) can be separately specified. The filter function is

\[ G(x, y; \sigma) = \exp \left( -\frac{x^2}{2\sigma^2} \right) \]

where \( \sigma_x = \sigma_y \) is the second derivative of Gaussian filter given in eqn. (18) is the straightforward extension of the Gaussian first derivative filter [16].

\[ s^2 g(x, y; \sigma) = \frac{(x^2 - \sigma_x^2)(y^2 - \sigma_y^2)}{2\pi \sigma_0^2} \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right) \]

For fingerprint images, this second derivative filter can enhance the ridge and suppress the valley for certain degree. To enhance the effectiveness of the filter or to make it more directional sensitive, the filter itself can be modified slightly by cooperating the cosine function (or plan wave) as follow:

\[ s^2 g(x, y; \sigma) = \frac{(x^2 - \sigma_x^2)(y^2 - \sigma_y^2)}{2\pi \sigma_0^2} \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right) \cos(2\pi f_x) \]

Where \( \varphi, \sigma_0, \sigma_x, \sigma_y \) and f are defined as those of Gabor filter. The filter’s appearance is shown in Fig. 6d. Compared to the well-known Gabor filter of which the appearance shown in Fig. 6c, the modified second derivative filter offers the very similar shape. In fact they are variations of each other.

Figure 7: appearance of filters: (a) Gaussian filter, (b) Second derivative of Gaussian filter, (c) Gabor filter, and (d) modified second derivative of Gaussian filter

VI. PERFORMANCE EVALUATION INDEX

Two indexes are well accepted to determine the performance of a fingerprint recognition system:

**False Rejection Rate (FRR):** For an image database, each sample is matched against the remaining samples of the same finger to compute the False Rejection Rate.
False Acceptance Rate (FAR): Also the first sample of each finger in the database is matched against the first sample of the remaining fingers to compute the False Acceptance Rate.

![Graph showing False Rejection Rate of Fingerprint template matching using SDG and FFT](image.png)

Table 1 False Rejection Rate of Fingerprint template matching using SDG and FFT

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![Graph showing False Acceptance Rate of Fingerprint template matching using SDG and FFT](image.png)

Table 2 False Acceptance Rate of Fingerprint template matching using SDG and FFT

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VII. CONCLUSIONS

A lot of work has been done in the area of fingerprint image enhancement. But despite the existence of numerous commercial fingerprint image identification/recognition systems there are still important challenges for further research.

The problems such as wet, dry and normal conditions of fingers, pressure of finger over the device are of significant importance. This paper provides a recent advances in fingerprint image enhancement techniques to improve the robustness of fingerprint image enhancement to change in finger position, finger condition and finger pressure. In this paper, in order to explain various enhancements method, we evaluate the computing efficiency for the two enhancement techniques are Second Derivative of Gaussian Filter and Fast Fourier Transformation, and use the statistical method to compare with performances of extraction minutiae. The result shows the better performance for the fingerprint enhancement is Second Derivative Of Gaussian Filter. All the experiments are performed in a Intel core i5 2.30GHz PC. We use databases of FVC2004.

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