A Two-Stage Classifier Using SVM and RANSAC for Face Recognition

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Abstract- **A novel face recognition scheme based on two-stage classifier, which includes methods of support vector machine (SVM), and random sample consensus (RANSAC), is proposed in this paper. The whole decision process is undertaken by cascade stages. The first stage with OAO-SVM (one-against-one) method picks out two classes with the least variations to the testing images. From the selected two classes, the second stage with "RANSAC" method is used for a fine match with testing images. A fine class with greatest geometric similarity to testing images is thus produced at second stage. This two-stage face recognition system has been tested on Olivetti Research Laboratory (ORL) databases, and the experimental results give evidence that the proposed approach is superior to the previous approaches based on the single classifier and multi-parallel classifier in recognition accuracy.**

I. INTRODUCTION

Recently, face recognition has been widely studied due to its potential applications. In general, face recognition system can be grouped into two categories of classifier system, one is single-classifier system and the other is multi-classifier system. The single-classifier systems, including neural network (NN) [1], Eigenface [2], Fisher linear discriminant (FLD) [3], SVM [4], HMM [5], and AdaBoost [6], are developed well in theory and experiment. On the other hand, the multi-classifier systems such as local and global face information fusion [7], neural networks committee (NNC) [8] are proposed in parallel process of different features or classifiers.

The SVM were originally designed for binary classification and it is based on the structural risk minimization (SRM) principle. Although several methods to effectively extend the SVM for multi-class classification have been reported on technical literatures [9,10], it is still an on-going research issue. The category methods of SVM for multi-class classification are one-against-all (OAA), one-against-one (OAO), directed acyclic graph support vector machine (DAGSVM) [11], and binary tree SVM [4]. In DAGSVM and binary tree SVM, their training phases are the same as those of the OAO method by solving $N(N\text{-}1)/2$ binary SVMs, where N is the numbers of class. However, in the testing phase of DAGSVM, it uses a rooted binary directed acyclic graph which has $N(N\text{-}1)/2$ internal nodes and N leaves. Each node is a binary SVM of ith and jth classes. On the other hand, the testing phase of binary tree SVM constructs a bottom-up binary tree for classification. The advantage of using a DAGSVM and binary tree SVM is less testing time than that of OAO (maximum vote) method. If one employs the same feature vector for SVM, NN, and AdaBoost, he will find the performance of SVM is better than that of NN and AdaBoost because the SVM will result in the maximum separating margin to the hyperplane of the two classes. And if the feature vector includes noisy data, and the noisy data possesses at least one of the following properties: (a) overlapping class probability distributions, (b) outliers and (c) mislabeled patterns [12], the hyperplane of SVM will turn out to be hard margin and overfitting. Furthermore, the SVM allows noise or imperfect separation, provided that a non-negative slack variable is added to the objective function as a penalizing term.

In our system, the extracted feature for SVM is discrete cosine transform (DCT) coefficients that are common used for image pre-processing. To combine the image feature of frequency, and space information, we propose a novel face recognition approach, which combines SVM and random sample consensus (RANSAC) [13] methods with the two-stage classifier system. The whole decision process is developed through consecutive stages, i. e., "one-against-one (OAO) of SVM" and "RANSAC", respectively. The first stage "OAO-SVM" uses the DCT features extracted from the entire face image. "RANSAC" is applied in the second stage, in which the epipolar geometry method with space information of the testing image is matched with the training classes that output from first stage, and then the image with the greatest match numbers of corresponding feature points is selected. The face database used for performance evaluation is retrieved from Olivetti Research Laboratory (ORL) face databases [14]. For the database, we use two different evaluation methods, which are OAO-SVM, and our proposed two-stage classifier.

The remainder of this paper is organized as following: In section II, the OAO-SVM and our proposed two-stage classifier are presented in detail. Experiment results using our method and the comparison to other approaches are given in section III. Conclusions and directions for further research are summarized and discussed in section IV.

II. THE PROPOSED METHOD

For face recognition, based on a coarse-to-fine strategy, we design a two-stage recognition system which combines OAO-SVM and RANSAC methods to increase the recognition accuracy. The detail of this system is demonstrated as following.

A. One-against-one (OAO) of SVM for face Recognition

In the OAO strategy, several binary SVM are constructed, but each one is constructed by training data from only two different classes. Thus, this method is sometimes called a "pair-wise" approach. For a data set with N different classes, this method constructs $C_2^N = N(N\text{-}1)/2$ models of two-class

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TABLE I
RECOGNITION PERFORMANCE COMPARISON OF DIFFERENT APPROACHES (ORL)

Methods	Error Rate (%)		Feature vector dimension
	Best	Mean	
Eigenface [18]	2	4	140
2D-PCA [17]	4	5	112×3
Binary tree SVM [4]	N/A	3	48
DCT-RBFNN [1]	0	2.45	30
CF^2C [22]	3	4	30
Fuzzy Fisherface [21]	2.5	4.5	60
Our proposed approach	0	1.375	30

B. Comparison with Previous Reported Results on ORL

Several approaches have been conducted for face recognition using the ORL database. The methods of using single classifier systems for face recognition are Eigenface [17,18], DCT-RBFNN [1], binary tree SVM [4], 2D-HMM [5], LDA [19], and NFS [20]. The methods of using multi-classifiers for ORL face recognition are fuzzy fisherface [21], and CF^2C [22]. Here, we present a comparison under similar conditions between our proposed method and the other methods described on the ORL database. Approaches are evaluated on error rate, and feature vector dimension. Comparative results of different approaches are shown in Table I. It is hard to compare the speed of different methods performed on different computing platforms, so we ignore the training and recognition time in each different approach. It is evident as indicated in the table that the proposed approach achieves best recognition rate in comparison with the other six approaches. In other words, our approach outperforms the other six approaches in respect of recognition rate.

IV. CONCLUSIONS

This paper presents a two-stage classification method for face recognition based on the techniques of SVM and RANSAC. The facial features are first extracted by the DCT at the first stage, OAO-SVM. Although the second stage (RANSAC) led to more accuracy in comparison with the first stage, its computation cost more in the geometric fundamental matrix F estimation. In order to decrease the computation time, we need to reduce the classes and images to only two training images to match with testing image in the second stage. The key of this method is to consolidate OAO-SVM for the output classes of the top two maximum votes so that the decision of the correct class could be made later by RANSAC in the second stage. The feasibility of the proposed approach has been successfully tested on ORL face databases, which are acquired under varying pose, and expression. Comparative experiments on the face database also show that the proposed approach is superior to single classifier and multi-parallel classifier.

Our ongoing research is to study the classification rate under a condition that the output of OAO is more than two classes, and to compare the relationship between recognition rate and computation time, trying to find an optimal classification system with superior recognition rate at the cost of reasonable computation time.

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