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Research Article

Face Recognition Based on SVM and GABOR Filter

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Abstract

In this paper, Support Vector machines (SVM)-based face recognition system is proposed. Here we used Gabor filter coefficients as features describing face images. Considering the desirable characteristics of spatial frequency and orientation selectivity of the Gabor filter, we design filter for extracting facial features from the face image. The feature vector based on Gabor filters is used as the input to the SVM classifier. The system has been evaluated on Yale face database-B. To reduce the computational complexity and memory consumption, the images are resized to 27×18 jpg format. Homomorphic filtering is used as a preprocessing operation. After preprocessing, the image is convolved with Gabor filters by multiplying the image by Gabor filters in frequency domain to obtain the Gabor features. These features are given to the SVM classifier for training and testing purpose. The results show that this method is the fastest one, having approximately 100% recognition rate.

Keywords: *Support Vector Machines, Gabor Filter, etc.*

1. Introduction

Over the past decade, face recognition has emerged as an active research area in computer vision with numerous potential applications including biometrics, surveillance, human–computer interaction, video-mediated communication, and content-based access of images and video databases. As real-world applications for face recognition systems continue to increase, the need for an accurate, easily trainable recognition system becomes more pressing. Current systems (M.D. Marsico, *et al*, 2013), (R. Chellappa, *et al*, 1995) have advanced to be fairly accurate in recognition under constrained scenarios, but extrinsic imaging parameters like pose, illumination, and facial expression still cause much difficulty in accurate recognition.

There has been a lot of research on face recognition over the past few years. They have dealt with different aspects of face recognition. Many algorithms have been proposed to recognize faces beyond variations in viewpoint, pose, illumination and expression. This leads to increase the sophisticated techniques for face recognition and has further enhanced the literature on pattern classification. Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data point will be in. In this paper, we study face recognition as a pattern classification problem.

We will use the Support Vector Machine for classification. Support Vector machines (SVMs) have been proposed as a new kinds of feed forward learning network C. Cortes, *et al*, 1995) for bipartite pattern recognition. A support vector machine constructs a hyperplane or set of hyperplanes in infinite-dimensional space, that can be used for classification, regression, or other tasks. A good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class called functional margin, since in general the larger the margin the lower the generalization error of the classifier. Hence the goal of the SVM is to maximize the margin between the vectors of class 1 and class 2.

Intuitively, given a set of points belonging to two classes, SVM finds the hyperplane that separates the largest possible fraction of points of the same class on the same side, while maximizes the distance from either class to the hyperplane. According to (V.N. Vapnik, 1998) this hyperplane is called optimal separating hyperplane (OSH) which minimizes the risk of misclassifying not only the examples in the training set (i.e. training errors), but also the unseen examples of the test set (i.e. generalization errors). The SVM is essentially developed to solve a two-class pattern recognition problem.

The paper is organized as follows. Section 2 describes the background containing study of preprocessing steps, Gabor filters for feature extraction and support vector machines for classifying face images. In section 3 the results of the experiments are analyzed. The final section includes the conclusions drawn after investigations.

2. Background

2.1 Preprocessing

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In the Preprocessing steps, first we had created 2 databases of images- first is having all images with different pose and illuminations of single person and second is containing images of different people and not the one in first database. After creating the databases, all these images are normalized with respect to their illumination changes using Homomorphic filtering. The Homomorphic filter Uses Butterworth High Pass Filter for performing filtering. The illumination is again normalized using adaptive histogram equalization. To reduce the computational complexity and memory consumption, the images are resized to 27×18 jpg format. Finally, for extracting the facial features, Gabor filtering is done.

2.2 Gabor Filters

In image processing, a **Gabor filter** is named after Dennis Gabor. It is a linear filter used for edge detection. Gabor filters have similar frequency and orientation representations to those of the human visual system, and it is seen that they are particularly appropriate for texture representation and discrimination. In the spatial domain, the 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image.

Since face recognition is not a difficult task for human beings, the selection of biologically motivated Gabor filters is a well suited to this problem. Modeling the responses of simple cells in the primary visual cortex, gabor filters are simply plane waves restricted by a Gaussian envelope function (B. Gupta, *et al*, 2010).

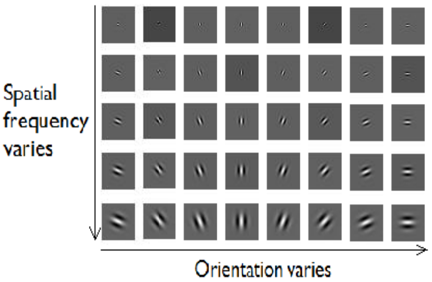

Fig. 1 Gabor filters corresponding to 5 spatial frequencies and 8 Orientation (Gabor filters in Time domain)

An image can be represented by the Gabor wavelet transform allowing the description of both the spatial frequency structure and spatial relations. Convolving the input image with complex Gabor filters with 5 spatial frequency (v = 0,…,4) and 8 orientation (μ = 0,…,7) captures the whole frequency spectrum, both amplitude and phase (Figure 5). In Figure 2, an input face image and the amplitude of the Gabor filter responses are shown below.

This feature set is given to the SVM classifier. In total 19440 features are extracted on a single image. The Classifier was trained on the previously described set of extracted facial components called feature vectors and on a set of randomly selected undesired face images. Also for testing purpose, the same Gabor features are extracted for the test image.

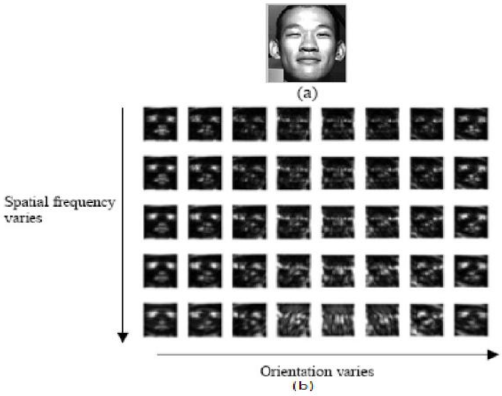

Fig.2 Example of a facial image response to above Gabor filters, 2(a) original face image (from Yale-B database), and (b) filter responses.

2.3 Support Vector Machines (SVM)

SVMs belong to the class of maximum margin classifiers. Support vector machines implement a very simple idea – they map pattern vectors to a high-dimensional feature space where a ‘best’ separating hyperplane (the maximal margin hyperplane) is constructed. They perform pattern recognition between two classes by finding a decision surface that has maximum distance to the closest points in the training set which are termed support vectors (G. Guodong, *et al*, 2000), (B. Heisele, *et al*, 2003). The goal of maximum margin classification is to separate the two classes by a hyperplane such that the distance to the support vectors is maximized. This hyperplane is called the optimal separating hyperplane (OSH). The decision function is fully specified by a subset of training samples called the support vectors. The kernel make non-separable problem separable and also it maps data into better representational space.

Thus, when we give the above drawn Gabor feature vectors to the linear SVM classifier, it classifies the training data into two sets and assigns 1 to the desired person’s images and 0 to all undesired people images.

3. Experimental Results

First we had created 2 databases of images- Database 1 is having all images with different pose and illuminations of single person. Fig. 3 is showing Database 1.

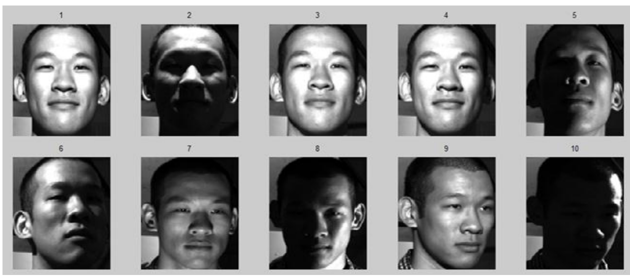

Fig.3 Database 1

In the second database images of different people are taken but making sure that it should not contain any image of the person in the first database. Following Fig.4 is showing the Database 2 of unknown people.

Fig.4 Database 2

For each face, the extracted values of the Gabor components were combined into a single feature vector. A face recognition system consisting of SVM classifiers was trained on these feature vectors in a one vs. all approach. In other words, an SVM was trained for a subject in the database 1 to separate her/him from all the other subjects in database 2. To determine the identity of a person at runtime, we compared the features of the input image with that of the features extracted during training of the SVM classifiers. If the identity associated with the facial features of classifier is matched with the features of input image, then the output was taken to be the identity of the face. If the features of input image are not matched with the support feature vectors, the face in the input image was rejected by the classifier.

Conclusions

SVMs provide a new approach to the problem of pattern recognition (together with regression estimation and linear operator inversion) with clear connections to the underlying statistical learning theory. It differs radically from comparable approaches such as neural networks. SVM training always finds a global minimum, and also their simple geometric interpretation provides fertile ground for further investigation. We noticed that the performance of the SVM critically depends on the choice of the kernel functions. We conclude that the SVM classifier seems to perform best but care needs to be taken to choose the best kernel for classification.

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