A New Two-Stage Method of Fingerprint Classification[1)]

WANG Chong-Wen[1,2]　LI Jian-Wei[2]　CHEN Wei-Min[2]
[1](*Software School, Beijing Institute of Technology, Beijing* 100081)
[2](*Optoelectronical College, Chongqing University, Chongqing* 400044)
(E-mail: wcwzzsw@bit.edu.cn)

Abstract A new two-stage method of fingerprint classification is proposed that is based on hidden Markov model (HMM) and support vector machine (SVM). This technique uses FingerCode as the representation of the fingerprint. After classifiers are trained, five pseudo 2-D HMM classifiers are used to firstly select the most possible two classification results. Furthermore, the corresponding SVM classifier is selected to make the final decision. In the end, this new approach is tested by 2000 images selected from the NIST-4 database and 1000 images from the CQU-VERIDICOM database. A classification accuracy of 91 percent and a classification consistency of 93.7 percent are achieved. The results demonstrate the effectiveness of this approach.

Key words Fingerprint classification, SVM, HMM, FingerCode

1 Introduction

Fingerprint classification provides an important index mechanism in the fingerprint database. An accurate and consistent classification can greatly reduce the time on fingerprint matching for a large database. Traditional fingerprint classification has been used by forensic experts who classify the fingerprints into some certain categories according to the global ridge and the furrow structure, which form special patterns in the central region of the fingerprint. For example, in [1] fingerprints have been classified into four main categories: loop, whorl, arch and accidental. Each category has been then further divided, thus resulting in a total of more than ten thousand categories. Due to the difficulty of designing thousands of classifiers with high accuracy, most automatic systems reduce the number of fingerprint types to subsets of classification defined by the forensic experts. For example, some academic institutes and manufacturers have typically concentrated on the five-class or four-class classification. The five classes are whorl, left loop, right loop, arch, and tented arch. For the four-class system, arch and tented arch are combined into one class. Recently, some academic institutes define a "new" classification system according to the "clusters" formed in certain feature space. In this paper, the five-class system is used, namely, whorl (W), right loop (R), left loop (L), arch (A), and tented arch (T).

2 Review of fingerprint classification

Several approaches have been developed for automatic fingerprint classification. These approaches can be generally categorized into six main categories.

1) Knowledge-based. The knowledge-based fingerprint classification technique[2,3] uses the locations and the number of singular points (core and delta) to classify a fingerprint into one of the five above-mentioned classes. The knowledge-based approach tries to capture the knowledge of a human being by deriving rules for each category by hand-constructing the models and therefore, does not require training. Since this method heavily relies on singularities, some problems arise in the presence of noisy or partial fingerprints, where singularity detection can be misled.

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2) Syntactic. Patterns are described by means of terminal symbols and production rules. The syntactic approach[4] uses a formal grammar to represent and classify fingerprints.

3) Network approach. The network approach is one of the most popular fingerprint classification methods. The PCASYS (pattern-level classification automation system) approach proposed[5,6] by Candela is the most promising approach. After computing and registering the directional images, a vector of 1680 elements is reduced to 64 elements by using the KL transform. At this stage, a PNN (probabilistic neural network) is used for assigning each 64-element vector to one class of the classification scheme.

4) Structure-based. Using the structural approach[7], the fingerprint directional image is segmented in regions by minimizing the variance of the element directions within the regions. From the segmentation of the directional image, a relational graph compactly summarizing the macro-structure of the fingerprint is derived.

5) Others. In [8], a fingerprint classification algorithm based on the multi-space KL transforms applied to the orientation field is proposed. Senior proposed in [9] a hidden Markov model classifier whose input feathers are the measurements (ridge angle, separation, curvature, etc.) taken at the intersection points between some horizontal and vertical fiducial lines and the fingerprint ridge lines. In [10], the frequency spectrum of the fingerprints is used for classification. These approaches show some promise.

6) Multistage or hybrid approach. In [11], the algorithm uses a novel representation (FingerCode) and is based on a two-stage classifier to make a classification. This two-stage classifier uses a K-nearest neighbor classifier in its first stage and a set of neural network classifiers in its second stage to classify a feature vector into one of the five fingerprint classes. The hybrid approaches[12,13] combine two or more approaches for classification.

According to [11], HMM (hidden Markov model) classifier and SVM (support vector machine) classifier are used in this study to form a two-stage classifier, with Finger Code as representation of the fingerprint. It has been tested on two databases and the results show it is robust even for poor quality images. Being the new techniques, HMM and SVM are given in a brief introduction in the following.

3 HMM & SVM

3.1 Hidden Markov models

A hidden Markov model[14] is a doubly stochastic process, with an underlying stochastic process that is not observable (hence the word hidden), but can be observed through another stochastic process that produces the sequence of the observations. The hidden process consists of a set of states connected with each other by transitions with probabilities, while the observed process consists of a set of outputs or observations, each of which may be emitted by each state according to some probability density function. Being using time-series modeling, HMM has been applied in several areas during the last 15 years, including speech recognition, language modeling, handwriting recognition, signature verification, etc.

3.2 Support vector machine

Support vector machines (SVMs)[15] perform pattern recognition for two-class problems, which are based on VC dimension and structural risk minimization (SRM) principle of statistical learning theory (SLT). According to the finite samples, it tries to form the best tradeoff between the complexity of model (learning accuracy for special training samples) and capacity of the machine (capability of distinguishing arbitrary sample) and further obtains the optimal generalization ability.

SVM comes from the optimal separating hyperplane for linear separable instance. Its basic idea is demonstrated in Fig. 1. What is called the optimal separation is that the separating line not only classifies correctly (training error is zero), but also maximizes the margin between the two classes.

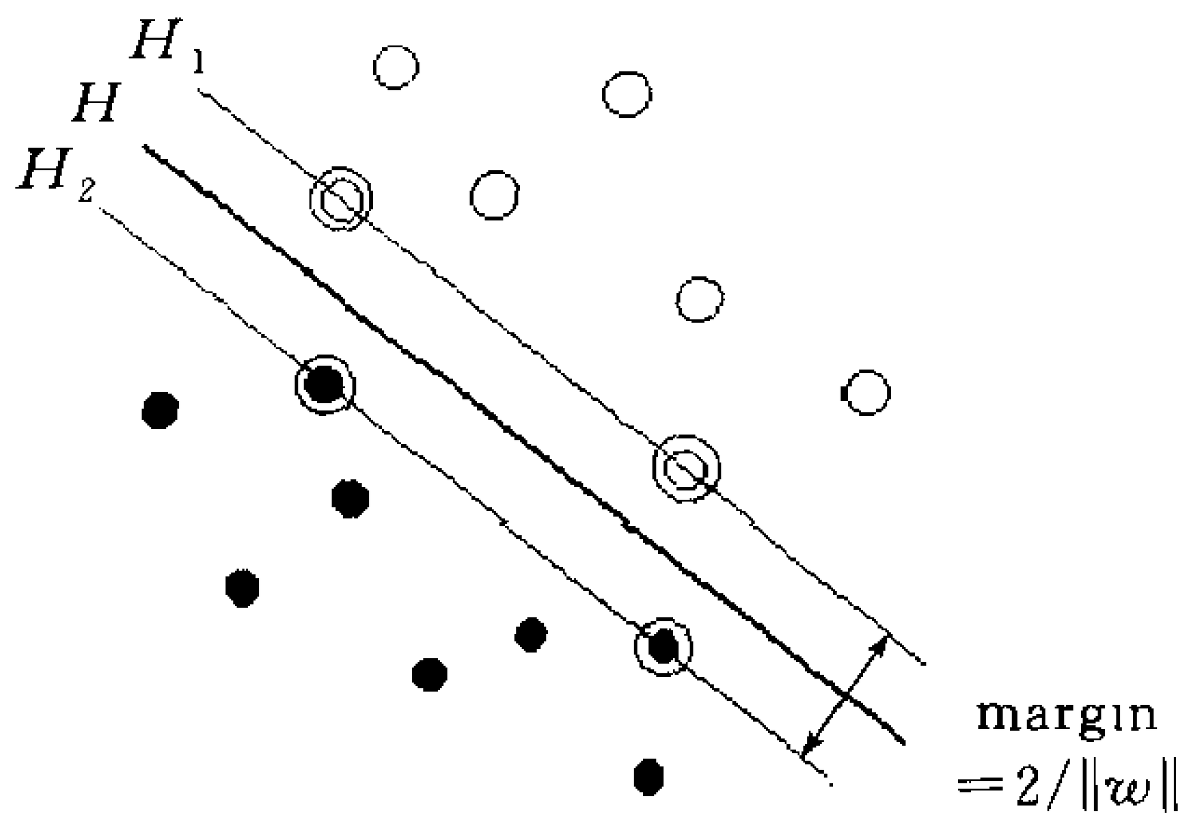


Fig. 1 Optimal separating hyperplane

Now, SVM has been applied in several areas, which include pattern recognition, regression estimating, probability density function, etc. Its accuracy even exceeds traditional methods.

4 Two-stage classifier

4.1 Classification Scheme

Fig. 2 shows how to classify the fingerprints using HMM and SVM classifiers. Firstly, FingerCode, as the representation of the fingerprint feather, has been produced after image pre-processing. Secondly, FingerCode is inputted into five HMM classifiers, namely, whorl classifier, right loop classifier, left loop classifier, arch classifier, and tented arch classifier. Every HMM classifier outputs the probability of belonging to the homologous category. After selecting the two most probable categories, the appropriate SVM classifier is used to make the final decision that which category this fingerprint belongs to.

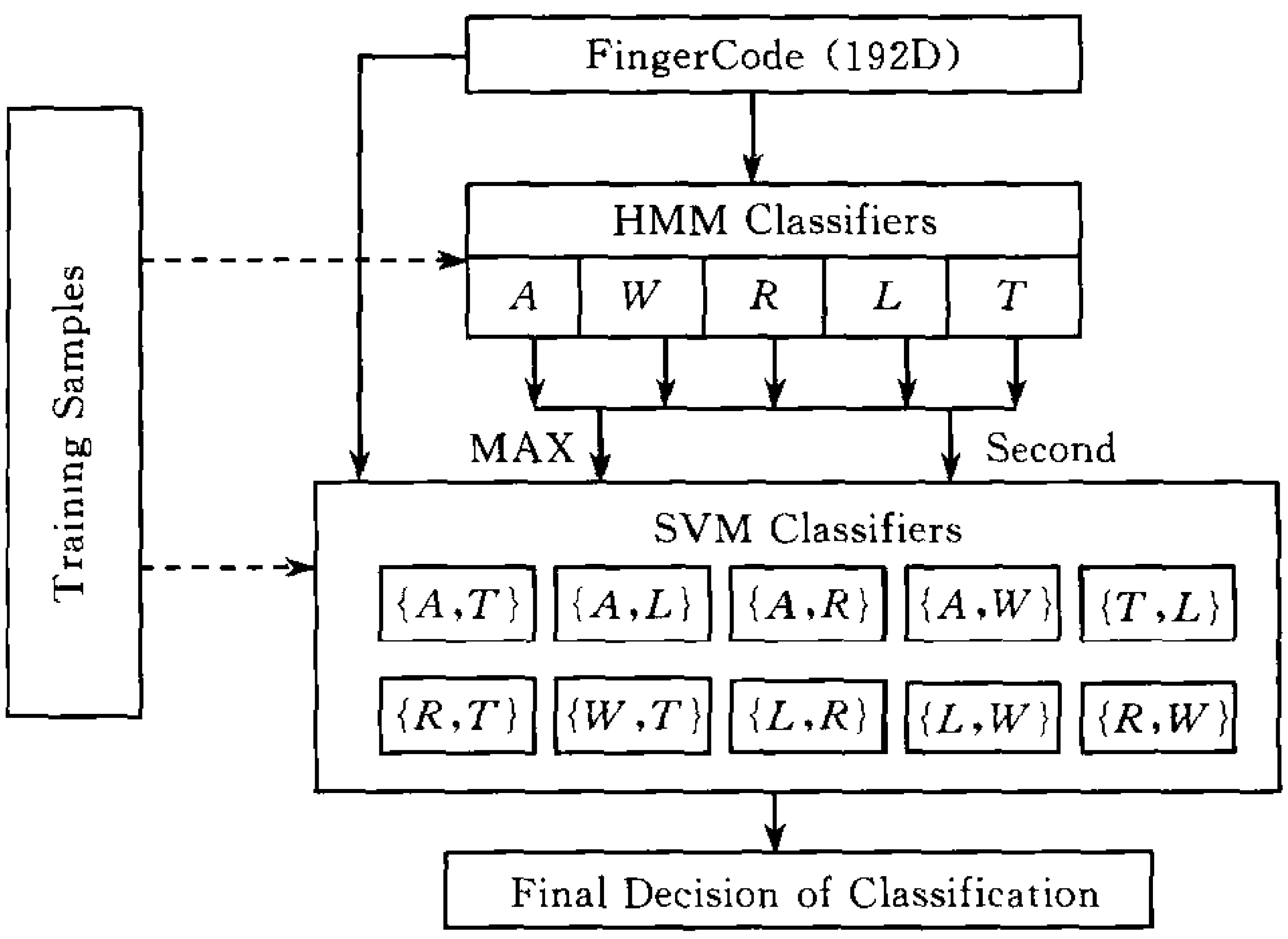


Fig. 2 Classification scheme based on HMM and SVM

4.2 Configuration of HMM classifier

Above all, it needs to be confirmed that how to classify fingerprints using HMM. An image of fingerprint is a 2-D signal, all information of which should be made full use of. However it is very difficult to constitute a completely connective 2-D HMM because this structural HMM is an NP-complete problem for learning and recognition. If using this structural HMM for fingerprint classification, it will take more computation and more time to train and classify. So it is worthless. In this study, a simplified 2-D HMM is provided.

Based on the process of FingerCode extraction, this paper puts forward a pseudo 2-D HMM. As we know, linking six concentric bands sequentially forms a FingerCode. If we name these bands as 1, 2, 3, 4, 5, 6 from inner to outer, the order of FingerCode should be invariable. This order will hint us to establish a Markov chain model from left to right as shown in Fig. 3. This special Markov chain starts from state 1 (or band 1) and ends in state 6 (or band 6), increasing with the number of state. Furthermore, for each band in a FingerCode, its codes are formed by eight sector codes linking. If we number each sector counter-clockwise from the horizontal positive direction, the order of the codes of each sector also should be invariable. So this order will help us to establish a Markov chain model from left to right as shown in Fig. 3, and the number of the states is just 8. If we regard the states of each line $O_y = \{o_{1y}, \cdots, o_{X_y}\}$ as a 1-D HMM and ulteriorly regard this 1-D HMM as a state of another HMM $O = \{O_1, \cdots, O_Y\}$, a pseudo 2-D HMM which consists of a group of 1-D HMMs is formed. Namely, a pseudo 2-D HMM contains a main HMM in which each state is a slave HMM. As illustrated in Fig. 4, the direction of super-state is vertical, and the direction of slave-states is horizontal. For FingerCode, the number of super-states is equal to the ones of bands, and the number of slave-states is the ones of sectors of each band. So we can define a pseudo 2-D HMM as following.

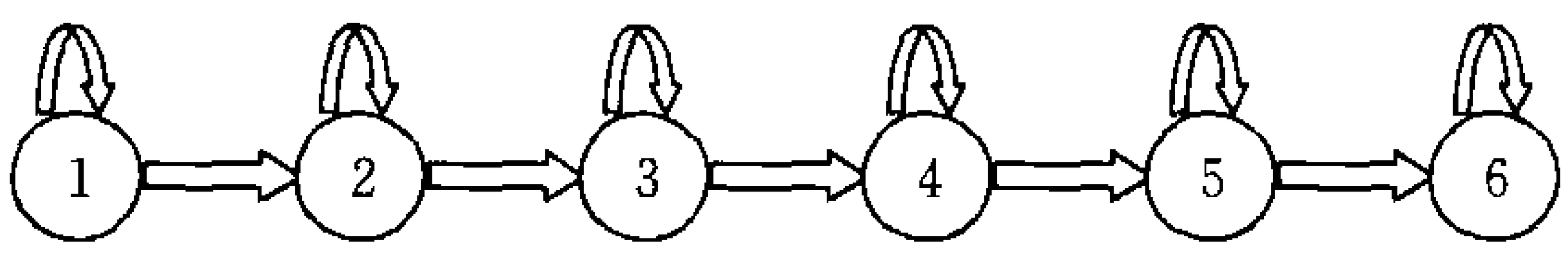


Fig. 3 1D HMM structure

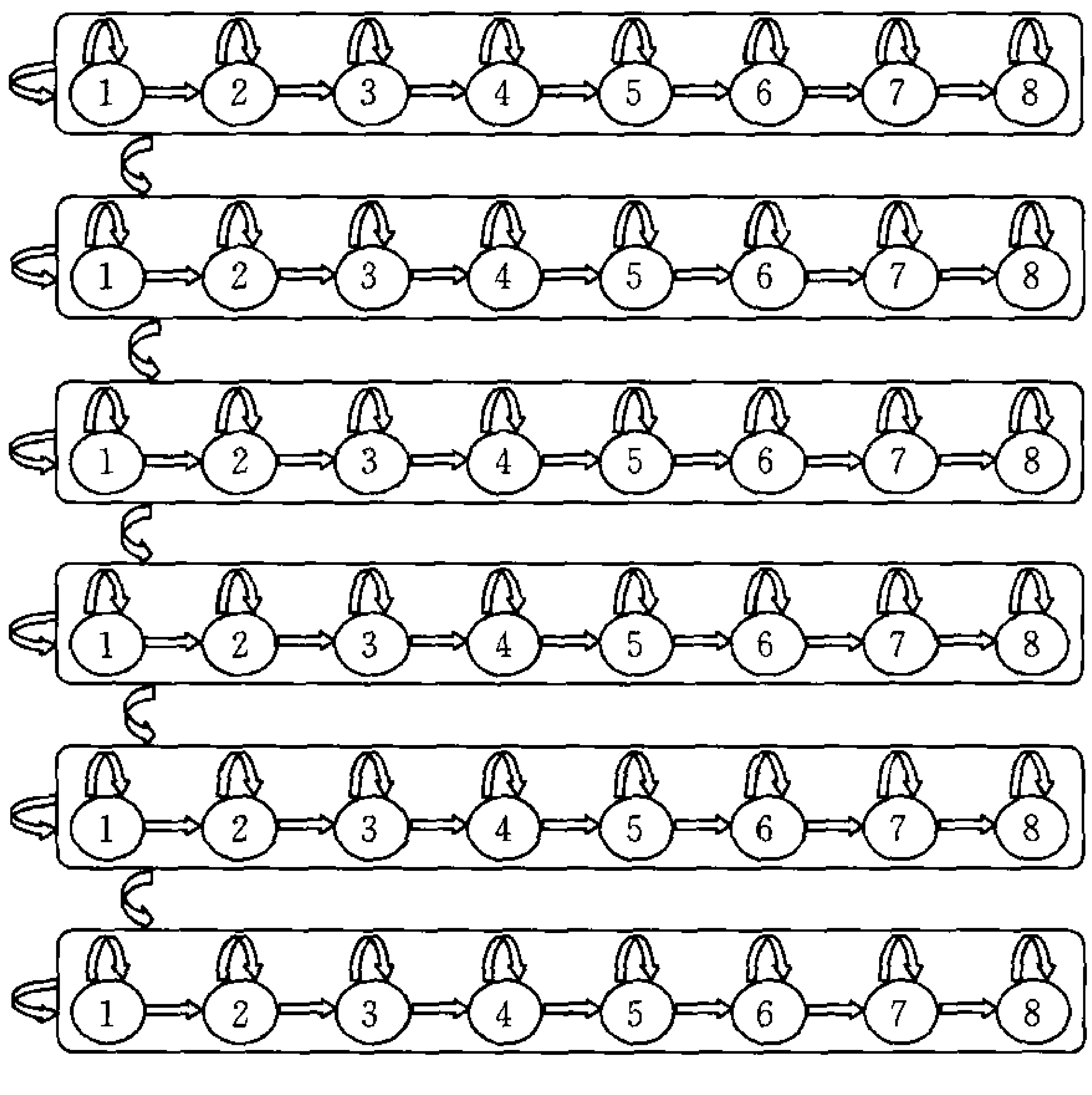


Fig. 4 P2D HMM structure

1) N: the number of super-state in vertical direction, it is 6 in Fig. 4;

2) A: the transition probabilities of super-state, $A = \{a_{kj} : 1 \leqslant k, j \leqslant N\}$;

3) Π: the initial state distribution of super-state, $\Pi = \{\pi_j : 1 \leqslant j \leqslant N\}$;

Λ: slave HMMs in horizontal direction, $\Lambda = \{\lambda^j : 1 \leqslant j \leqslant N\}$; it is a series of 1-D HMMs corresponding to super-state, each λ^j is a 1-D HMM.

So a pseudo 2-D HMM is denoted as $\eta = (N, A, \Pi, \Lambda)$. From this definition, we can find that there is no difference in nature from the 1-D HMM. All algorithms used for the 1-D HMM which include state estimation, revaluation expression, etc. can be slightly modified to fit the pseudo 2-D HMM. In this study, we have used Viterbi algorithm for recognition and Baum-Welch algorithm for learning.

4.3 Configuration of SVM classifier

The SVM classifier is a typical one for two-class problems. If applying this classifier to the multi-class problems, there will be three strategies listed in the following.

1) Distinguish w_i from the others

It is also called $\omega_i/\overline{\omega_i}$, namely, an M-class problem is divided M two-class ones. This approach needs M two-class classifiers.

2) Distinguish each other

It is also called ω_i/ω_j, namely, a two-class classifier can only separate into two classes. To separate all M classes, $C_M^2 = M(M-1)/2$ two-class classifiers are needed.

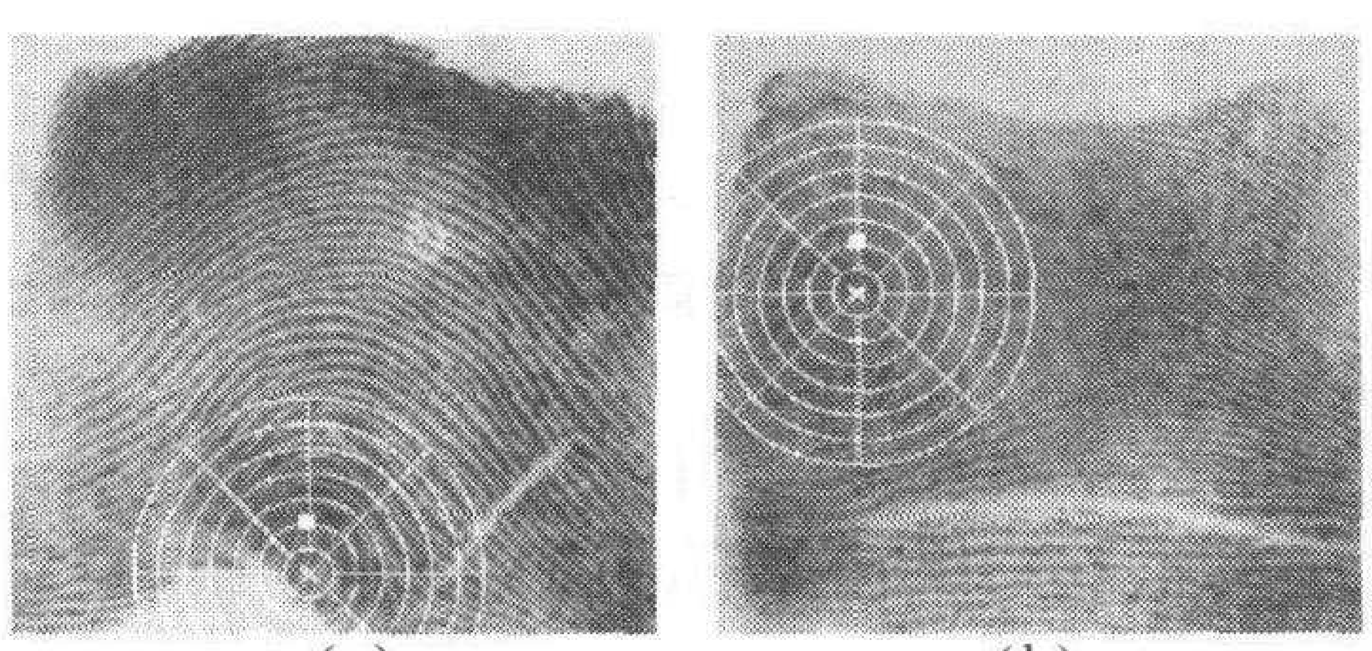
3) Multi-stage classification using binary tree

Firstly, M classes are divided into two sets, which contain some classes. Secondly, inputting pattern is determined to belong to which set. In succession, each set is divided into two subsets using binary tree and two-class classifiers are used gradually, the final classification decision is made in the end.

SVM classifiers in this study are used after classification by HMMs classifiers. Every HMM classifier outputs the probability of belonging to homologous category. After selecting the two most probable categories, the appropriate SVM classifier is used to make final decision that which category this fingerprint belongs to. So the strategy 2) is the most satisfying. We need to construct $C_5^2 = 10$ SVM classifiers to distinguish any two classes for the five-class fingerprint classification problem.

5 Experimental Results

In this study, the classification accuracy and consistency of this two-stage approach were tested. Because fingerprint classification usually uses global feathers of the fingerprint, the image of the fingerprint used to test should be relatively integrated. We validated the results of our fingerprint classification algorithm on the NIST-4 database and CQU-VERIDICOM database. The NIST-4 database consists of 4000 fingerprint images (image size is 512×480) coming from 2000 fingers. Each finger has two impressions. Each image is labeled with one or more of the five classes (W, R, L, A, and T) by experts. About 17% of the fingerprint images in the NIST-4 database are labeled with two labels, which shows that there is disagreement among the human experts about a large number of fingerprints. Simultaneously, there are some images whose reference point is detected near the edge of the image and, therefore, a valid tessellation could not be established for these images (Fig. 5) by using the approach in [11]. So we excluded the images that had more labels or whose valid tessellation could not be established when we made use of NIST-4 to test. From the residual 3300 images, we took out 1000 fingerprints to form our learning set to train the HMM & SVM classifiers, and the test set contained the other 1000 fingerprints. No matter it was the training set or the test set, the proportion of fingerprints belonging to each class was the same (20%). In database CQU-VERIDICOM, the fingerprints were



(a) (b)

Fig. 5 Examples of images where a valid tessellation could not be established obtained by capacitive sensor from 50 users and each user was asked to provide 10 different impressions of each finger of 6 different fingers — the little finger and the index finger were not used. A set of 3000 fingerprint images (image size is 300×300) were collected. We made use of CQU-VERIDICOM database to test the classification consistency. Because there are many images for each finger in CQU-VERIDICOM database, we can compute the classification consistency by looking over the results of many images for the same finger. From the CQU-VERIDICOM database, we took out 1000 relatively integrated images that came from 200 fingers (5 impressions for each finger) to train or classify.

To improve the performance of the classifiers, we should optimize the parameters of the classifier. For the pseudo 2-D HMM of five classes (W, R, L, A, and T), we used dual Baum-Welch algorithm for learning, and Forward-Backward algorithm and Viterbi algorithm for classification. After adjusting through training, we set the initial parameters of the pseudo 2-D HMM as: 6 and 4 for the numbers of super-state and slave-state, respectively. For SVM classifiers, we used two kernel function classifiers. One is polynomial SVM, the other is radial basis function (RBF) SVM. These two SVM classifiers are trained by using $\mathrm{SVM}^{\mathrm{light}}$ algorithm. Through training, polynomial SVM is good when module is equal to 3, but RBF SVM performs better while its parameter δ is 1. So we use RBF SVM and its parameter δ is 1. In addition, we find that the number of support vectors is $1/5 \sim 1/2$ of the training samples, and for different classifiers, there are a majority of support vectors to overlap. Table 1 shows the classification accuracy on NIST-4database.

Table 1 Experiments Results for the two-stage classification

True Class	Assigned Class				
	W	R	L	A	T
W	182	10	5	2	1
R	1	185	1	3	10
L	3	0	188	4	5
A	2	0	3	178	17
T	0	4	6	14	176

From experiments, the classification accuracy on NIST-4 database was 91% for the five-class problem. Although performance of our classifier is better than that in reference[11], there is still certain gap to the state of the art approach. We analyzed those false classification and found that the following reasons made classification improper: 1) It fails on some very bad quality fingerprint images where no ridge information is presented in the central part of the fingerprint. 2) It also fails to correctly classify twin loop images, which are labeled as whorl in the NIST-4 database. For these images, the reference point location algorithm used in [11] picks up the upper core and considers that as the center. The image looks like a loop in the region of interest which leads to a misclassification of W as L or R. 3) misclassification because of the subtle difference between arch and tented arch. This misclassification, in particular, the latter two reasons show that the approach to locate the reference point used in the reference[11] is suspectable. A more rational method should be investigated in the future.

In the fingerprint classification task, another metric of performance evaluation is the classifier consistency. The purpose of the fingerprint classification task is to index the fingerprint database, supposing a fingerprint is "wrongly" classified during the indexing. However, if another impression of the same finger is again misclassified as the same category, the indexing scheme would still be effective. We made use of CQU-VERIDICOM database to test classification consistency of this two-stage classifier. We used 400 fingerprint images to train our classifiers, and the other 600 images were used to test. Experiments results showed that the classification consistency of this approach achieved 93.7% for the five-class classification. Of course, if it is used in practical application, its classification consistency will go down because of capturing area of fingerprint sensors being too small.

6 Conclusion

In this paper, a new two-stage method of fingerprint classification is proposed that is based on hidden Markov model (HMM) and support vector machine (SVM). Firstly, FingerCode[11] as representation of fingerprint feather has been produced after image pre-processing. After the classifiers being trained, five pseudo 2-D HMM classifiers are used to originally select the most possible two classification results. Furthermore, the corresponding SVM classifier is selected to make the final decision. Experimental results show that the performance of our approach has obtained or exceeds the present popular fingerprint classifiers, although it is not as good as the state of the art approach. Using HMM and SVM to establish a two-stage classifier is a new idea, we think that we can improve the performance by using more optimum parameters and effective features, and we will investigate more in future to improve the classification accuracy and the classification consistency.

References

1 Liu Shao-Cong. New Dactyloguaphy. Hefei: Anhui Publishing Company, 1984. 52~89 (in Chinese)

2 Karu K, Jain A K. Fingerprint classification. *Pattern Recognition*, 1996, **29**(3): 389~404

3 Hong L, Jain A K. Classification of fingerprint images. In: Proceedings of the 11th Scandinavian Conference on Image Analysis, Kangerlussuaq, Greenland. 1999. 781~795

4 Kameshwar Rao C V, Black K. Type classification of fingerprints: A syntactic approach. *IEEE Transactions on Pattern Analyze and Machine Intelligence*, 1980, **2**(3): 223~231

5 Wilson C L, Candela G T, Watson C I. Neural network fingerprint classification. *Journal of Artificial Neural Networks*, 1993, **1**(2): 203~228

6 Candela G T, Grother P J, Watson C I, Wilkinson R A, Wilson C L. PCASYS: A pattern-level classification automation system for fingerprints. NIST Tech. Report NISTIR 5647, 1995. 1~5

7 Maio D, Maltoni D. A structural approach to fingerprint classification. In: Proceedings of the 13th ICPR, Vienna, 1996. 75~91

8 Cappelli R, Maio D, Maltoni D. Fingerprint classification based on Multispace KL. In: Proceedings of Workshop on Automatic Identification Advances Technologies, Nanjing, 1999. 117~120

9 Senior A. A hidden Markov model fingerprint classifier. In: Proceedings of the 31st Asilomar Conference on Signals, Systems and Computers, Washington, 1997. 306~310

10 Fitz A P, Green R J. Fingerprint classification using hexagonal fast Fourier Transform. *Pattern Recognition*, 1996, **29**(10): 1587~1597

11 Jain A K, Prabhakar S, Hong L. A multichannel approach to fingerprint classification. *IEEE Transactions on Pattern Analyze and Machine Intelligence*, 1999, **21**(4): 348~359

12 Cappelli R, Maio D, Maltoni D. Combining fingerprint classifiers. In: 1st International Workshop on Multiple Classifier Systems, Cagliari, 2000. 351~361

13 Marcialis G L, Roli F, Frasconi P. Fingerprint classification by combination of flat and structural approaches. In: AVBPA, 2001. 241~246

14 Rabiner L. A tutorial on hidden Markov models and selected application in speech recognition. *Proceedings of IEEE on Signal Processing*, 1989, **77**(3): 256~286

15 Vapnik V N. The Nature of Statistical Learning Theory. NY: Apringer-Verlag, 1995. 20~240

WANG Chong-Wen Received his master and Ph. D. degrees from Chongqing University in 1999 and 2002, respectively. Now he is working at Beijing Institute of Technology. His research interests include image processing, pattern recognition, and software engineering.

LI Jian-Wei Professor, working at Chongqing University. His research interests include image processing, pattern recognition, and GIS.

CHEN Wei-Min Received his master degree from Chongqing University in 2001. Now he is a doctor candidate at Chongqing University. His research interests include image processing and pattern recognition.

一种新型的两级指纹分类方法

王崇文[1,2]　　李见为[2]　　陈为民[2]

[1]（北京理工大学软件学院　北京　100081）

[2]（重庆大学光电工程学院模式识别研究室　重庆　400044）

（E-mail：wcwzzsw@bit.edu.cn）

摘　要　提出了一种利用隐马尔可夫模型（HMM）和支持向量机（SVM）的两级指纹分类新方法．该方法采用指纹编码（FingerCode）作为指纹的特征表述，在对分类器进行训练之后，首先用 5 个伪二维 HMM 对待分类指纹进行类别初选，确定最可能的两种指纹分类结果，再用相应的 SVM 分类器做最终判决．最后使用 NIST-4 数据库中的 2000 幅指纹和 CQU-VERIDICOM 数据库的 1000 幅指纹对该方法进行了实验，其分类的准确性为 91%，连续性为 93.7%，这证明了该方法的有效性．

关键词　指纹分类，支持向量机，隐马尔可夫模型，指纹编码

中图分类号　TP391.4

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