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A Review of Fingerprint Image Pre-processing

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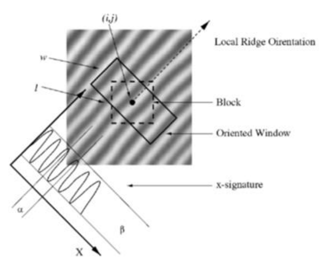
Graphical abstract



Abstract

Fingerprints are the most widely used form of human identification and verification due to their uniqueness and permanence. For that reason, many Automatic Fingerprint Identification Systems (AFIS) have been commercially produced and accepted by the international community. Though their performance is good, there is still room for improvement. One of the main concerns is poor fingerprint images that are caused by capturing devices. Thus, to improve the efficiency of AFIS, both image enhancement and feature extraction methods are required to be implemented. An effective feature extraction depends on the quality of its image whereby high image quality would normally produce genuine features. On the other hand, poor quality would lead to fake features that will result in false acceptance. This paper reviews several state-of-the-art methods of fingerprint image pre-processing including gray level normalization, noise removal and segmentation.

Keywords: Fingerprint image enhancement; image segmentation; feature extraction; gradient filter; Gaussian filter

■1.0 INTRODUCTION AND BACKGROUND

A biometric is the automatic recognition of a person based on physiological measurements or behavioral traits. Fingerprints are considered the most important type of physiological human biometrics. They have been used for personal recognition in forensic applications such as criminal investigations, and in the civilian sector for border access control systems, national identity card validation and as authentication processors. The uniqueness and immutability of fingerprint patterns, as well as the low cost of associated biometric equipment make fingerprints more desirable than other types of biometrics [1]. A person fingerprints develop during the fourth or the fifth month conception. Fingerprint patterns remain much the same throughout a person's life, unless an individual gets injured in an accident. The age of a person does not affect fingerprint patterns but injury does. Fingerprint biometric identification is low cost because it involves pattern recognition using IT equipment and does not require laboratory wet tests such as blood test [2]. Generally speaking, fingerprint based recognition systems work in two modes: verification and identification. In verification mode, the systems verify the person's identity using a 1:1 comparison between the person's fingerprints and those stored in the record.

However, the process used in fingerprint identification systems is more complex than the process employed during verification, especially with large databases because fingerprint identification requires that the input fingerprints be compared with all the fingerprints in the database to look for a match. In identification mode, the systems verify the person's identity using 1:N comparison between the person's fingerprints and all those stored in the database [3].

To perform fingerprint identification, both matching accuracy and processing time are critical issues. To achieve efficient identification of a fingerprint, fingerprints in the database are organized in a number of mutually exclusive classes that share similar properties. This process is called fingerprint classification. In order to design a more accurate automatic system for identification, pre-processing of the fingerprints has to be done to enhance and extract the fingerprint features [4]. Before classification can occur, the fingerprint pattern has to be transformed into a format which is suitable for classification. The flow of process in this study can be summarized diagrammatically as illustrated in the diagram shown in Figure 1.

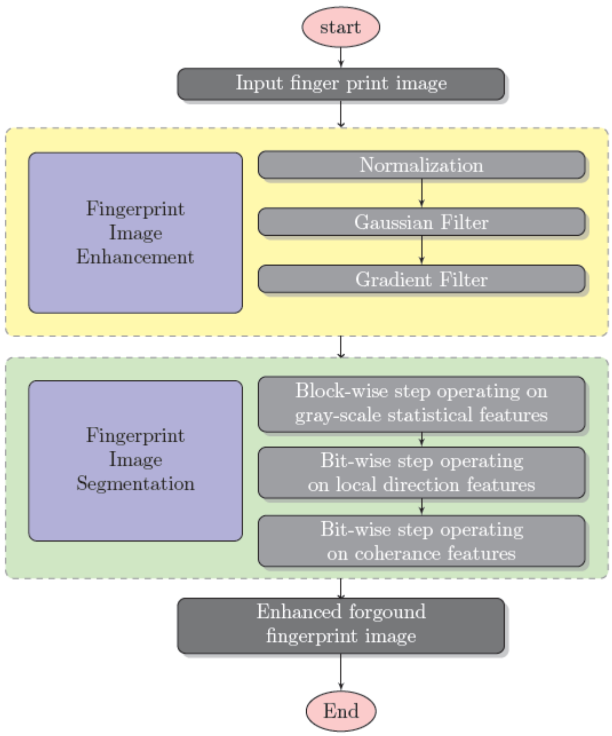


Figure 1 Flow chart of the preprocessing of the fingerprint images

2.0 FINGERPRENT IMAGE ENHANCEMENT

Applying enhancement algorithms to fingerprint images is necessary for recovering the image quality of fingerprints. For the fingerprint image quality to have good intensity there must be a high contrast between ridges and valleys.

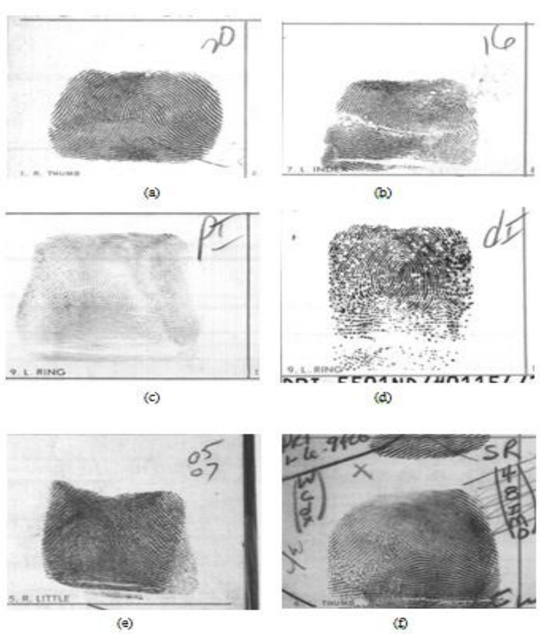


Figure 2 Quality of fingerprint image (a) Good, (b) Broken/cut, (c) Low contrast, (d) Dry, (e) Wet, and (f) Stain

There must also be clear continuity in the ridge structures. An example of a high quality fingerprint image can be seen in Figure 2(a) while low quality fingerprint images are shown in Figures 2(b)-(f). With regards to Figures 2(b)-(f), low quality images can be characterized by low contrast, the presence of high noise levels and having big distortions; whereby these combined effects are known as spurious effects. Image enhancement employed by Hong *et al*. operated as three enhancement stages which were; processing on well-defined region, processing on recoverable corrupted region, and processing on unrecoverable corrupted region [5].

2.1 Normalization

New intensity value for each pixel in a fingerprint image can be determined with image normalization. The normalization method of image enhancement can be applied to pre-specify the mean and variance values used for other operations. One of the reasons images are of non-uniform illumination is that the capturing process might be affected by non-uniform ink intensity or non-uniform contact with the fingerprint capture device. These effects result in different distortion levels that cause variation in gray-level values along the ridges and valley structures. Normalization is used to standardize the intensity values in an image by adjusting the range of gray-scale values so that it lies within a desired range of values as shown in Figures 3(a)-(b). Normalization is done to remove the effects of sensor noise and finger pressure difference. Hong developed a fast fingerprint enhancement algorithm based on the convolution of the image with Gabor filters tuned to the local ridge orientation and ridge frequency. Since the mean and variance can change in different regions of a fingerprint image, the aforementioned technique can be implemented in a local mode [5]. Another approach that was implemented for image normalization is an adaptive fingerprint image normalization method [6]. Then, an improvement methods was proposed that were based on a block-wise approach to obtaining mean and variance values [7, 8].

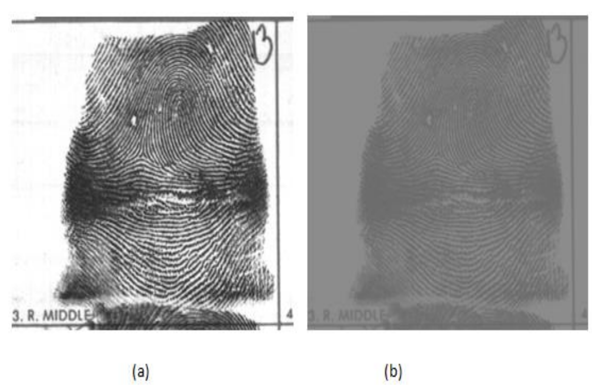


Figure 3 (a) image before normalize process (b) after normalize process

2.2 Gaussian Filter

Gaussian noise in fingerprint images is caused by poor illumination of the fingerprint pattern due to the inferiority of the image capturing device and the high temperature of the sensor. The Gaussian filter performs linear smoothing to smooth the image and remove the noise. Functionally, a Gaussian filter is similar to mean a filter. The degree of smoothing of the Gaussian filter is normally expressed in terms of the standard deviation, σ. A 1-D Gaussian distribution is expressed as:

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \tag{1}$$

Whereas a 2-D Gaussian distribution is defined as:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

The goal of a Gaussian filter is to use the distribution as a point spread function which can be performed by a convolution mask. Convolution is the process of moving the mask from the upper-left corner to the lower-right corner and replacing the value of the center pixel in the image by the value of *I'(x,y)*. The value of *I'(x,y)* can be calculated by summing the products of the filter coefficients and the corresponding image pixels in the area spanned by the filter mask. If the image size is "M rows by N columns", and the kernel has "m rows by n columns", then the size of the output image will have M - m + 1 rows, and N - n + 1 columns. Mathematically, the convolution can be written as

$$I'(i, j) = \sum_{u=1}^{m}\sum_{v=1}^{n} I(i+u-1, j+v-1)G(u,v), \tag{3}$$

Where i has values from 1 to M - m + 1 and j has values from 1 to N - n + 1.

Normally, the filter mask is a two dimensional array in which the values of the mask coefficients affect the nature of the image. In Figure 4 the integer values of convolution masks that approximate a Gaussian filter for σ = 1.4 is shown below.

$$\frac{1}{256}\begin{bmatrix} 21 & 31 & 21 \\ 31 & 48 & 31 \\ 21 & 31 & 21 \end{bmatrix}$$

(a)

$$\frac{1}{115}\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix}$$

(b)

Figure 4 Convolution masks: (a) 3 by 3 Gaussian smooth filter, (b) 5 by 5 Gaussian smooth filter

The Gaussian filter has been used extensively in fingerprint image enhancement [9]. Chikkerur used the Gaussian filter kernel of size 3 by 3 for smoothing orientation field [10]. Furthermore, another study used the Gaussian filter for smoothing gradient information of fingerprint images [11, 12]. Wang also implemented the use of the Gaussian filter for fingerprint enhancement, specifically for the singular point region [13]. Jain utilized the Gaussian filter kernel of size 7 by 7 for smoothing the orientation field [14].

2.3 Gradient FLTER

A variety of nonlinear smoothing filters have emerged. One of which is the gradient filter. Hong and Jain proposed the use of a sinusoidal-shape wave along a direction normal to the local ridge orientation for fingerprint image enhancement. Their method is shown in Figure 5. Here, a window of size *I* by *W (32 by 16)* ridges (size is measured using the number of ridges) was taken first. Each block was centered on the pixel, and the x-signature of ridges and valleys within the oriented window were computed and stored (refer to Figure 6) [14-5].

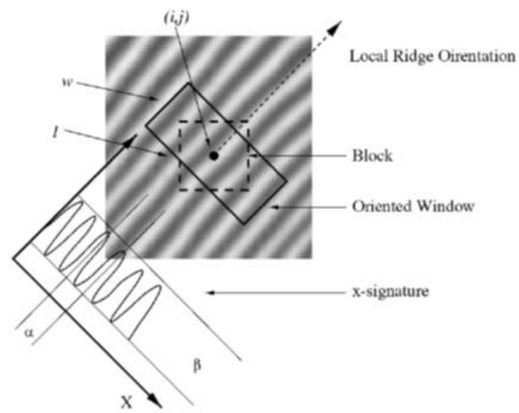


Figure 5 Oriented window and x-signature

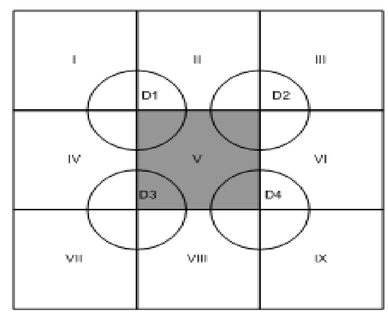


Figure 6 A site consists of 3 by 3 blocks with the target block **V** in the center and four overlapping neighborhood D1, D2, D3, D4

3.0 FINGERPRINT SEGMENTATION

Fingerprint segmentation isolates features that have similar characteristics. The fingerprint image is split into two regions, the foreground and the background regions. The foreground region is the area containing ridges and valleys, while the background region corresponds to the fingerprint image borders. The background regions are located at points that have no useful fingerprint information. The images local intensity can be used to separate the foreground region from the background region, provided that the background region is of uniform and lighter intensity than the foreground[1-15-16]. Image quality is vital for segmentation to be accurate. In practice, fingerprint images are usually of low quality and affect the accuracy of segmentation. In most cases, the low quality of fingerprint images is the result of noise, false traces, blurs ridges and an indistinct boundary. The presence of noise stems mostly from dust and grease on the surface of live-scan fingerprint scanners or ink-on-paper rolled fingerprint, while false traces are the result of the image acquisition process. On the other hand, the blur ridges and indistinct boundary are due to dryness or wetness of the fingerprint and the use of a fixed size window during fingerprint capture. These factors affect the foreground and background regions of the fingerprint equally. These also make it difficult to isolate one from the other. An illustration of the influence of the previously mentioned factors can be seen in Figure 7, in which noise has a diverse effect on segmentation especially when it interpolates image information. However, detecting and correcting the fingerprint images of such factors should be of concern so that the ridge and valley structures contained in the fingerprint image can be differentiated. Generally, the two steps of fingerprint segmentation; are the block-wise and the bit-wise steps. A block wise step is used to extract the foreground of fingerprint image from the background. The foreground of the extracted fingerprint is normally corrupted by noise. The bit-wise step is used to remove noise and other unwanted interferences by operating in the domains associated with image gray-scale statistical features, local directional features or coherence features. Since the bit-wise based segmentation step is time consuming, the block-wise step is preferred especially for automated processes [17, 18].

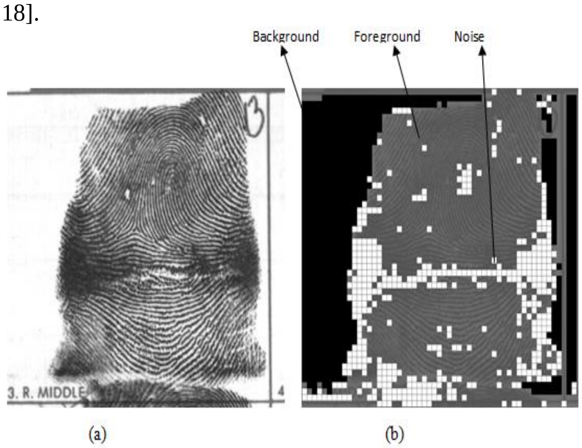


Figure 7 Fingerprint image, (b) Highlight background regions, foreground regions, and noise regions in the fingerprint image

3.1 Block-wise Step Operating on Gray-scale Statistical Features

Segmentation using gray-scale statistical features of the fingerprint operates on the principle that the random components of a random variable which contain two or more random variables can be separated using the properties of the mean and variance. The mean of the gray-level values in the foreground region is usually lower than that of the background region of the fingerprint image. On the other hand, the variance of the gray-level values in the foreground region is found to be higher than that of the background region. The technique of using the mean and variance of the gray-scale fingerprint image pattern does not work well with low quality fingerprint images [17-19-20].

Mehtre and Chatterjee, partitioned fingerprint image into blocks of 16 by 16 pixels and segmented the image using a block-wise histogram approach for the values of image direction. The block-wise histogram approach might not be appropriate for low contrast images and images with uniform intensity regions. According to Mehtre and Chatterjee the shortcomings of the variance gray-level method could be overcome by the use of composite method that combines the histogram of the image direction and the variance of the gray-level in each block [21, 22]. The fingerprint is isolated from noisy background areas using the variance of gray-level in a direction orthogonal to the orientation field in each block of size 16 by 16. Ratha *et al.*, underlying assumption was that the noise regions have no directional dependence, whereas regions of interest exhibit a very high variance in the direction orthogonal to the orientation of the fingerprint pattern and a very low variance along the ridges. In other words, the background has low variance for all direction [23]. Maltoni and Coppelli, used the same method as [23] but in their approach some pre-processing method adopted by [24] was used to crop and manually align the fingerprint images prior to the segmentation process [16]. A technique to improve the quality of fingerprint images using the gray-level mean and variance was presented by Wang, Wang, and Xu (2009) who used the combination of block mean and variance, after normalizing the image [25]. This method was used for sensor noise and pressure difference correction.

3.2 Bit-wise Step Operating on Local Directionality Features

For the local directional features, the fingerprint image gradient characterizes not only the image contrast but also the structure of the ridges' direction. These properties of the local directional features make it more appropriate for feature segmentation. The gradient information of fingerprint images has been in use for years. Maio and Maltoni reported using the mean of image gradient magnitude in each image block to separate the foreground region from the background region. The method used by Maio and Maltoni (1997) was found to be better for segmenting the foreground from the background due to the fact that the gradient response was high in the foreground region and low in the background region [26, 27]. Yin also used the mean of the image gradient magnitude by combining the image coherence values [28]. Zhu and Chengpu, they use of a coarse segmentation approach. In their approach, the coarse segmentation was used to isolate the foreground from the background. The orientation estimation of each image block for ridge blocks (that is, correct orientation) was made with regards to the orientation of non-ridge block (that is, incorrect orientation) [29, 30]. The correct orientations were referred to as the foreground, while the incorrect orientation as the background. In another report by Zhu a step-wise approach was proposed. One of which was already discussed and the second step presented the use of an average gray-scale value of the remaining ridge blocks to exclude the remaining ridge regions from the foreground.

Dong and Yu presented image gradient projection as a way of eliminating the background regions by using the coherence values to exclude the regions of irregular distortions of the image. Their work also extracted the ridge edges of fingerprint image, and employed morphological operations to obtain the foreground regions [31, 32]. Qi and M. Xie, proposed the average magnitude of the gradient and the variance of the gradient vector's directional image were combined to accurately segment important features from the less important ones [33]. Their method took into consideration the two most prominent properties of the fingerprints, which are ridge clarity and the slow change of texture orientation [33]. C. Sanet el al. and Tao Gu *et al*. used an unsupervised fingerprint segmentation algorithm. Their algorithm explored the simplified properties of a scale-space toggle operator and a multi-scale directional operator that are used to estimate the image background information [34-35]. The properties of a scale-space toggle include suppression of the image extremes. However, the multi-scale operator estimates the orientation field of each pixel by dividing the semicircle into discrete directions and computing standard deviations of the gray values for the set of line segments along each direction [36].

3.3 Bit-wise Step Operating on Coherence Features

The coherence feature is known as the strength of the local window gradients centered on the processed point along the same dominant orientation. Usually, the coherence feature is higher in the foreground than in the background, but has been observed to be influenced significantly by boundary signal and noise [32]. Since, the single coherence feature is not sufficient for robust segmentation, a systematic combination of several features is necessary [37]. According to Bazen, the use of a bite-wise segmentation technique based on the coherence features is advantageous for noisy images, though the morphological methods must be used to smooth-out the regions [38]. Their approach showed better accuracy in segmentation of noisy images. According to Bazen, the segmentation technique is based on three pixel features coherence, mean, and variance which are computed for each pixel [17]. The use of coherence in their work was to measure how well the gradients point in the same direction. When the fingerprint consists of only parallel line structures, the coherence will be considerably higher in the foreground than in the background. From their experimental results it was observed that their method provided more accuracy in the number of successful segmented regions. However, their method was observed to be affected by computational complexity that was higher than most of the other described block-wise approaches. Yin in [39] proposed a novel fingerprint segmentation method. The researchers made use of the bit-wise approach but it was based on quadric surface model with similar features just like that of [40]. Klein in Fingerprint Image Segmentation Based on Hidden Markov Models (2002) made use of gray-scale mean, gray-scale variance, and gradient consistency along with the Gabor aperture to get the responses that are based on the hidden Markov model (HMM) for segmentation [29]. Their work was aimed at solving the problem of fragmented segmentation for fingerprint images. The segmentation approach employed by Klein *et al.* was follows: 1) the fingerprint image was first decomposed into foreground, background and low-quality regions, 2) the pixel features were then modeled as the output of a hidden Markov process. The researchers observed that the performance of the HMM-based segmentation was highly dependent on the choice of pixel features. In a later work of [42] the block-wise feature algorithm for segmentation was adopted. This segmentation approach used three block features, namely; the cluster degree, the mean, and the variance. The block-wise feature was implemented in [28] but in their work only two block features were used, which were the mean of gradient magnitude and the coherence. Comparisons were made between mean and gradient magnitude and between the gradient magnitudes with a threshold value of the gradient. The threshold value of gradient magnitude G_{th} was set to impact on determining the foreground, G_{th} which is defined as:

$$G_{th} = c \times (|Gr(i,j)|_{\max} - |Gr(i,j)|_{\min}) + |Gr(i,j)|_{\min} \quad (4)$$

Where $|Gr(i,j)|_{\max}$, $|Gr(i,j)|_{\min}$ are the maximum and minimum values of gradient magnitude, respectively, and c is the threshold factor. The threshold parameters were used so that all the regions that fell outside the threshold were regarded as "invalid regions" in the foreground. The sets of connected elements with a low coherence value and the contours of the valid regions were located so that the orientation fields could be kept.

4.0 CONCLUSION

Fingerprint preprocessing is a challenging task that has captured the interest of researches over the past 30 years. A number of approaches and preprocessing strategies have been proposed to solve this problem. However, ways to improve algorithms, especially those developed for pre-processing still need to be validated. A feature based flow diagram has been generated which provides a basis for the user to understand the approach used for preprocessing in fingerprint classification. Using segmentation, the foreground of the fingerprint image can be extracted accurately. The benefit of using enhancement is to improve the grayscale image quality. Hence a combination of these techniques can be used to maximize the accuracy of fingerprint classification, verification and recognition.

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