Fingerprint Segmentation Based on Pixel Feature and Fuzzy Theory

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Abstract
Complex structure and low quality of fingerprint bring much difficulty in segmentation. In this paper, we present a new algorithm for fingerprint segmentation based on pixel feature and fuzzy theory. Firstly, a new feature, GR (gray range) is added to improve the correctness of pixel classification; then combined with other traditional features, three standard patterns are constructed and classification is realized by closeness degree and MMP (maximal membership principle); finally, a selection step is designed to remove much of unnecessary region. Instead of removing the whole remaining region, we focus on a balance between necessary region and unnecessary one by entropy of the two images. Even for low quality fingerprint, the algorithm can obtain a reasonable segmentation by adjusting the size of window. Furthermore, all parameters are adaptable and the method is applicable for fingerprints database. Extensive experiments demonstrate the efficiency of our algorithm.

Keywords- fingerprint segmentation, pixel feature, fuzzy theory, closeness degree, maximal membership principle

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1. Introduction

Automatic fingerprint identification (or recognition) system has been widely used in many fields in the world, just because fingerprint has some advantages such as high performance, and easily-captured in security, commerce, industrial, civilian and forensic applications [1-4]. Segmentation is a key step for automatic fingerprint identification to achieve satisfactory performance by rapidly focusing on some regions with special meaning. Fingerprint segmentation usually obtains two results: one is to focus on the region of interest (ROI), and the other is to remove noise that maybe affects feature extraction. It is notable that the latter could remove some useful information from the original fingerprint, which will decrease the matching score in genuine matching. There are two types of fingerprint segmentation methods from the object of processing: based on the pixel level and based on the block level. Both of them classify pixels (or blocks) into foreground and background using different feature or different classification methods. Some features such as coherence, mean and variation (CMV) are used in fingerprint segmentation with quadric surface model instead of linear classification [5]. The model coefficients in their method are acquired by feed-forward neural network and 30 representative fingerprint images respectively from FVC2000 DB1, DB2, and DB3. The precise of the coefficients is dependent on the selected fingerprints. Harris corner point as an energy feature is used to discriminate foreground and background [6]. This method included choosing appropriate threshold and a heuristic selection algorithm, which makes the method difficult. Some authors divided a fingerprint into high quality ridge region, recoverable low quality region, unrecoverable low quality region, non-ridge region and remaining ridge region. They used two steps for fingerprint segmentation to exclude the remaining ridge region from the foreground [7]. But some segmentation results have brought additional information or lost partial edge information. Another algorithm combined Markov chain with Monte Carlo method is applied into fingerprint segmentation [8]. This method is similar to deformable contour template, but it includes more steps such as parameter selection, initialization and iteration termination condition. Gradient projection and gradient coherence criteria with morphological operations are used to get the exact foreground region of the fingerprint [9]. Automatic labeling based linear neighborhood propagation is designed for fingerprint segmentation [10].

Most existing segmentation can obtain satisfactory results. However, fingerprint segmentation is pre-work in automatic fingerprint identification, and a complex segmentation method is bound to affect system performance and time consumption. This paper proposed a method for fingerprint segmentation based on pixel feature and fuzzy theory. Pixel features are coherence, standard deviation, GR, and Harris point energy. Another usual feature, mean is not used in the first step, but used in the second step to remove some unnecessary region. Fuzzy theory can solve many ambiguous problems, such as classification of pixel in the edge or other uncertainty in fingerprints.

This paper is organized as follows. Section 2 gives some knowledge of fuzzy theory especially concerned in the proposed algorithm. Section 3 presents our segmentation method in detail. Section 4 provides the experimental results on fingerprint database. Finally, concluding remarks and future works are given in Section 5.

2. Some Knowledge about Fuzzy Theory

In this section, we only describe some knowledge used in our segmentation method about fuzzy theory. More detailed content can be seen in references about fuzzy logic [11-13]. Fuzzy theory is firstly given by Zadeh L.A. in 1965 and it can change traditional binary logical to the interval \([0,1]\). Let \(A\) be fuzzy set, \(\mu_A : A \mapsto [0,1]\), namely, \(\forall x \in A, \mu_A(x) \in [0,1]\). \(\mu_A\) can be called membership function, and \(\mu_A(x)\) is the degree of membership for the element \(x\) to fuzzy set \(A\), which shows the extent (or magnitude) that \(x\) belongs to \(A\). Obviously, fuzzy set is different to common Cantor set in that the element can belong to the fuzzy set at its degree of membership.

The distance between two sets can measure their separation, and can be defined varying with different problems [14, 15]. For two fuzzy sets, we can define a measurement to be called closeness degree between them, which can show the magnitude of the closeness of the two sets. A usual definition of closeness degree is based on Hamming distance (Euclid distance also can be used). For \(x\) and the two fuzzy sets, \(A, B\), assuming degrees of membership are respectively \(\mu_A(x)\) and \(\mu_B(x)\), then the Hamming distance between \(A\) and \(B\) is \(\rho(A, B) = \sum_{i \in I} |\mu_A(x_i) - \mu_B(x_i)|\). In fact, this can be generalized in high dimension space, and revised as Eq. (1)

\[
Ham(A, B) = \frac{1}{|I|} \sum_{i \in I} |\mu_A(x_i) - \mu_B(x_i)|
\]

(1)

where \(i \in I\) and \(|I|\) is the number of element in an index set \(I\). The longer the hamming distance between \(A\) and \(B\), the smaller closeness degree they have. So the closeness degree can be defined as

\[
Closeness(A, B) = 1 - Ham(A, B)
\]

(2)

Apparently, this definition of closeness degree has an important property, namely, for the same two fuzzy sets, the closeness will be 1 and the two very different sets, the closeness will be close to zero.

As we know, fingerprint is composed of ridges and valleys. The region where the ridges and the valleys are alternative can be defined foreground, and other region can be background. The region where it can not be easily determined to be foreground or background can be defined edge. However, some edges maybe exist in the foreground especially for those fingerprints with low quality or discontinuous ridges. So, fingerprint segmentation is more difficult under this condition. For simplifying the detection of edge, we can assume that edge in this paper is the overlapping region of foreground and background for fingerprints with good quality, but edge will be at the balance location between losing information and reserving information for worse fingerprints (with discontinuous ridges or region). Every pixel only exists in foreground, background or edge that we can define. When foreground, background and edge can be viewed as three standard patterns, fingerprint segmentation will be to classify every pixel into one of the three patterns, and the key of this idea is how to describe the standard patterns, which will be discussed in the following section.

have been published but are not well known. Describe new or substantially modified methods, give reasons for using them and evaluate their limitations. Include number of observations and the statistical significance of the finding when appropriate. Detailed
statistical analyses, mathematical derivations, and the like may sometimes be suitably presented in the form of one or more appendices.

3. Fingerprint Segmentation

During the capture of fingers, there are much uncertainty such as the location, the pressure, the wet, the dirty and the harm, which will result in complex structure and low quality of fingerprints. The uncertainty in a fingerprint will bring the difficulty in image processing, but will also assure the feasibility of applying fuzzy theory into fingerprint segmentation. We can divide a fingerprint into three parts: foreground, background and edge. It is notable that foreground, composed of ridges and valleys, can be ROI (short for region of interest) and background is the region not belonging to the foreground. Edge is the overlap region of foreground and background for good fingerprint but balance location for bad inversely. Fingerprint segmentation can be viewed as classifying every pixel into one of the three patterns by some features and principals. In image processing, a very usual feature is gray but it can not discriminate background from fingerprint, because bright pixels exist in both foreground and background, which is different with other optical images. So other features will be used in the proposed method and listed in the following sub-section.

3.1 Feature Extraction

The number of features (namely, the dimension of feature vector) will directly influence pixel classification in fingerprint. The length of feature vector is too short to realize rightly pixels’ classification. Because the extraction of feature in our method is based pixel and its neighborhood, the acquisition of feature vector with high dimension will be very complicated, even influence the effectiveness of the whole system. So, we used four features to maintain the balance between the rightness of classification and time consumed in feature extraction. The description about the four features is given detailed in the following.

Many features can be applied into the description of fingerprint. In order to focus on our method, some of features in the references are directly used here. Considering that the mean value is low in foreground but high in background for a fingerprint, which is different to the other two features. So, the mean is not used in the first step of our segmentation method. The three important features, coherence (Coh), variance (Var), and strength of Harris-Corner points (R) are respectively defined as follows:

$$Coh = \frac{\sqrt{(G_{xx} - G_{yy})^2 + 4G_{xy}^2}}{G_{xx} + G_{yy}} \quad (3)$$

where $G_{xx} = \sum_{y} G_{x}^2$, $G_{yy} = \sum_{x} G_{y}^2$, $G_{xx} = \sum_{y} G_{x} G_{y}$, and $(G_{x}, G_{y})$ is the local gradient, $W$ is the window centered on the present pixel.

$$Var = \sum_{w} (I - Mean)^2 \quad (4)$$

where $Mean$ is the mean of $W$ and $Mean = \frac{1}{|W|} \sum_{w} I$. For simplifying the work of data processing, standard deviation $\sqrt{Var}$ is used.
\[ R = \frac{I_x^2 I_y^2 - I_{xy}^2}{I_x^2 + I_y^2} \]  

(5)

where \( I_x, I_y, \) and \( I_{xy} \) denote the partial derivatives in the present pixel \((x,y)\).

Another feature, GR will be used in the algorithm. Its definition is

\[ GR = \max(\cdot) - \min(\cdot) \]  

which shows variance range and discretion margin of data distribution. Experiments show that there is a higher GR in foreground and a lower one in background for a fixed window (the size: 17×17 in Fig.1). The figure can show that the spatial distribution of GR in a fingerprint.
3.2 Pattern Description
As referenced at the beginning of this section, foreground, background and edge can be viewed as three standard patterns, and we can use some features and membership functions to measure the distance between every pixel and every pattern. As a usual, membership function is given by expert or experimental knowledge. Considering that the stronger coherence, the more extent it belongs to the foreground, so as variance, strength, and GR, so we choose membership function like as:

\[ f(x) = e^{\frac{-(x-\mu)^2}{2\sigma^2}} \]  \hspace{1cm} (7)

It is notable that there are different parameters for the different patterns. The parameters can be determined by the given database. Here, the three membership functions of patterns are respectively:

\[ \mu_f(x) = e^{\frac{(x-\text{max}(f))^2}{2\sigma(f)^2}} \]  \hspace{1cm} (8)

\[ \mu_b(x) = e^{\frac{(x-\text{min}(f))^2}{2\sigma(f)^2}} \]  \hspace{1cm} (9)

\[ \mu_e(x) = e^{\frac{(x-\text{max}(f)+\text{min}(f))^2}{2\sigma(f)^2}} \]  \hspace{1cm} (10)

where \( f \) is a feature matrix based pixel level in a fingerprint, and \( \text{min}(f) \) is the minimum of the matrix \( f \), correspondingly, \( \text{max}(f) \) is the maximum. Apparently, the degree of membership will be 1 for the standard pattern. According to Section 2, the distance between standard pattern and pixel can be measured by the closeness degree and the distance can realize the classification.

3.3 Segmentation
Assume \( f_i(i\in I) \) be features of the present pixel, and the membership degrees be respectively \( \mu_f(f_i) \), \( \mu_b(f_i) \) and \( \mu_e(f_i) \), the closeness degree can be obtained by:

\[ \text{closeness(pixel, pattern)} = 1 - \frac{1}{|I|} \sum_{i=1}^{I} |1 - \mu_{\text{pattern}}(f_i)| \]  \hspace{1cm} (11)
where $\text{pattern} \in \{f,b,e\}$. The right coefficient $\frac{1}{|I|}$ in the above equation is to normalize the computation result. Classification can be realized by the Maximal Membership Principle, namely,

$$\begin{align*}
(x,y) & \in \arg \max \{\text{closeness}(\text{pixel}, f), \text{closeness}(\text{pixel}, b), \text{closeness}(\text{pixel}, e)\} \\
& \in \text{(12)}
\end{align*}$$

For preserving more information of edge, segmentation will be given by the following:

$$A(x,y) = \begin{cases} 
I(x,y), & (x,y) \in f \text{ or } e \\
0, & (x,y) \in b
\end{cases} \quad \text{(13)}$$

### 3.4 Notation

As we know, when fingerprints are being captured, they are often influenced by factual elements and random condition, which makes some pixels and region have a higher gray mean than other pixels in foreground, for example, the third original fingerprint in Fig.1. So, a selection step can be added in the proposed algorithm based another feature, gray mean, to obtain a better segmentation, which can be denoted by

$$B(x,y) = \begin{cases} 
A(x,y), & \text{mean}(x,y) \leq (1+p) \cdot \text{mean}(f) \\
0, & \text{else}
\end{cases} \quad \text{(14)}$$

where $\text{mean}(x,y)$ is the mean value of region centered pixel $(x,y)$ in the original image and $\text{mean}(f)$ is the mean value of foreground in the former segmentation. The parameter, $p \in (0,1)$ will determine the magnitude of information in the segmentation result. If the remaining region is all abandoned in segmentation, it maybe loses some information in ROI and result in a worse matching in fingerprint minutiae. In order to show it, we experiment on some fingerprints to extract minutiae. In Fig.2, we select four fingerprints in FVC2002, respectively 35_5, 35_8, 94_1 and 94_4. If the inner of the marked region is removed in the first two fingerprints or the outer of the marked region is removed in the last two fingerprints, the matching score will be directly influenced, especially for a fixed threshold. So we will aim to finding a balance between reserving information and removing unnecessary region, moreover, we hope that we can’t add other information such as ‘black hole’ (which will influence the minutia extraction or other following work in fingerprint application system) in the foreground. Although different results are listed in the experiment under different parameters, an adaptive parameter can be chosen with an initial size $(17 \times 17)$ by optimizing

$$p = \arg \min_{p} (\text{Entropy}(I,B)) \quad \text{(15)}$$

where $\text{Entropy}(\cdot, \cdot)$ is the joint entropy of two images, $I$ and $B$ are respectively the original fingerprint and the present segmentation result. Certainly, we can obtain the optimized parameter by the derivation of the entropy curve.

Experiments show that the optimized parameter is small for low quality fingerprints. But for good quality fingerprints, the parameter is bigger. Moreover, a better quality fingerprint, the bigger parameter is, vice versa. To get a better segmentation, the size of window can be adjusted in the proposed algorithm, especially for the fingerprints with a bad quality.
4. Experiment
In order to testify the efficiency of the algorithm, we do experiments on FVC2002. The database consists of 800 fingerprint images (100 distinct fingers, 8 impressions each) with the size of 560 × 296. For the length limitation of this paper, we only list the segmentation results of some fingerprints in DB2. It is notable that the fingerprints listed here are very typical in the fingerprint database. Our experiments are run in the computer with 2.10GHZ, 764MB.

The first experiment is to show segmentation results with selection step in Fig.3. The size of window is 17 × 17 in the first experiment for noise reduction, which is a better size for fingerprint processing [5], and the parameters, $p$ are respectively 0.6, 0.4 and 0.2. The left column is the original fingerprints, and the middle column is the segmentation without selection step, and the right column is the segmentation with selection step. From Fig.3, we can see the proposed method can segment fingerprints and the selection step can remove much of unnecessary fingerprint edge and the remaining region especially for good quality fingerprints. However, the selection step can not obtain a better result for fingerprints with discontinuous ridges. We will adjust the size of window for these fingerprints in the following experiment.

The second experiment is to testify the segmentation varying with the parameter $p$. The size of window is still 17 × 17. The results of segmentation are showed in Fig.4, the first row are results of segmentation from fingerprint 84_5 with $p = 0.4$, $p = 0.6$ and $p = 0.8$; the second row are ones from fingerprint 29_4 with $p = 0.1$, $p = 0.4$ and $p = 0.7$; the third row are ones from fingerprint 91_1 with $p = 0.1$, $p = 0.2$ and $p = 0.3$. From the results in Fig.4, we can see that the bigger the parameter $p$, the much information the remaining, vice versa. For fingerprint 84_5 and fingerprint 29_4, the middle column will be best in this experiment and adaptive parameters are respectively $p = 0.6$ and $p = 0.4$ because of a wider edge or a bigger remaining region. It is notable that there is almost no apparent difference for fingerprints with the discontinuous ridges.

The third experiment is to discover joint entropy between the original fingerprint and segmentation result and to get an optimal parameter. Here, the size of window in the

Fig.2. Original fingerprints and minutiae.
algorithm is still $17 \times 17$. Only the fingerprints having discontinuous ridges are shown in Fig.5. The left column is the original fingerprints and the right column is the variance of the joint entropy varying with different parameters. From Fig.5, when the joint entropy gets firstly its minimum, the corresponding parameter is often smaller ($<= 0.3$) in the interval (0,1).

The last experiment is to show segmentation results with different size of window for fingerprints with discontinuous ridges in vision. Here, the size of window are respectively $17 \times 17$, $41 \times 41$ and $75 \times 75$. At the optimal parameters, the segmentation results of fingerprint 91_1 in the first column, fingerprint 1_8 in the second column, and fingerprint 46_8 in the third row are shown in Fig.6. This experiment shows that a bigger size can conserve more information, however, it can also bring unnecessary fingerprint edge, but for fingerprint with discontinuous ridges, a better segmentation can be obtained when using a bigger window.
Fig. 3. The results of segmentation: the first column: original fingerprints; the second column: segmentation results without selection step; the third column: results with selection step.
Fig. 4. The first row: the segmentation of 84_5 with $p=0.4$, $p=0.6$ and $p=0.8$; the second row: the segmentation of 29_4 with $p=0.1$, $p=0.4$ and $p=0.7$; the third row: the segmentation of 91_1 with $p=0.1$, $p=0.2$, and $p=0.3$. 

(g) $p=0.1$  
(h) $p=0.2$  
(i) $p=0.3$
Fig. 5. The upper row is the original fingerprint and joint entropy with different parameters from fingerprint 1_8; the middle row is form fingerprint 46_8; the bottom row is from fingerprint 91_1.
5. Conclusion and Future Work

Fuzzy theory can supply fingerprint segmentation for feasibility just because of uncertainty in fingerprint. The proposed algorithm is easy to implement and can obtain a satisfactory result for fingerprint, especially for good quality fingerprint. For the remaining region in fingerprint, a selection step can remove much of unnecessary region. We needn’t remove all in order to reserve enough information for the fingerprint recognition or other application and we only find a balance between information and redundancy. Even for some fingerprints with low quality such as discontinuous ridges, the proposed algorithm can get a better segmentation by changing the size of window. It is important that the proposed algorithm is typical based on fuzzy theory, and the parameter determined is adaptive and optimal for any fingerprint in database.

However, the proposed algorithm is designed based on pixel level, which maybe influence the speed of algorithm. Whether the algorithm is used in the block level or not, this will improve the speed of the algorithm. It will be our research tendency in future.
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