Gender Recognition Using a Min-Max Modular Support Vector Machine

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Abstract. Considering the fast respond and high generalization accuracy of the min-max modular support vector machine (M^3-SVM), we apply M^3-SVM to solving the gender recognition problem and propose a novel task decomposition method in this paper. Firstly, we extract features from the face images by using a facial point detection and Gabor wavelet transform method. Then we divide the training data set into several subsets with the 'part-versus-part' task decomposition method. The most important advantage of the proposed task decomposition method over existing random method is that the explicit prior knowledge about ages contained in the face images is used in task decomposition. We perform simulations on a real-world gender data set and compare the performance of the traditional SVMs and that of M^3-SVM with the proposed task decomposition method. The experimental results indicate that M^3-SVM with our new method have better performance than traditional SVMs and M^3-SVM with random task decomposition method.

1 Introduction

Gender recognition is one of the most challenging problems for face recognition researchers. Commonly, gray-scale or color pixel vectors, subspace transformed features, wrinkle and complexion, and local facial feature with Gabor wavelet transformation are chosen as features for recognition[4][3][5]. Then classifiers such as k-nearest-neighbor, neural networks and SVMs are often used to gender recognition. Among these classifiers, SVMs seem to be superior to all other classifiers[4]. The advantage of SVMs is to find the optimal linear hyper-plane such that the expected classification error for unseen samples is minimized. However, similar to almost traditional classifiers, SVMs treat all data in one class as a whole in training phase, and will perform coarsely than the method of further dividing the training data set of each class into a number of subsets.

In our previous work, we have proposed a 'part-versus-part' task decomposition method[1] and developed a new modular SVMs, called M^3-SVM, for solving

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large-scale pattern classification problems[2,6]. In this paper, we apply M^3-SVM to solving the gender recognition problem and use a prior knowledge about age information in task decomposition. We perform simulations on a real-world gender data set to compare the generalization accuracy achieved by traditional SVMs and M^3-SVM with our proposed task decomposition method.

2 Feature Extraction for Gender Recognition

The well-performed face feature extraction method that has been developed by Omron Corporation will be used to generate feature vectors for our M^3-SVM classifiers. The main idea of the face feature extraction is to detect the face in an image firstly and then locate the facial points including eyes, nose and mouth. Gabor wavelet transform is then used to extract the facial point characteristics which are combined to form a feature vector[5]. The extracted feature vectors are processed as the input to our recognition system. For more details about this feature extraction method, one can see the paper[5]. Here we will only simply describe the scales of the gallery sets and probe sets for our M^3-SVM gender recognition system in Section 5.

3 Min-Max Modular Support Vector Machine

M^3-SVM is firstly introduced in[2], and our studies show that it have three main advantages over traditional SVMs: (1) Massively parallel training of SVMs can be easily implemented in parallel computing systems; (2) Large-scale pattern classification problems can be solved efficiently; and (3) The generalization accuracy can be obviously improved. Hereto we have succeeded in applying M^3-SVM to several pattern recognition problems such as: large scale text categorization [6] and multi-view face recognition [7].

4 A Task Decomposition Strategy for Gender Recognition

M^3-SVM needs to divide the training data set into several subsets in its first step. So how to divide the training data set effectively is an important issue. Although dividing the data set randomly is a simple and straightforward approach, the geometric relation among the original training data may be damaged[6]. The data belonging to a reasonable cluster may be randomly separated into other clusters. From the viewpoint of SVM, random task decomposition might lead the boundaries of subproblems complex. In this paper, we propose a new task decomposition strategy, called prior knowledge based strategy (PK), for dealing with gender recognition problem.

By using existing random (RAN) task decomposition method [6], we divide training data set into several subsets randomly. Although this is the most simple and straightforward approach and might lead a lower generalization accuracy in most cases than other M^3-SVM with reasonable decomposition strategies. It will still generate better performance than traditional SVMs. Because, despite of not deliberately choosing, M^3-SVM is still 'finer' than SVMs.

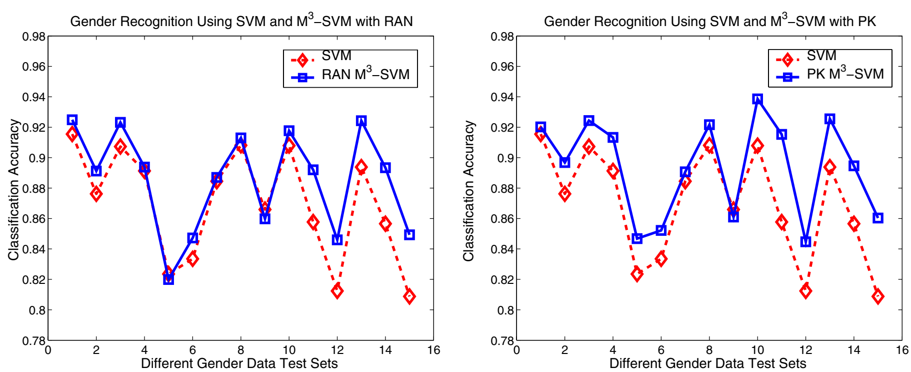
In prior knowledge based strategy, we use the age information for gender data decomposition. Considering that we have had the personal age information in each data set for male and female, respectively, we naturally sort the samples using this age information from young to old, and then divide them into different subsets. As an example, we divide the male and female samples into 7 subsets, respectively, which range from 0∼9, 10∼19, 20∼29, 30∼39, 40∼49, 50∼59, and over 60 years old, respectively.

5 Experiments

In this section, we present experimental results on the gender data sets to compare the traditional SVMs with M^3-SVM using our proposed task decomposition method. All SVMs are linear SVM from LibSVM[8] and the parameter C is set to 1.

The gallery sets used for training include 786 male samples and 1,269 female samples, which have the same vector dimension of 1,584, including different age groups respectively. The probe sets used for test include 15 kinds of gender data. These data represent frontal image, various degree view face, face with glasses and different expressions and so on. The number of test samples belonging to these 15 kinds of gender data are 1278, 1066, 820, 819, 816, 805, 805, 805, 813, 814, 815, 805, 819, 816 and 816, respectively.

From Fig. 1 we can see that all M^3-SVM with different task decomposition strategies can improve the classification accuracy by a high degree. For example, M^3-SVM with PK task decomposition strategy achieved 91.53% and 86.03% correct rates on two probe sets, which are better than tranditional SVMs (85.77%



(a) (b)

Fig. 1. The comparative results of SVMs with M^3-SVM based on two different decomposition strategies. (a) Results of SVM and M^3-SVM with random strategy; (b) Results of SVM and M^3-SVM with the proposed strategy.

and 80.88%). The reason we consider is that the original complex borders between two classes for SVMs are further simplified by decomposing the complex data sets into relatively simpler subsets, and then the solutions to the subproblems are combined by M^3-SVM without losing generalization, meanwhile its modular structure improves the response speed of the whole system. And as the analysis performed in Section 4, a more reasonable decomposition strategy will perform better than the random one.

6 Conclusions

We have proposed a new task decomposition method using age information for M^3-SVM to deal with gender recognition problem. We have compared our method with the traditional SVMs. From experimental results, we can draw the following conclusions: a) The proposed task decomposition method can help to improve the generalization of M^3-SVM. b) Prior knowledge based task decomposition method could be more efficient than random decomposition method in the aspect of generalization performance. How to choose an optimal task decomposition strategy for M^3-SVM is still an open problem.

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