Short Paper

Fingerprint Classification in DCT Domain using RBF Neural Networks*

CONG JIN AND PING JIN+
Department of Computer Science
Central China Normal University
Wuhan, 430079 P.R. China
+*Price Quota Center*
CNPC Huabei Petroleum
Hebei, 062552 P.R. China

Fingerprint classification is a fundamental method for the identification of people. Fingerprint classification is based on the immutability and the individuality of fingerprint. Because of the large collections of fingerprints and recent advances in computer technology, there has been increasing interest in automatic classification of fingerprint. In this paper, an efficient method for fingerprint classification based on the discrete cosine transform (DCT), fuzzy *c*-means clustering (FCM), the Fisher's linear discriminant (FLD) and radial basis function (RBF) neural networks is proposed. Experimental results show that the proposed method achieves excellent performance with high correctly recognition rate, very low reject rate, and very less running time.

Keywords: fingerprint classification, RBF neural networks, FLD, FCM, DCT

1. INTRODUCTION

The market for classification and authentication using biometric technologies is experiencing strong growth. Currently, the dominant technology is based on fingerprint classification, known to be one of the most reliable personal classification methods because of their invariance and uniqueness. Some of these applications include forensic classification, access control (such as networks, directories and file access) and ATM card verification. Since manual fingerprint classification is tedious, time consuming and expensive, there is a great demand for automatic fingerprint classification methods [1].

Fingerprint classification performance highly depends on the preprocessing steps where various ways to extract and represent distinguishable features among classes can be applied. Many classification approaches to detect singular points [2] are known in the literatures. Examples of these algorithms are based on sliding neural networks [3], statistical approaches [4], and nonlinear discriminant analysis [5]. However, these approaches provide somewhat unsatisfactory results for extraction of singular points. They often ignore a true pair of core-delta that is close to each other. Moreover, although neural net-

Received November 28, 2007; revised April 1, 2008 & December 31, 2008; accepted January 8, 2009.
Communicated by Pau-Choo Chung.
* This work was supported by the Natural Science Foundation of Hubei (China) and Grant No. 2008CDB349.

works have already been applied in fingerprint classification [6, 7], it is very difficult that to decide suitable number of the neurons in the hidden layer.

In this paper, we propose an approach for fingerprint classification based on DCT, FLD, FCM, and RBF neural networks. Fingerprint classification doesn't depend on singular points of the fingerprint image, and adopt whole feature of the fingerprint. For greatly reducing dimensionality of the original fingerprint image, fingerprint features are first extracted by the DCT. In order to obtain the most invariant and discriminating feature of fingerprint, the FLD is further applied to the feature vectors. Before implementing the FLD, FCM is applied for guaranteeing optimal projection direction for the FLD as well as determines the number of hidden neurons of the RBF neural networks for fingerprint classification. After the FLD is applied, there are no overlaps between classes and the architecture and parameters of RBF neural networks are determined according to the distribution properties of the training patterns. These technologies are used for improving fingerprint classification performance and lowing running time.

This paper is organized as follows. In section 2, we describe the DCT-based feature extraction method, and FCM algorithm, and the FLD in the DCT domain. The architecture of RBF neural networks and parameter estimation approach are introduced in section 3. Experimental results are exhibited, in section 4. Finally, a conclusion is stated in section 5.

2. FEATURE EXTRACTION

We simply apply the DCT on the entire fingerprint image for greatly reduces dimensionality of the original fingerprint image. So, all frequency components of a fingerprint image by applying the DCT on the entire fingerprint image can be obtained. In addition, some low-frequency components are only related to the illumination variations which can be discarded.

In the proposed method, the image is divided into 8×8-pixel blocks that are each transformed into 64 coefficients for reconstruction from the DCT basis functions. The two dimensional DCT can be written in terms of pixel values $f(i, j)$ for $i, j = 0, 1, \ldots, N - 1$ and the frequency domain transform coefficients $F(u, v)$.

After obtaining an $N \times N$ DCT coefficient matrix of a fingerprint image with size $N \times N$, we scan the DCT coefficient matrix in a zig-zag manner starting from the upper-left corner and subsequently convert it to a one-dimensional $(1 - D)$ vector X.

2.1 Clustering

FCM is a clustering technique that is separated from hard *k*-means that employs hard partitioning, and it is widely used in RBF neural networks. In this paper, the classes are split in terms of their Euclidean distances. It is unreasonable to split the classes according to the degree of overlap because there are still great overlaps between classes after performing the DCT. Moreover, the following FLD will reduce the within-class scatter and, thus, make the sparsely distributed training samples in each subclass tighter.

The FCM employs fuzzy partitioning such that a feature vector can belong to all groups with different membership grades between 0 and 1. Detailed algorithm of fuzzy *c*-means proposed by Bezdek [8] in 1973.

After obtaining fuzzy partition matrix U, by iteratively updating the cluster centers and the membership grades for each feature vector, FCM iteratively moves the cluster centers to the "right" location within a feature vector set. However, FCM does not ensure that it converges to an optimal solution. Because of cluster centers (centroids) are initialize using U that randomly initialized. For robustness, in this paper, we preferred FCM several times each starting with different initial centroids. After the clustering algorithm and the FLD are implemented, the sparsely distributed training samples cluster more tightly which simplifies parameter estimation of the RBF neural networks in the sequel.

2.2 Fisher's Linear Discriminant

The FLD is one of the most popular linear projection methods for feature extraction. The details about the FLD can be found in [9]. The FLD is used to find a linear projection of the original vectors from a high-dimensional space to an optimal low-dimensional subspace in which the ratio of the between-class scatter and the within-class scatter is maximized. In this paper, in order to obtain the most salient and invariant feature of fingerprint, the FLD is applied in the DCT domain.

The discriminating feature vectors P projected from the DCT domain to the optimal subspace can be calculated as follows

$$P = E_{optimal}^{T} \cdot X. \tag{1}$$

Where X are the DCT coefficient vectors, and $E_{optimal}$ is the FLD optimal projection matrix.

3. CLASSIFICATION USING RBF NEURAL NETWORKS

3.1 Structure Determination

RBF neural network has many advantages such as simple structure [10], rapid training process and good extend ability *etc*. So it can be applied to many fields, especially, in the aspects of pattern classification and function approach. In the proposed method, the traditional three-layer RBF neural networks are employed for classification.

We employ the most frequently used Gaussin function as the radial basis function since it best approximates the distribution of data in each subset. In fingerprint classification applications, the RBF neural networks are regarded as a mapping from the feature hyperspace to the classes. Therefore, the number of inputs of RBF neural networks is determined by the dimension of input vectors. In this paper, the DCT vectors after implementing the FLD are fed to the input layer of the RBF neural networks. The number of outputs is equal to the class number.

The hidden neurons are very crucial to the RBF neural networks, which represent the subset of the input data. After the clustering algorithm is implemented, the FLD projects the training samples into the subspace in which the training samples are clustered more tightly. In the proposed method, the number of subclasses (*i.e.*, the number of hidden neurons of the RBF neural networks) is determined by the previous clustering process.

3.2 Parameter Estimation of RBF Neural Networks

Two important parameters are associated with each RBF unit, the center C_i and the width σ_i.

3.2.1 Center estimation

Each center should well represent each subclass because the classification is actually based on the distances between the input samples and the centers of each subclass. In our experiment, the mean value of the training samples in every subclass is chosen as the RBF center as follows

$$C_i = \frac{1}{n^i}\sum_{j=1}^{n^i} P_j^i. \tag{2}$$

Where P_j^i is the jth sample in the ith subclass and n^i is the number of training samples in the ith subclass.

3.2.2 Width estimation

The width of an RBF unit describes the properties of a subclass because the width of a Gaussian function represents the standard deviation of the function controlling the amount of overlap of Gaussian function. Our goal is to select the width that minimizes the overlaps between different classes so as to preserve local properties as well as maximize the generalization ability of the network. In our experiment, the following method for width estimation is applied

$$d(j, i) = \left\| C_j^l - C_i^k \right\| \tag{3}$$

$$d_{med}(i) = med\{d(j, i)\}, \quad i, j = 1, 2, ..., u, \; i \neq j \quad k, l = 1, 2, ..., s, \quad k \neq l \tag{4}$$

where C_i^k is the center of the ith cluster belonging to the kth class and $d_{med}(i)$ is the median distance from the ith cluster to the centers belonging to other classes. The width σ_i of the ith cluster is estimated as follows

$$\sigma_i = \frac{d_{med}(i)}{\sqrt{|\ln \eta|}} \tag{5}$$

where η is a factor that controls the overlap of this cluster with other clusters belonging to different classes. By selecting the proper factor η, a suitable overlaps between different classes can be guaranteed.

$$E = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{\mu}(t_i^j - y^j(P_i))^2 \tag{6}$$

where t_i^j is the target value for output unit j when the ith training sample P_i is fed to the network, $y^j(P_i) = \sum_{k=1}^{s} w(j, k)R_k$, R_k is the kth output of the RBF unit, s is the number of RBF units generated according to the clustering algorithm and n is the total number of training samples. The linear least square [11] can solve this problem.

Let α and β be the number of input and output neurons respectively, $R \in R^{s \times n}$ the RBF unit matrix, and $G = (G_1, G_2, \ldots, G_n)^T \in R^{s \times n}$ the target matrix consisting of "1's" and "0's" with exactly one per column that identifies the processing unit to which a given exemplar belongs. To find an optimal weight matrix $W^* \in R^{s \times n}$, the Eq. (6) is minimized as follows

$$W^* = (GR^+)^T \tag{7}$$

where R^+ is the pseudoinverse of R and is given by

$$R^+ = (R^T R)^{-1} R^T. \tag{8}$$

4. EXPERIMENTAL RESULTS

To evaluate the proposed method, a set of experiments is performed under the following conditions.

We report the results of our fingerprint classification system on the NIST24 database for the five-class fingerprint classification problem, which are right loop (*R*), left loop (*L*), whorl arch (*W*), tented arch (*T*), and arch (*A*). Fingerprints are varied in the five basic classes. For fingerprint classification, it is very important to obtain distinct and formal samples. If the samples are either un-distinct or un-formal, classified result will be affected awfully gravely. Due to this reason, the neighborhood 100 × 100 pixels of the central grain are chosen as samples of fingerprint. Ten different thumb fingerprints are shown in Fig. 1, which are selected from the neighborhood 100 × 100 pixels of the central grain. Fingerprints are picked again from the same people, as the testing patterns, shown in Fig. 2.

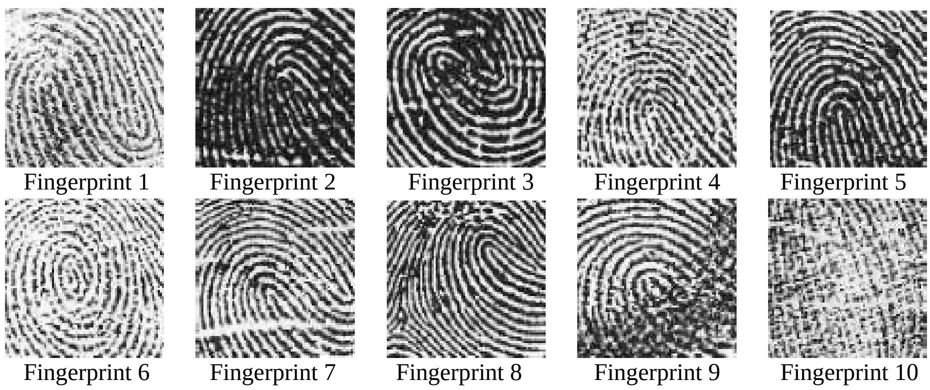

Fig. 1. Ten fingerprints as the prototypes in the database.

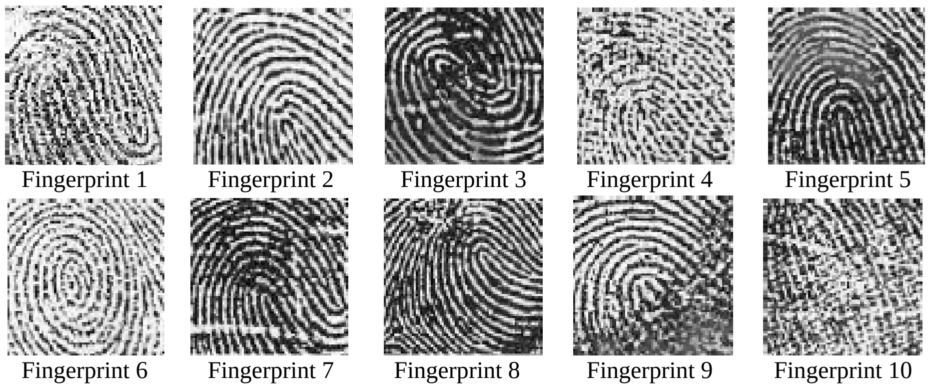

Fig. 2. Ten testing fingerprints as the testing patterns.

In experiments, the dimension of feature vectors fed into the RBF neural networks is 30, the overlapping factor η is 0.1, and 50 DCT coefficients are used.

For FCM algorithm, weighting exponent $m = 2.5$. Stop if error is less than 0.001 or previous iteration times 50 have been performed.

To illustrate the classification performance, fingerprint 4 (see Fig. 1) is used. The classification result is shown in Table 1.

Besides above experiment, 400 fingerprint images are randomly selected as the testing patterns. If not obtaining the classification results, called reject classification. Classification result is shown in Table 2. In order to validate the performance of our method, this method was tested with the NIST24 standard fingerprint database and the fingerprint database which consists of fingerprint images of size 300 × 300. We also compared our method with other three methods [12-14]. We selected 4,000 fingerprint images in the NIST24 used our method for classification fingerprint. Experiment result is shown in Table 3.

By observing Table 3, we discover that the performance of the proposed fingerprint classification approach is somewhat better than the other three methods, but average running time of the proposed classification approach is far less than the other three methods. Experiment result is shown in Table 4.

Table 1. Classification results of the 10 fingerprints in Fig. 2, with the fingerprints prototypes in Fig. 1.

Testing pattern	Classification result
Fingerprint 1	Fingerprint 4
Fingerprint 2	Fingerprint 2
Fingerprint 3	Fingerprint 3
Fingerprint 4	Fingerprint 4
Fingerprint 5	Fingerprint 5
Fingerprint 6	Fingerprint 6
Fingerprint 7	Fingerprint 8
Fingerprint 8	Fingerprint 8
Fingerprint 9	Fingerprint 5
Fingerprint 10	Fingerprint 10

Table 2. Classification success rates and reject rates.

True class	Classification results					Correctly rate	Reject rates
	W	*R*	*L*	*A*	*T*		
W	361	9	13	4	5	90.25%	2.00%
R	4	374	1	9	8	93.50%	1.00%
L	8	6	363	9	7	90.75%	1.75%
A	6	2	6	370	10	92.50%	1.50%
T	2	9	13	11	355	88.75%	2.50%

Table 3. A comparison of four fingerprint classification methods on the NIST24 database.

Methods	5-class accuracy rate %	5-class reject rate %
Ref. [12]	90.0	1.80
Ref. [13]	85.5	1.83
Ref. [14]	90.5	1.80
Proposed	91.4	1.81

Table 4. Average time for four fingerprint classification methods.

Methods	Time (Seconds)
Ref. [12]	3.872
Ref. [13]	5.161
Ref. [14]	2.756
Proposed	1.615

5. CONCLUSION

In this paper, we propose a fingerprint classification approach based on the techniques of DCT, FCM, FLD, and RBF neural networks. These technologies perform the classification in the lower dimensional space, no overlaps between classes, and the construction of the RBF neural networks designed full-automatically. They ensure that high-quality classification performance and fast perform of fingerprint classification. The experimental results show that novel approach not only has high classification accuracy, but also the time cost is very low.

REFERENCES

1. L. Wang and M. Dai, "Application of a new type of singular points in fingerprint classification," *Pattern Recognition Letters*, Vol. 28, 2007, pp. 1640-1650.
2. N. Yager and A. Amin, "Fingerprint classification: a review," *Pattern Analysis and Applications*, Vol. 7, 2004, pp. 77-93.
3. G. A. Drets and H. G. Lijenström, "Fingerprint sub-classification: A neural network approach," *Intelligent Biometric Techniques in Fingerprint and Face Recognition*, 1999, pp. 109-134.
4. V. S. Srinivasan and N. N. Murthy, "Detection of singular points in fingerprint images," *Pattern Recognition*, Vol. 25, 1992, pp. 139-153.

5. C. H. Park and H. Park, "Fingerprint classification using fast ourier transform and nonlinear discriminant analysis," *Pattern Recognition*, Vol. 38, 2005, pp. 495-503.
6. K. A. Nagaty, "Fingerprints classification using artificial neural networks: A combined structural and statistical approach," *Neural Networks*, Vol. 14, 2001, pp. 1293-1305.
7. H. V. Neto and D. L. Borges, "Fingerprint classification with neural networks," in *Proceedings of the 4th Brazilian Symposium on Neural Networks*, 1997, pp. 66-72.
8. J. C. Bezdek, "Fuzzy mathematics in pattern classification," Ph.D. Thesis, Applied Mathematics Center, Cornell University, Ithaca, 1973.
9. R. Brunelli and T. Poggio, "Face recognition: features versus templates," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 15, 1993, pp. 1024-1053.
10. S. Haykin, *Neural Networks: A Comprehensive Foundation*, Macmillan Publishers, New York, 1994.
11. C. M. Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press, New York, 1995.
12. A. K. Jain, S. Prabhakar, and L. Hong, "A multichannel approach to fingerprint classification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 21, 1999, pp. 348-359.
13. D. Maio, D. Maltoni, A. K. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition*, Springer, New York, 2003.
14. G. T. Candela, P. J. Grother, C. I. Watson, R. A. Wilkinson, and C. L. Wilson, "PCASYS – A pattern-level classification automation system for fingerprints," Technical Report, NISTIR 5647, 1995.

Cong Jin (金聪) received the M.S. degrees in Applied Mathematics from Harbin Institute of Technology, Harbin, Heilongjiang, China, in 1990. She received the Ph.D. in Institute for Pattern Recognition and Artificial Intelligence, Huazhong University of Science and Technology, Wuhan, China, in 2006. From 1993 to 2003, she was a Lecturer and then become as Professor at the Hubei University, Wuhan, Hubei, China. From 2003 to now, she is a Professor of the Department of Computer Science, Central China Normal University, Wuhan, Hubei, China. She has published more than 100 papers on image processing, and algorithm design. Her main research interests include digital image processing, pattern recognition, and intelligence information processing, *etc*.

Ping Jin (金平) is a certified account in Price Quota Center, CNPC Huabei Petroleum, Hebei, China. He has published more than 10 papers on data processing, statistics analysis, and digital image processing. His research interests include date processing, computer network, and statistics analysis.