Effective Fingerprint Classification by Localized Models of Support Vector Machines

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Abstract. Fingerprint classification is useful as a preliminary step of the matching process and is performed in order to reduce searching time. Various classifiers like support vector machines (SVMs) have been used to fingerprint classification. Since the SVM which achieves high accuracy in pattern classification is a binary classifier, we propose a classifier-fusion method, multiple decision templates (MuDTs). The proposed method extracts several clusters of different characteristics from each class of fingerprints and constructs localized classification models in order to overcome restrictions to ambiguous fingerprints. Experimental results show the feasibility and validity of the proposed method.

1 Introduction

Fingerprint classification is a technique that classifies fingerprints into the predefined categories according to the characteristics of the image. It is useful for an automated fingerprint identification system (AFIS) as a preliminary step of the matching process and is performed in order to reduce searching time. Fig. 1 shows the examples of fingerprint classes.

Various classifiers, such as neural networks, k-nearest neighbors, and SVMs, have been widely used in fingerprint classification [1]. Since the SVM which shows good performance in pattern classification was originally designed for binary classification, it requires a combination method in order to classify multiclass fingerprints [2].

Fig. 1. Five fingerprint classes in the NIST database 4. (a) Whorl, (b) Right loop, (c) Left loop, (d) Arch, (e) Tented arch.

Many classifier-fusion methods have been investigated for the purpose of extending binary classification to multiclass classification or for improving classification accuracy [4]. Especially, the decision templates (single-DTs) have produced good performance in recent applications [5]. Since this method abstracts the outputs of the classifiers to a template, there is a limitation of applying it to complex problems with ambiguous samples such as fingerprints [6]. For the effective combination of SVMs in order to classify fingerprints, we propose multiple decision templates (MuDTs) that localized fusion models with clustering algorithm. The MuDTs decompose one class into several clusters to produce decision templates of each cluster. The proposed method is validated on the NIST database 4 using FingerCode features.

2 Related Works

2.1 The FingerCode

The FingerCode, as proposed by Jain in 1999, was extracted from NIST database 4 using a filter-based method. The algorithm set a registration point in a given fingerprint image and tessellated it into 48 sectors. Then, it transformed the image using the Gabor filter of four directions (0° , 45° , 90° , and 135°). Ridges parallel to each filter direction were accentuated, and ridges not parallel to the directions were blurred (Fig. 2). Standard deviations were computed on 48 sectors for each of the four transferred images in order to generate the 192-dimensional feature vector called FingerCode. Jain achieved 90% accuracy at a 1.8% rejection rate with two stage classification of K-NN/neural networks using these features [3].

Fig. 2. Flow diagram of the FingerCode feature vector [3]

2.2 Support Vector Machines

The SVM is a technique for binary classification in the field of pattern recognition. This technique maps an input sample to a high-dimensional feature space and finds the optimal hyperplane that minimizes the recognition error for the training data using the non-linear transformation function.

Let n be the number of training samples. For the i th sample x_i with class label $c_i \in \{1, -1\}$, the SVM calculates

$$f(x) = \sum_{i=1}^n \alpha_i c_i K(x, x_i) + b, \quad K(x, x_i) = \Phi(x) \cdot \Phi(x_i). \quad (1)$$

Coefficient α_i in Eq. (1) is non-zero when x_i is a support vector that composes the hyperplane. Under all other conditions, it is zero. The kernel function $K(x, x_i)$ is easily computed by defining an inner product of the non-linear mapping function.

To classify fingerprints using SVMs, decomposition strategies such as one-vs-all, pairwise, and complete-code are needed [7].

2.3 The Decision Templates

The decision templates (single-DTs) generate templates of each class by averaging the decision profiles (DPs) for the training samples. For the M -class problem with L classifiers, $DP(x_i)$ of the i th sample is

$$DP(x_i) = \begin{bmatrix} d_{1,1}(x_i) & \cdots & d_{1,M}(x_i) \\ \vdots & d_{y,z}(x_i) & \vdots \\ d_{L,1}(x_i) & \cdots & d_{L,M}(x_i) \end{bmatrix}, \quad (2)$$

where $d_{y,z}(x_i)$ is the degree of support given by the y th classifier for the sample x_i of the class z . When DPs are generated from the training data, Eq. (3) estimates the decision template DT_c of the class c .

$$DT_c = \begin{bmatrix} dt_c(1,1) & \cdots & dt_c(1,M) \\ \vdots & dt_c(y,z) & \vdots \\ dt_c(L,1) & \cdots & dt_c(L,M) \end{bmatrix}, \quad dt_c(y,z) = \frac{\sum_{i=1}^n ind_c(x_i) d_{y,z}(x_i)}{\sum_{i=1}^n ind_c(x_i)} \quad (3)$$

$Ind_c(x_i)$ has a value of 1 if x_i 's class is c , otherwise it has a value of zero.

In the test stage, it computes the distance between the DP of a new sample and the decision templates of each class. The class label is decided as the class of the most similar decision templates [5].

3 Multiple Decision Templates

In order to construct the MuDTs, we composed decision profiles with 5 one-vs-all SVMs (whorl, right loop, left loop, arch, and tented arch versus all). Decision profiles of each class $DP_{whorl}(x), \dots, DP_{tented\ arch}(x)$ were clustered with a SOM algorithm (Eq. (4)). Each $DP(x)$ mapped a sample to the cluster (k, l) using Euclidean distance, with $w_{i,j}$ as the weight of the (i, j) th cluster [8].

$$\|DP(x) - w_{k,l}\| = \min_{i,j=1,\dots,N} \{\|DP(x) - w_{i,j}\|\} \quad (4)$$

Fig. 3. A template of one-vs-all SVMs with its graphical representation

A decision template $DT_c^{k,l}$, which is the template of a cluster (k,l) of class c , was computed by Eq. (5). $Ind_c^{k,l}(x_i)$ refers to an indicator function of 1 if x_i belongs to the (k,l) th cluster of class c . If this is not the case, it refers to zero.

$$DT_c^{k,l} = \begin{bmatrix} dt_c^{k,l}(1,1) & \cdots & dt_c^{k,l}(1,M) \\ \vdots & dt_c^{k,l}(y,z) & \vdots \\ dt_c^{k,l}(L,1) & \cdots & dt_c^{k,l}(L,M) \end{bmatrix}, \quad dt_c^{k,l}(y,z) = \frac{\sum_{i=1}^n ind_c^{k,l}(x_i) d_{y,z}(x_i)}{\sum_{i=1}^n ind_c^{k,l}(x_i)} \quad (5)$$

Since the SVM is a binary classifier, we represented the output of a classifier to one column with positive and negative signs (Fig. 3). Sixteen decision templates of a class were estimated by clustering 4×4 SOM as shown in Fig. 4.

Fig. 4. Construction and classification of 4×4 MuDTs (case of whorl class)

The classification process of the MuDTs is similar to that used with single-DTs'. The distance between the decision profile of a new sample and each decision template of clusters is calculated (Fig. 4), and then the sample is classified into the class that contains the most similar clusters. In this paper, the Euclidean distance (Eq. (6)) is used to measure the similarity for its simplicity and good performance [5].

$$dst_c^{i,j}(x) = \sqrt{\sum_{y=1}^L \sum_{z=1}^M (dt_c^{i,j}(y,z) - d_{y,z}(x))^2}, \quad \min_{c=1,\dots,M} (\min_{i,j=1,\dots,n} dst_c^{i,j}(x)) \quad (6)$$

4 Experimental Results

4.1 Experimental Environments

We have verified the proposed method on the NIST database 4. The first set of impressions of the fingerprints (F0001~F2000) were used as the training set while the second set of impressions of the fingerprints (S0001~S2000) were used as the test set. Jain's FingerCode features were used after normalization (+1 ~ -1). The FingerCode rejected a few fingerprint images in both the training set (1.4%) and the test set (1.8%) [3]. The LIBSVM package (available at <http://www.csie.ntu.edu.tw/~cjlin/libsvm>) was used for the SVM classifiers. The Gaussian kernel with $\sigma^2 = 0.0625$ was selected based on the experiment.

4.2 MuDTs Versus DTs

The MuDTs of the one-vs-all (OVA) SVMs yielded an accuracy of 90.4% for the 5-class classification task. For the 4-class classification task, 94.9% was achieved. The confusion matrices of the one-vs-all SVMs combined with the single-DTs and MuDTs with the Euclidean distance are shown in Table 1 and Table 2. Because the MuDTs produce multiple classification models for one class, they classify ambiguous fingerprint images more accurately than single-DTs (Fig. 5).

Table 1. Confusion matrix for the single-DTs of OVA SVMs

	W	R	L	A	T
W	380	6	8	0	0
R	7	357	1	6	21
L	7	0	363	13	13
A	1	2	1	347	60
T	1	8	9	37	316

Table 2. Confusion matrix for the MuDTs of OVA SVMs

	W	R	L	A	T
W	380	6	7	0	1
R	9	369	1	5	17
L	8	0	366	14	10
A	1	4	1	356	50
T	1	10	6	38	304

4.3 Comparison with Other Methods

The winner-takes-all, ECCs, BKS, and single-DTs methods were compared with the MuDTs. The Euclidean distance was used for ECCs, single-DTs, and MuDTs. For the

Fig. 5. Classification of ambiguous fingerprints

BKS method, when ties or new output patterns occurred, the winner-takes-all method was alternatively used. As shown in Table 3, the MuDTs achieved the highest accuracy of 89.5%~90.4%. Given the simplicity of the SOM algorithm with the low-dimension vector, despite the additional step for clustering at the training phase, there is nearly no difference between the classification times of the MuDTs and single-DTs. It took about 60ms on a Pentium 4 (2.4 GHz) machine to train the SOM with 2,000 fingerprints which can be ignored, compared to the training time of the SVMs.

Table 3. The accuracies of various classifier fusion schemes (%)

Fusion methods	One-vs-all	Pairwise	Complete-code
Winner-takes-all	90.1	87.7	90.0
ECCs	90.1	88.6	90.0
BKS	88.8	89.4	89.3
Single-DTs	89.8	88.3	89.5
MuDTs	90.4	89.5	90.3

5 Conclusion

This paper has proposed an effective classifier fusion method (MuDTs) to classify ambiguous fingerprint images which show more than one characteristic in terms of fingerprint class. The outputs of one-vs-all SVMs for the training data were clustered by the SOM to decompose the class into several clusters to separate and examine diverse characteristics. The localized decision templates were estimated for each cluster, and then the MuDTs were constructed. Experiments were performed on the NIST database 4 using FingerCodes. We achieved 90.4% for 5-class classification with 1.8% rejection, and 94.9% for 4-class classification. Experimental results show the effectiveness of the multiple templates method with higher accuracy than other methods. In future work, we will investigate effective classifier decomposition methods with appropriate cluster maps to maximize the effectiveness of the MuDTs.

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