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Fingerprint Classification Using Fuzzy-neural Network and Other Methods

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ABSTRACT

The fingerprints are unique to each individual; they can be used as a means to distinguish one individual from another.Therefore they are used to identify a person. Fingerprint Classification is done to associate a given fingerprint to one of the existing classes, such as left loop, right loop, arch, tented arch and whorl. Classifying fingerprint images is a very complex pattern recognition problem, due to properties of intra-class diversitiesand inter-class similarities. Its objective is to reduce the responsetime and reducing the search space in an automatic identificationsystem fingerprint (AIS), in classifying fingerprints. In these papers we present a system of fingerprint classificationbased on singular characteristics for extracting feature vectorsand neural networks and fuzzy neural networks, SVM and Knearest neighbour for classifying.

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1. INTRODUCTION

Biometrics is a set of techniques used to identify or verify the identity of an individual. There are several biometric techniques one of those techniques is the fingerprint, which is biometric dominant used in the world compared to other technologies. The fingerprint identification is greatly improved, but it suffers from the time of identification, because the identification time increases with the number of images in the database, which implicate the need to introduce fingerprints types to reduce the search space. The fingerprint classification is a process to classify the input fingerprint image in one of the predefined classes, such as left loop, right loop, and whorl, twin loop or arch. It reduces the time complexity in a biometric system by limiting the search in the class of the fingerprint to verify or to identify the identity of an individual. A number of approaches to fingerprint classification have been developed. [16] reviews some works based on automatic classification of fingerprints.

2. FINGERPRINT TYPES

The fingerprint is the pattern of the skin surface of the fingers. Its biological properties are well understood. It is used for centuries and its identification is valid established. Fingerprints are classified according to an old system of decades: the Henry system. The classification is based on the general topography of the fingerprint and allows defining families such as loops (left and right), arches and whorl, which comprise 95% of human fingerprints (Figure. 1):

2.1. Arch

The arches are the less common patterns; they include only 5% of human fingers. The arch pattern is made up of ridges lying one above the other. The ridges enter on one side and flow or appear to flow out from the other side. There are two types of arch and tented arch, they are similar, except that at least one ridge shows a high curvature on tented arch type.

2.2. Whorl

The whorl correspond to 30% of human fingers, this fingerprint type includes lines are wound around a point, forming a kind of vortex.

2.3. Loop

The loops are the most common patterns; they represent 60% of human fingers. One or more of the ridges enters on either side of the impression, re-curves, touches or crosses the line running from the delta to the core and terminates on or in the direction of the side where the ridge or ridges entered. Loops can more specifically be classified as right loop and left loop by observing the left hand. If the ridges flow in the direction of the thumb, it can be classified as right loop and if it flows in the direction of the little finger then it can be categorized as left loop.

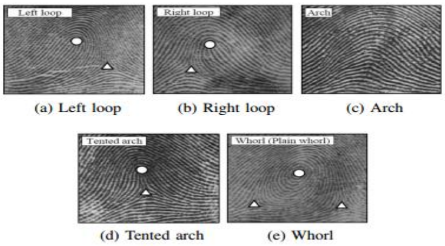

Figure 1. Fingerprint types

3. FINGERPRINT IMAGE ENHANCEMENT

The method adopted to enhance the fingerprint image is the Fast Fourier Transform (FFT). We divide the image into small processing blocks (32 by32 pixels) and perform the Fourier Transform according to:

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) * \exp\left(-j2\pi * \frac{ux}{M} + \frac{vy}{N}\right) \quad (1)$$

For u = 1, 2,…, 31 and v = 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 TF = abs(F (u; v)) = |F (u; v)|.

$$g(x,y) = F^{-1}(F(u,v) * |F(u,v)|^{k}) \quad (2)$$

Get the enhanced block according to equation 2. Where F^{-1}(F (u; v)) is given by:

$$f(u,v) = \frac{1}{MN} * \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} F(u,v) * \exp\left(j2\pi * \frac{ux}{M} + \frac{vy}{N}\right) \quad (3)$$

For u = 1, 2,…, 31 and v = 1,2,…,31

The k in formula (2) is an experimentally determined constant, which we choose k = 0.45 to calculate. While having a higher “k” improves the appearance of the ridges, filling up small holes in ridges, having too high a “k” can result in false joining of ridges. Thus a termination might become a bifurcation. Figure 2 presents the image after FFT enhancement.

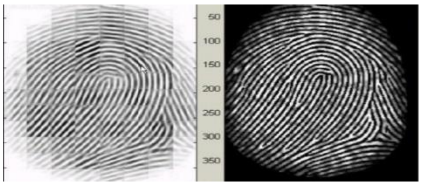

Figure 2. Fingerprint enhancement by FFT. Enhanced image (left), Original image (right)

4. FEATURES EXTRACTION

The extraction process of fingerprint code is presented below:

4.1.Block direction estimation

The orientation field of a fingerprint represents the intrinsic nature of fingerprint (Fig. 3). This is an essential stage to determine ridges of fingerprint and to find the region of interest of fingerprint.

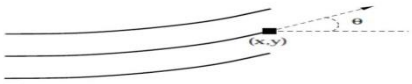

Figure 3. Ridge local direction of pixel(x, y)

The steps to estimate the direction to pixel (i, j) are:

a. Step 1: divide the image G on blocs of w x w (16 x 16).
b. Step 2: Calculate the gradient values along x-direction $\partial_x(i,j)$and y-direction $\partial_y(i,j)$for each pixel of the block. Two Sobel filters are used to fulfil the task.
c. Step 3: The local orientation of the pixel (i, j) can be estimated using the following equations:

$$V_x(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2 * \partial_x(i,j).\partial_y(i,j) \quad (4)$$

$$V_y(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} (\partial_x(i,j).\partial_y(i,j))^2 \quad (5)$$

$$O(i,j) = \frac{V_x(i,j)}{V_y(i,j)} \quad (6)$$

$$\theta_1(i,j) = \frac{1}{2}.tan^{-1}O(i,j) \quad (7)$$

$$\theta(i,j) = \theta_1(i,j) + \frac{\pi}{2} \quad (8)$$

Where O (i, j) is the estimate of the square of any orientation center pixel block (i, j), and $\theta(i,j)$is the orientation angle. Figure 4 illustrates the estimation result of orientation fields of a fingerprint.

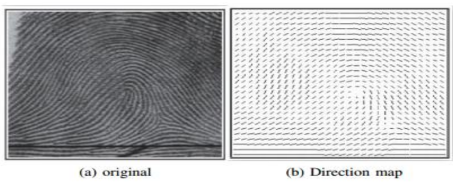

Figure 1. Direction map [1]

4.2. ROI extraction by Morphological operations

Two Morphological operations called “OPEN” and “CLOSE” are adopted. The “OPEN” operation can expand images and remove peaks introduced by background noise (Figure. 7). The “CLOSE” operation can shrink images and eliminate small cavities (Figure. 6).

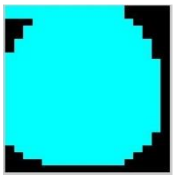

Figure 5. Original Image

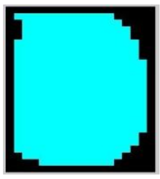

Figure 2. After CLOSE operation

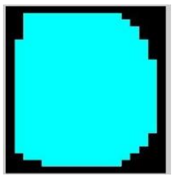

Figure 3. After OPEN operation

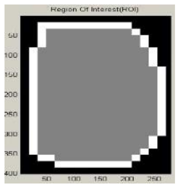

Figure 7. Region of interest (ROI) + Bound

Figure. 7 show the interest fingerprint image area and it’s bound. The bound is the subtraction of the closed area from the opened area. Then the algorithm throws away those leftmost, rightmost, uppermost and bottommost blocks out of the bound so as to get the tightly bounded region just containing the bound and inner area.

4.3. Core detection

Several algorithms are used to detect global features for fingerprint such as “core”. However, most of them are based on the direction of the fingerprint. In our project, we use a more practical, simple and elegant algorithm: it is the Poincare index algorithm proposed by Kawagoe and Tojo [3].

4.3.1. Poincare index algorithm

Let fingerprint direction, Poincare index is calculed by given formulas:

$$Poincare(i,j) = \frac{1}{2\pi}\sum_{k=0}^{n-1}\Delta(k) \tag{9}$$

$$\Delta(k) = \begin{cases} \delta(k)|\delta(k)| < 2\pi \\ \delta(k)+\pi \qquad \delta(k) \le \frac{-\pi}{2} \\ \pi - \delta(k) \qquad \delta(k) \ge \frac{\pi}{2} \end{cases} \tag{10}$$

$$\delta(k) = \theta\left(x_{(k+1)modN}, y_{(k+1)modN}\right) - \theta(x_k, y_k) \tag{11}$$

And it goes in the opposite direction clockwise from 0 to N-1. For our case we took the N value as being equal to 4 [2]. Indeed, the Poincare index of a closed curve admits still one of the following values: 0, 0.5 and -0 .5. Regarding fingerprint, the pixel (i,j) is in a singular core region or delta depending on the value of Poincare index at this pixel(i,j) :

a. if Poincare (i, j) = 0.5, the pixel (i, j) is in a singular core region;
b. if Poincare (i, j) = -0.5, the pixel (i, j) is in a singular delta region;
c. else, le pixel (i, j) is not in a singular region;
d. If you have found several “cores”, we consider the core that is on the central cavity.

The next step is to choose the directions of sixteen neighbouring blocks of the core point of fingerprint. These directions are the characteristics vector of fingerprint or the code fingerprint.

5. CLASSIFICATION

We consider four methods for classification, those methodsare KNN, Neural network, Fuzzy neural network and SVM.

5.1. KNN

In pattern recognition, the k-Nearest Neighbours algorithm [4] (or k-NN for short) is a non-parametric method used for classification. The input consists of the k closest training examples in the feature space. The output is a class membership. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k= 1, then the object is simply assigned to the class of that single nearest neighbour. K-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The K-NN algorithm is among the simplest of all machine learning algorithms.

5.2. SVM

Support vector machine [12] (SVM) [Vladimir Vapnik 1995] are supervised learning models with associated learning algorithms that analyse data and recognize patterns, used for classification and regression analysis, given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a nonprobability binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

5.3. ANN

The multilayer neural networks [13] are built usually from three layers; Input layer, hidden layer (there may be several hidden layers) and output layer.The method of changing weight is easy with the algorithm of Rosenblatt [14], but it involves some learning limitations because the unknowing of the hidden layers number. Therefore it is necessary to propagate the error from the last layer to the first.Multilayer neural perceptron use the sigmoid activation function; it allows the necessary nuances for proper use of back-propagation.

5.4. Neuro-fuzzy network (ANFIS)

ArticialNeuro-Fuzzy Inference Systems (ANFIS)[15] are a class of adaptive networks that are functionally equivalent to fuzzy inference systems. They represent Sugeno e Tsukamoto fuzzy models and they can be trained by a hybrid learning to identify the parameters of the association function of the single output type systems Fuzzy Inference of Sugeno (FIS) [15].

A combination of the square and back-propagation gradient descent methods are used for the parameters of the training of the FIS and functions to model a given set of input / output data. The program ANFIS is available Matlab fuzzy toolbox.

6. RESULTS AND DISCUSSIONS

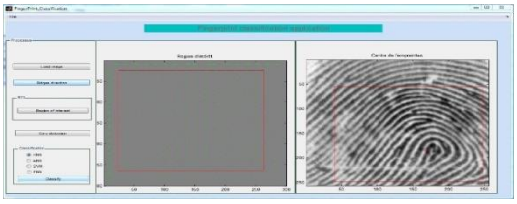

Figure 9. Implementation

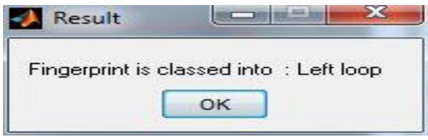

Figure 10. Classification Result

The result of classification is given by message box as follow:

6.1. Results

The following results are obtained for a training base containing 88 fingerprint images (8 arch, 24 left loop, 32 right loop and 24 of whorl) and a testing base with 35 fingerprints Images (5 arc, 10 left loop, 10 right loop and 10 whorl). The figure below shows the recognition rate of fingerprint images based on number of neighbours chosen, we see that the maximum recognition rate is obtained with a number of nearest neighbours equal to 15, the rate is 77.1429 %.

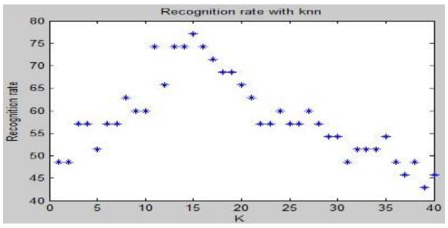

Figure 11. Recognition rate with KNN

6.2. Training step

Table 1. Training rate for all methods

	Left loop	Whorl	Right loop	Arch	Total
SVM	100%	100%	100%	100%	100%
ANN	100%	100%	100%	100%	100%
FNN	100%	87.50%	91.66%	50.00%	88.63%

6.3. Testing step

Table 2. Testing rate with differents methods

	Left loop	Whorl	Right loop	Arch	Total
KNN	70%	100%	70%	60%	77.14%
SVM	30%	100%	50%	40%	57.14%
ANN	70%	80%	90%	80%	80%
FNN	100%	70%	80%	80%	82.85%

6.4. Discussions

KNN classifier gives good results with a number of nearest neighbours equal to 15. It determines the fingerprint belonging to class whorl with rate of 100%, and the medium rate for others. The SVM classifier recognizes also the fingerprint image of our test database belonging to the class of whorl with rate of 100%, but the rate is so low for others. The artificial neural network recognizes the images of fingerprints with rate almost equal for all classes. In general it gives good result for all classes. The neural-fuzzy network recognizes with rate sure the images of fingerprint belonging to Class left loop and with very good rate for the other classes. In general we find that the neural-fuzzy networks give the results compelling comparing to neural networks that also shows its strength comparing to 15 NN that recognizes classes with a rate of 77.14%, and finally we find SVM that give the low results in this case that is the classification of fingerprint.

7. CONCLUSION

In this work we present the extraction process of characteristics to fingerprint based on the direction block estimate of fingerprint and a comparative study of methods of classification SVM, NN, FNN and KNN. As perspectives of this work, we believe that the system performance could be improved by adding other information to the characteristics vector of fingerprint and the use of other methods of classification such as genetic algorithms.

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