Face Recognition Using RBF Kernel Based Support Vector Machine

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Abstract—**Face recognition has been an active research area over the last 30 years. It has been studied by scientists from different areas of psychophysical sciences and those from different areas of computer sciences. Support Vector Machines (SVMs) have been recently proposed as a new technique for pattern recognition. In this paper, the SVMs with a binary tree recognition strategy are used to tackle the face recognition problem. We illustrate the potential of SVMs on the ORL face database, Georgiatech face database, and personally prepared database, containing quite a high degree of variability in expression, pose, and facial details. We compare the performance of RBF kernel based SVM with SVMs based on other kernel functions for face recognition. Comparison is also performed on different available techniques of developing multiclass SVMs.**

Index Terms—**Face recognition, support vector machine, radial basis function.**

I. INTRODUCTION

The face is our primary focus of attention in social interaction, conveying identity and emotion. We can recognize thousands of faces learned throughout our lifetime and identify familiar faces at a glance even after years of separation. Face recognition has also become an important issue in many applications such as security systems, biometrics, access control, law enforcement, surveillance systems, credit card verification and criminal identification. The importance of face recognition rises from the fact that a face recognition system does not require the cooperation of the individual while the other identification systems need such cooperation. This skill of humans is quite robust, but it is sometimes difficult to recognize faces for us, in case of change in facial expression, illumination, aging, rotation, size, disguisedness etc. These issues are equally important when we deal with accuracy of face recognition systems.

Although it is clear that people are good at face recognition, it is not at all obvious how faces are encoded or decoded by the human brain. Developing a computational model of face recognition is quite difficult, because faces are complex, multi-dimensional visual stimuli. Therefore, face recognition is a very high level computer vision task, in which many early vision techniques can be involved.

The problem of face recognition can be stated as follows: Given still images or video of a scene, identifying one or more persons in the scene by using a stored database of faces [1]. The problem seems to be mainly a classification problem: Training the face recognition system with images from the known individuals and classifying the newly coming test images into one of the classes is the main aspect of the face recognition systems. . In this work, it is assumed that all the images used to train or test the system are face images. But the major step of human face identification is to extract the relevant features from facial images. Research in the field primarily intends to generate sufficiently reasonable familiarities of human faces so that another human can correctly identify the face. The question naturally arises as to how well facial features can be quantized. If such a quantization if possible, then a computer should be capable of recognizing a face given a set of features using some best available classification scheme. Although there are several classification algorithms such as ANN [2], k-Nearest Neighbor, ICA [3], LDA [4], PCA [5] etc. exist for face verification and identification, but performance of SVM is better than other algorithms, if database is not quite large.

In Section 2 and subsections, proposed face recognition system is described. Then in Section 3, we present the face recognition experiments by RBF based SVMs and carry out comparisons with other SVM kernels. The conclusion is given in Section 4.

II. PROPOSED FACE RECOGNITION SYSTEM

The processed used in face recognition system can be explained using the following block diagram.
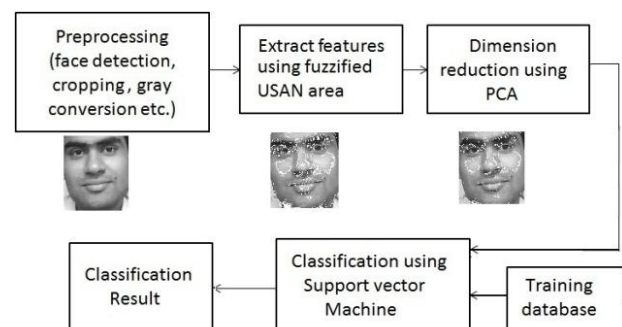

Fig. 1. Block diagram of face recognition system.

A. Database Preparation

Database is prepared using ORL face database, Georgiatech database and personally collected images. Initial conditions for selection and preparation of face databases can be summarized for the proposed system are as following:
- All images must be taken in similar and uniform illumination conditions.
- No physical obstruction.

- Camera at the same distance from face.
- We need to take only eyebrows to chin part of face.
- Images must be in gray format or changed to gray format.
- Images should be of equal size and small, for best results and fast processing.

B. Features Extraction

Salient features are extracted from biometric images to uniquely represent the acquired image in the form of a numeric template which can be enrolled in a system database for comparison, matching or classification purposes. Other advantages of feature extraction are dimensionality reduction, normalisation, security and faster recognition of individuals. Edge detection is one of the most important steps in image processing and forms the fundamental basis for extracting low level features such as edges, corners and intersection points in biometric image systems. Extraction of facial features like lips, eyes, eyebrows and hand geometry measurements are also made possible by applying edge detection algorithms on biometric images.

Many edge detection techniques are reported such as Sobel, Prewitt and Roberts [1]. These operators use local gradient methods to detect edges under a specified direction. One of the biggest problems in these edge detectors is that they do not perform properly under noisy conditions. Canny [2] tried to overcome this problem by convolving the image with the first order derivatives of Gaussian filter for smoothing in the local gradient direction followed by edge detection using thresholding. Marr and Hildreth [6] proposed a method that finds edges by exploiting information of the zero crossings of the image Laplacian. Non-linear filtering techniques for edge detection also saw much advancement through the SUSAN method [7]. More recent techniques pose the edge detection as a fuzzy reasoning problem. Fuzzy logic employs morphological edge extraction method. Ho et al. [8] have used both global and local image information for fuzzy categorization and classification based on edges. In proposed system, Ho's approach is combined with concepts derived from the SUSAN corner detector. In SUSAN (Smallest Univalue Segment Assimilating Nucleus) corner detector, each image point is associated with a local area of similar brightness. This area is known as USAN and it contains a lot of information about the structure of the image.

USAN area is fuzzified to obtain two dimensional features and edges. The fuzzy membership function indicates the degree of contrast in each neighbourhood pixel. In fuzzy image processing, pixel grey values are treated as an array of fuzzy singleton sets [8]. The fuzzification process transforms these grey level values into membership function value that indicates the degree of variation constituting an edge in a particular location. We used Gaussian Membership Function for this purpose.This is a very important step in terms of dimensionality reduction and space-time complexity. Because size of data to be processed is reduced significantly, and it results in decrease in processing time as well as storage cost. The result after applying fuzzy edge detection is shown in following figure.
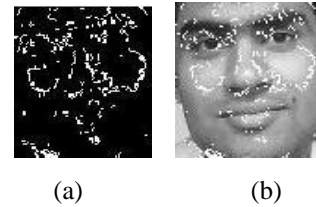

(a)   (b)

Fig. 2. (a) Detected edges and (b) their annotation on face.

Even it is also found by experiments that slight variation of pose (rotation of face by 10 to 20 degrees) gives slight variation in these connected pixels. In the next step we applied PCA (principle component analysis) on the initial feature vectors to reduce the dimensionality and thus processing time. Now we can apply classification algorithm to test the system performance and accuracy of recognizing the test face images.

C. Classification

Support Vector Machines (SVMs) have been recently proposed by Vapnik and his co-workers [9] as a very effective method for general purpose pattern recognition. Intuitively, given a set of points belonging to two classes, an SVM finds the hyperplane that separates the largest possible fraction of points of the same class on the same side, while maximizing the distance from either class to the hyperplane. According to Vapnik [9], this hyperplane is called Optimal Separating Hyperplane (OSH) which minimizes the risk of misclassifying not only the examples in the training set but also the unseen examples of the test set.

Support vector machines (SVMs) [10] are originally designed for binary classification problem. How to effectively extend it for multi-class classification problem is still an on-going research issue. Several methods have been proposed where typically we construct a multi-class classifier by combining several binary classifiers. Some methods also have been proposed that consider all classes at once. As it is computationally more expensive to solve multi-class problems, comparisons of these methods using large-scale problems have not been seriously conducted yet.

The support vector machine [11], given labelled training data

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{\ell}, \quad \mathbf{x}_i \in \mathbf{X} \subset \mathbb{R}^d, \quad y_i \in \mathbf{Y} = \{-1, +1\},$$

constructs a maximal margin linear classifier in a high dimensional feature space, $\Phi(\mathbf{x})$, defined by a positive definite kernel function, $k(\mathbf{x}, \mathbf{x}')$, specifying an inner product in the feature space,

$$\Phi(\mathbf{x}).\Phi(\mathbf{x}') = k(\mathbf{x}, \mathbf{x}').$$

A common kernel is the Gaussian radial basis function (RBF),

$$k(\mathbf{x}, \mathbf{x}') = e^{-\gamma ||\mathbf{x} - \mathbf{x}'||^2}$$

The discriminant function implemented by a support vector machine is given by

$$f(\mathbf{x}) = \left\{ \sum_{i=1}^{\ell} \alpha_i y_i k(\mathbf{x}_i, \mathbf{x}) \right\} + b.$$

To find the optimal coefficients α, of this expansion it is sufficient to maximize the functional,

$$W(\alpha) = \sum_{i=1}^{\ell} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{\ell} y_i y_j \alpha_i \alpha_j k(\mathbf{x}_i, \mathbf{x}_j),$$

Which can be considered here as a cost function for optimization.

Previous subsection describes the basic theory of SVM for two class classification. A multi-class pattern recognition system can be obtained by combining two class SVMs. Usually there are many available schemes for this purpose. One is the one-against-all strategy to classify between each class and all the remaining; The other is the one-against-one strategy to classify between each pair. We adopt the latter one for our face recognition system.
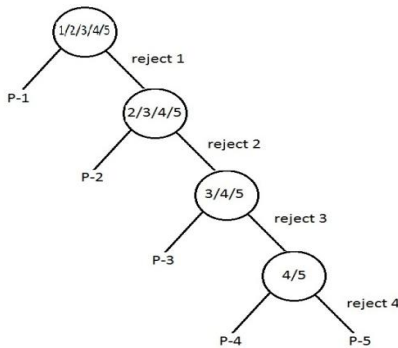

Fig. 3. One against all technique to build for multiclass SVM.

We propose to construct a bottom-up binary tree for classification. Suppose there are five classes in the data set, the decision tree is shown in figure 3, where the numbers 1-5 encode the classes. Note that the numbers encoding the classes are arbitrary without any means of ordering. By comparison between each pair, one class number is chosen representing the "winner" of the current two classes. The selected classes (from the lowest level of the binary tree) will come to the upper level for another round of tests. Finally, the unique class will appear on the top of the tree.

D. Experimental Results

In our experiments, from the ORL [12] and Georgiatech face database, we randomly selected 5 individuals for the training set, and their different images for testing. There were 10 images per individual, and thus a total of 50 images were used in the experiments for training. Each image contains some variation in pose, expressions, glasses/no glasses etc for each individual.
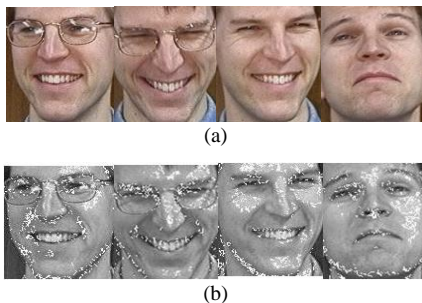

(a)

(b)

Fig. 4. (a) Face images from Georgiatech database (b) Extracted features.

Some example faces from Georgiatech database is shown in figure 4. The private database was prepared by taking images of 5 individuals, 15 images of each in different face pose. The face angle was varied 0-25 degrees in left as well as right. The images were preprocessed and the method is applied by taking 12 images for training and 3 images for testing.

TABLE II: COMPARISON OF RECOGNITION FOR DIFFERENT SVM KERNEL FUNCTIONS.

SVM kernel function	Linear	Quadratic	Polynomial	RBF
Recognition rate	88.6%	91.3%	95.3%	97.0%

We compared the performance of the system taking different databases altogether and found that RBF kernel based SVM gives the best result as shown in table II.

Fig. 4. Graphical user interface

In our research work, for convenience, we have performed experiments by associating the databases and programs with graphical user interface.

III. CONCLUSION

We have presented the face recognition experiments using linear support vector machines with one against all multiclass classification strategy and Radial Basis Function as kernel function for SVM. As shown in the comparison with other techniques, it appears that the RBF SVMs can be effectively trained for face recognition. The experimental results show that the RBF SVMs are a better learning algorithm than other kernel function approaches of SVM for face recognition.

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