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Fingerprint Classification Using Least Square Orientation and Quick Propagation Algorithms

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Abstract

Fingerprint Classification provides an important indexing mechanism in a fingerprint database. An accurate and consistent classification can greatly reduce fingerprint matching time for a large database. We present a fingerprint classification algorithm which is able to achieve accuracy better than previously reported in the literature. We classify fingerprints into seven categories: plain arch, tented arch, left loop, right loop, plain whorl, central pocket whorl and double loop whorl. The least square orientation estimation algorithm uses a novel representation to make a classification. It has been tested on 4,000 images in the NIST-4 database. For the seven-class problem a classification accuracy of 94.08 percent is achieved. For the five-class problem (whorl, right loop, left loop, arch and tented arch) we are able to achieve a classification accuracy of 97 percent.

Keywords: fingerprint classification, least square Orientation, grey levels, sampling, quick propagation

INTRODUCTION

Several approaches have been developed for automatic fingerprint classification. These approaches can be broadly categorized into four main categories. (i) model-based (ii) structure based (iii) frequency based (iv) syntactic based. Model based fingerprint classification technique uses the locations of singular points (core and delta) (Karu and Jain, 2006; Pankanti, *et al.*, 2007). A model based approach tries to capture the knowledge of a human expert by deriving rules for each category by hand constructing the models and therefore, does not require training. A structure based approach used the estimated orientation field in a fingerprint image to classify the fingerprint. In another structure based approach, B-spline curves are used to represent and classify fingerprints (Wilson *et al.*, 1993). A syntactic approach uses a formal grammar (Chong *et al.*, 1997). Frequency based approaches use the frequency spectrum of the fingerprints for classification (Jain *et al.*, 2007).

In the following section, we present the details of our fingerprint classifications. In the second section we present the problem description. In section three we present our algorithm. In section four, we present datasets. Section five deals with our system performance. The conclusions are given in the last section.

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PROBLEM DESCRIPTION

For two decades this system was considered the most accurate method of identification. It was only in the first years of the new century that police began to appreciate and accept a system of identification based on the classification of finger ridge patterns known as fingerprints. Today, the fingerprint is the pillar of modern criminal identification.

Fingerprint Classification

The most widely used classification method is based on Henry's classification (Figs. 1a to 1h) which consists of eight classes.

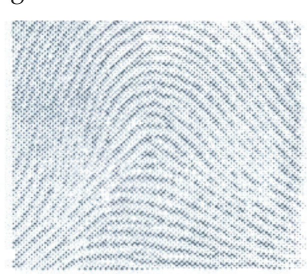

Fig.1(a) Plain arch

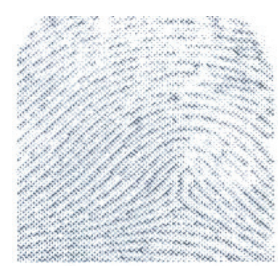

Fig.1(b) Tented arch

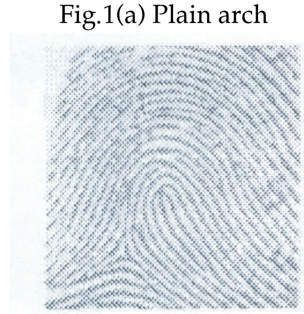

Fig.1(c) Left loop

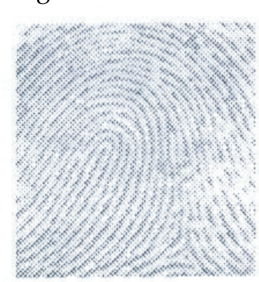

Fig.1(d) Right loop

Fig.1(e) Plain Whorl

Fig.1 (f) Central pocket whorl

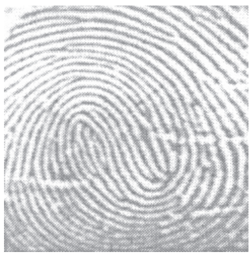

Fig.1(g) Double loop

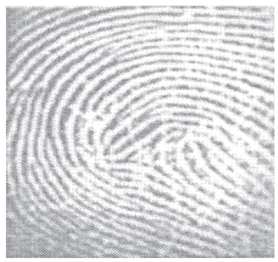

Fig.1(h) Accidental Whorl

Fig. 1. Hentry's Classification of fingerprints
(a) Plain arch, (b) Tented arch, (c) Left loop (d) Right loop (e) Plain whorl (f) Central Pocket Whorl
(g) Double loop Whorl (h) Accidental whorl

Plain arch: Fingerprint patterns in which the ridge enter on one side, rise in the middle and flow (or) tend to flow out from other side fig 1(a).

Tented arch: The same tendency to enter from one side and flow out from the other side with the exception that the ridges from either an angle (or) an Up thrust at the center fig 1(b).

Radial (or) Left Loop: Loops whose ridges flow toward radius bone (toward the thumb) are called radial loop fig 1(c).

Ulnar (or) Right Loop: Loops whose ridges flow in the directions of ulnarbone (toward the little finger) are called ulnar loop fig 1(d)

Plain whorl: Any pattern with atleast two deltas and one recurring ridge which may be a spiral or any variation of a circle is called a plain whorl fig 1(e).

Central Pocket Whorl: The central pocket Loop has two deltas and at least a ridge making a complete circuit as in the plain loop Fig 1(f).

Double Loop: The Double (or) twinned loop, consists of two deltas and two separate loops. fig 1(g)

Accidental Whorl: The accidental whorl is a pattern consisting of a combination of two or more different types of patterns, with the exception of the plain arch, with two (or) more deltas fig 1(h)

Preprocessing

Each fingerprint pattern is divided into 256 sampling squares or windows, each containing 12x–12 binary bits. Because the slope of ridges in each window is constant, the ridges of each window could be represented by a directional code. By choosing only four directional codes, we can generate a close approximation of the fingerprint impressions and meanwhile, limit the number of possible combinations of directional codes for the feature extraction process.

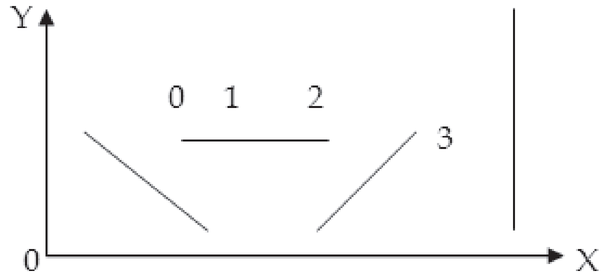

Fig. 2. Pre- Processing

Figure (2) shows the four directional codes, 0 and 1, 2 and 3 which are making angles of $-45^o, 0^o, 45^o, 90^o$ with respect to the xy coordinates respectively. Hence, each sampling square contains one of the above directional codes which represents the dominate slope of the ridges running through the sampling square. The directional code of each sampling square is determined using a preprocessor consisting of skeletonizaton tracing and code detection.

First the patterns are scanned using a computer controlled scanner. Then the digitized 256 multi-grey level patterns are transformed into binary level. The transformation is achieved using a dynamic threshold grey level that is the average grey level of each sampling square is used as the threshold grey level. Thus tranformation is simply the mapping of all data points having grey level more than the threshold value t_{kl} to one and all others to zero.

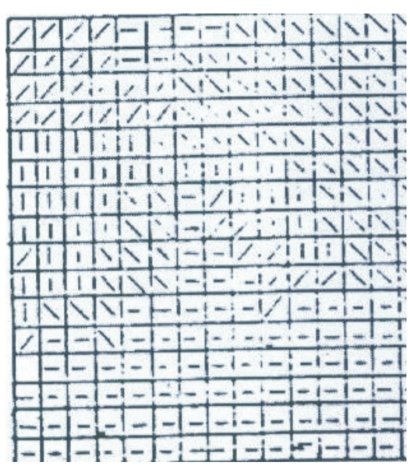

Fig. 3. Segmentation

Hence, the mapping f is:

$$f\,(gijkl > t_{kl}) \rightarrow 1$$
$$f\,(gijkl \leq t_{kl}) \rightarrow 1$$

$$k, l = 1 \ldots 12$$
$$g = 0, 1 \ldots 256$$

$$t_{kl} = 1/144 \sum_{i}^{12} \sum_{j}^{12} gijkl$$

Where gijkl is the grey level of a data point i,j in the sampling square k, l and t_{kl} is the threshold grey level of the sampling square k,l. The dynamic threshold grey level is used because of the non uniform intensity of the fingerprint patterns. This nonuniformity is mainly due to the variation in the amount of ink and pressure used in the different areas of the finger when the fingerprint is taken.

PROPOSED METHOD

In the proposed method for fingerprint classification using the neural network has two main advantages (i) it can tolerate the presence of ambiguous fingerprint images in the training set and (ii) it can effectively identify the most difficult figerprint images in the test set. In the existing method of classification of fingerprint has five classes namely Arch, Tented arch, Left loop, Right loop and whorl (Fitz and Green, 2006; Ross *et al.*, 2008). But, in the proposed method the whorl class is subdivided into plain whorl, central pocket whorl and double loop whorl which makes seven classes as shown in Fig. (4).

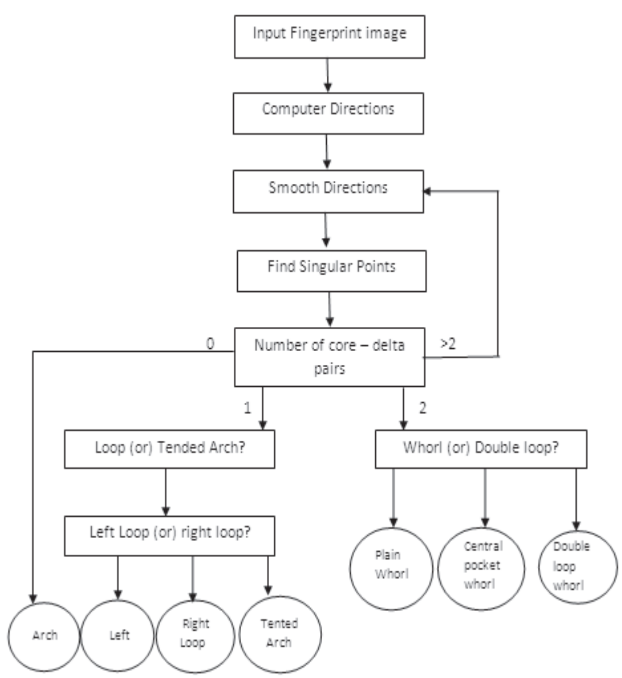

Fig. 4. Flow Chart

Algorithm

Any point that can be consistently detects in a fingerprint image can be used as a registration point (center point because we prefer this point to be positioned at the center of the image). In a fingerprint image, the core point presents such a consistent point. Therefore in our algorithm, we define core point as the center point (Xc, Yc) we use the core point detection algorithm described in (Hong and Jain, 2008) which is presented below.

1. Estimate the orientation field O using the least square orientation estimation algorithm (Jain *et al.*, 2007). Orientation field O is defined as an N x N image, where O (i,j) represents the local ridge orientation at pixel (i,j). An image is divided into a set of non overlapping windows and a single local orientation is defined for each window.

2. Smooth the orientation field in a local neighborhood. Let the smoothed orientation field be represented as O′.

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

4. For each pixel (i,j) in O′ compute the poincareindex and assign the corresponding pixel in A a value of one if the Poincare index is (1/2). The Poincare index at pixel (i,j) enclosed by a digital curve, which consists of a sequence of pixels that are on (or) within a distance of one pixel apart from the corresponding curve, is computed as follows :

$$\text{Poincare}\,(i,j) = \frac{1}{2\pi}\,(k) \sum_{k=0}^{N_{\psi}-1} \Delta(k)$$

$$\Delta(k) \begin{Bmatrix} \delta\,(k) \\ \pi + \delta\,(k), \\ \pi - \delta\,(k), \\ \text{if } |\delta\,(k)| < \dfrac{\pi}{2} \\ \text{if } |\delta\,(k)| \leq \dfrac{\pi}{2} \end{Bmatrix}$$

Otherwise

$$\delta(k) = O'(\psi x(k), \psi y(k))\,^{a}O(\psi x(k), \psi y(k)$$

$$K' = (K + 1) \bmod N\psi$$

where $\psi x(.)$ and $\psi y(.)$ are the x and y coordinates of the closed digital curve with Ny pixels.

5. Find the connected components in A. If the area of a connected component is larger than seven, a core is detected at the centroid of the connected component. If it is larger than 20, two cores are detected at the centroid of the connected component.

6. If more than two cores are detected, go back to step2.

7. If two cores are detected, the center is assigned the coordinates of the core point with the lower y value (the upper core). If only one core is detected, the center is assigned the coordinates of the core point.

8. If no core point is detected, compute the covariance matrix of the vector field in a local neighborhood (q x q) of each point in the orientation field shown in fig.(5).

Fig. 5. Segmentation of 48 Sectors

DATA SETS

The NIST - 4 database consists of 4000 fingerprint

images (image size is 512 x 480) from 2000 fingers. Each finger has two impressions (first and second). Each image is labeled with one or more of the seven classes (PA, TA, RL, LL, PW, CW, DW). To simplify the training procedure, we make use of only the first label of a fingerprint to train our system. For testing, however, we make use of all the labels for a fingerprint and consider the output of our classifier to be correct if the output matches any one of the labels.

The images in the NIST - 4 databases are numbered f0001 through f2000 and s0001 through s2000 each number represents a fingerprint from a different finger. We form our training set with the first 2000 fingerprints

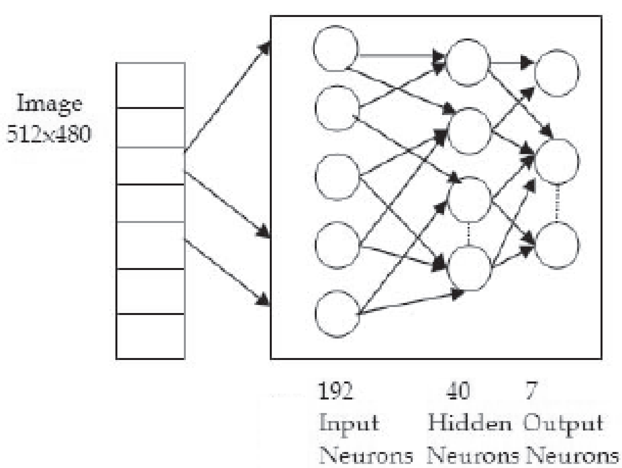

Fig.6. Feed forward neural network

from 1000 fingers (f0001 to f1000 and s0001 to s1000). Classification accuracies can be significantly increased by using datasets whose records follow the natural distribution of fingerprint classes because the more common types of fingerprints (loop and whorl) are easier to recognize. The test set of 2000 fingerprints amounts to a reject rate of 1.8 percent.

Training

Our proposed method was neural network which had been trained to distinguish between the corresponding pair of classes and the input pattern had then been sent to the selected neural network for further classification

Performance Issues

We have trained a multilayer feed forward neural network using a quick propagation algorithm (Fahiman, 2008). The neural networks has 192 input neurons, 2040 hidden neurons in one hidden layer, and seven output neurons corresponding to the seven classes. We obtain an accuracy of 94.08 percent for the seven class classification task. For the five class classification task, an accuracy of 97.4 percent is achieved. The confusion matrix for the neural network classification is shown in Table1.

Table 1. Classification Results

True Class		Assigned Class						
	PA	TA	RL	LL	PW	CW	D W	%
PA	400	390	6	2	1	0	1	097.5
TA	400	9	387	3	1	0	0	096.7
RL	400	0	2	386	10	0	2	096.5
LL	400	0	1	6	392	1	0	098.0
PW	312	0	0	2	3	298	6	395.5
CW	252	0	0	1	0	1	21	284.0
DW	63	0	1	0	1	2	2	5790.4
658.6/7 = 94.08%								

The classification results are summarized in Table 1 by applying the proposed least square orientation and multilayer feed forward model. The average accuracy rate of the over all seven classes is 94.08% with 1.8% rejection rates which is comparable to other methods presented in the literature. However, the multilayer feed forward and least square orientation model classifies the fingerprint into seven classes while other methods only make the classification of five classes as in the Henry classification system. The result is shown in fig.7.

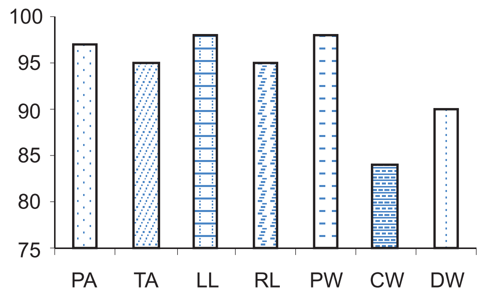

Figure 7. Results of the classes

CONCLUSION

We have developed the least square orientation estimation algorithm which gives better accuracy than previously reported in the literature on the NIST - 4 databases. We have tested our algorithm on the NIST - 4 databases and a very good performance has been achieved (94.08 percent for the seven class classification problem). Although the classification results of the central pocket whorl and double loop whorl are still unsatisfied, our proposed method can successfully perform the classification task.

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