

SVM and ANN-based Comparison of Face Recognition System

P. Uma Mageswari, Research Scholar, Adhiparasakthi College of Arts and Science, G.B. Nagar, Kalavai, India.

Prof. S. Aravindan, Assistant Professor, Department of Computer Science, Adhiparasakthi College of Arts and Science, G.B. Nagar, Kalavai, India.

Abstract— Face recognition is a very important component of human intelligence. For individual identity faces are rich in information. Since last few years, face recognition have been most important and successful applications of machine learning and computer security. The major method for face recognition consists of two steps. (1) The first method in feature extraction, for instance Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Components Analysis (ICA), and other approaches. (2) The second method in classification, such as Artificial Neuron Network (ANN), Support Vector Machine (SVM), Nearest Neighbor (NN), and others. ANN and SVM are two well-known machine learning techniques that are widely used in many areas. In this study we tried NN and SVM for facial recognition with two different feature selection methods including PCA and ICA. We used faces as dataset to compare the algorithms.

Keywords— NN, ANN, SVM, PCA, ICA, LDA, face recognition

I. INTRODUCTION

These days requirements of biometric security is very much needed for providing ID verification, identification accuracy, security for terrorist attacks, robbery, Authentication etc. The necessity of biometric system has increased rapidly because of its effectiveness, efficiency and its availability. So, one of the most authenticated and flexible security system is facial feature recognition [1].

Face recognition is not easy due to its large noise during the input. Basically there are few sources of noise which are light, position, expressions, ageing, block, and low resolution [4][5]. The difference in brightness changes the appearance of the face drastically. It is found that the dissimilarities between images of the same person taken under changing light are greater, than the images of different persons under same light. Change in positions in an image is also a subject of concern in face recognition. The differences in a position create serious difficulties for the identification of the input images. That is due to the available image in the database might have single view of the faces, which may change in position with the input image and so result may have error. As the age increases, the physical appearance of a user also increases which affect the face recognition systems accuracy. The absence or the lack of the input is also one of the challenges for the system. This is generated when some parts of the face are lacking. This is also possible due to eyeglasses, mustache, cap and other obstacle for taking image of face clearly. This problem can affect the classification process on Face Recognition.

Images taken from cameras are generally of small face region and so it is of low resolution. Such low-resolution image contains of very less information, as maximum information are missing [5]. This may affect recognition speed significantly. Next difficulty in face recognition is generated by its high dimensionality. Normally, an image data is composed of pixels. To process those data, we require convert into an array, where the length equal to the number of pixels. These results in a huge dataset, that is difficult to process without some feature selection and extraction methods. The main difficulty for classification arises from the nature of face recognition the classification is a multi-class classification. So, traditional classification methods such as SVM are not directly applicable. Also as the number of user in the biometric systems is huge, we have many classes.

In order to have a better performance, we require classification methods, which can handle multi-class classification with a huge number of classes [3]. In this study, we chose face database as our data. We have used Principal Component Analysis and Independent Component Analysis for feature selection and use one-vs.-all SVM and ANN for classification. Our study shows that SVM gives a better classification after PCA and ICA feature selection than ANN. Also ICA gives an improved representation of data features than PCA considering variances of classification accuracy.

A. Feature Selection:

Feature selection from face or extraction of a data is essential preprocessing task in biometric systems. As face data is of

high dimension, and contains many noises, face feature selection is necessary to reduce the dimension and remove some noises. Techniques for facial feature selection can be separated into clusters dependent on the info used:

1. Appearance based
2. Geometry based
3. Knowledge based
4. 3D Vision based

- In appearance: The values of luminance or gradients in the given region are analyzed. Object features are selected by reducing the image data.

- In geometry-based: The location associated to the face portions is assumed. These could be distances and angles and they are generally described as a graph.

- In knowledge-based approach: our knowledge about human face is used for features extraction. This can be color, regularity, placement of face parts, such as eyes, mouth, nose, ear etc.

- In 3D vision-based: 3D model of faces are created for face analysis.

In our project, we used PCA and ICA, which are from appearance-based approaches, to select features from our dataset.

B. Principal Component Analysis (PCA):

PCA is one of the most common and simplest image analysis method. In this method mean vector μ and the covariance matrix of the training data set are calculated. For the covariance matrix eigenvectors arranged by the corresponding eigenvalues are extracted. Eigenvectors associated with the highest eigenvalues carry most of the object energy. Matrix A is made by selecting k first eigenvectors. Data X representation in the new area is defined by the formula [2]:

$$X' = A' (X - \mu)$$

This method takes to the dimensionality reduction without reducing most appropriate data. Matrix A is normally calculated by the singular value decomposition (SVD) decomposition and selecting eigenvectors corresponding to the maximum variances if the dimensionality of data is very high, such as image data.

C. Independent Component Analysis (ICA):

The other method for feature selection we used is Independent Components Analysis (ICA). The functionality of this method can be defined on the blind source separation. Assuming, that there are n independent scalar sources of the signal $x(t)$ for $i = 1 \dots n$, where t represents for the time index i, $1 \leq t \leq T$. For k dimensional data vector derived from the sensor in the time index, following equation can be given by

$$s(t) = Ax(t)$$

Here A is a k by n matrix $A=k*n$ [2]. The goal of the ICA is to find independent components resulting from the observations. So, for image analysis we have the assumption that all images from our data are composed of independent sources, as shown in Fig. 1. In our analysis, we use the weights of ICs for each example as the features in our classification.

D. Independent Component Analysis (ICA):

In classification using the face features, there are four popular classifiers: Support Vector Machine (SVM), Hidden Markov Model (HMM), Artificial Neural Network (ANN), and Self-organizing Map (SOM). In this project, we used SVM and ANN as classifier to do the classification.

E. Support Vector Machine (SVM):

One of the widely used classification methods in face recognition system is Support Vector Machine[1]. For the linear classification of the linearly separated data SVM maximizes margins between two half-spaces given by the equations:

$$H1: X_i w + b \geq +1 \text{ for } y_i = +1,$$

$$H2: X_i w + b \leq -1 \text{ for } y_i = -1$$

Here w and b are the parameters of a hyper-plane parallel to and fitted in the middle of the half-spaces H1 and H2. X_i corresponds to the ith support vector and y_j corresponds to its class: +1 or -1 [6]. Margin between hyper-planes is equal

$$m = 2/|(w)|$$

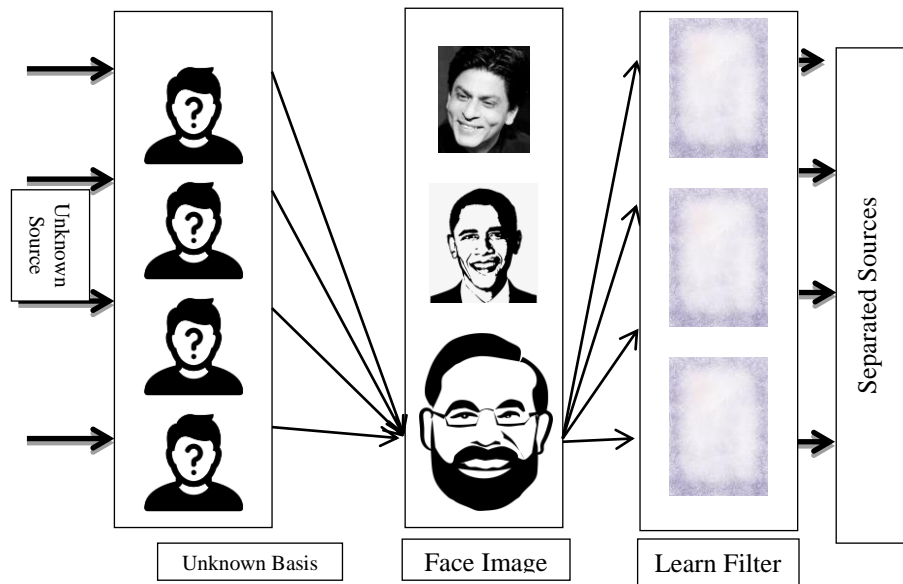


Fig. 1. Find independent components from mixed signals

The method is taken from the facts that H_1 and H_2 depends on some of the data samples support vectors. Though, SVM is normally designed for binary classification. So some changes are needed to make it applicable for multi-class classification. Generally there are three groups of strategies for multi-class classification using SVM: 1. one-vs-all strategy, 2. Pair-wise-strategy 3. Bayesian SVM.

One-Vs-all approach build a SVM model for each classes, and for a test sample, it finds the probability of the sample to belong to each class, and then allocate the sample with the corresponding label.

Pairwise-strategy generally constructs a binary tree for classification and decides whether a sample belongs to a class following the tree.

Bayesian SVM methods combine Bayesian with SVM and can achieve the same purpose without large training.

In our experiments, we use one-Vs-all strategy to implement our SVM. As this approach need only P training and P classification, where P is the number of classes. For other two approaches, the training process is too expensive, though it may give a little lighter expense in testing.

F. Artificial Neural Network:

Artificial Neuron Network is next widely used classifier for face recognition after SVM. ANN is a based on modeling of human decision. It is a multi-element structure analyzing the data using neurons. Neurons are connected with well-defined weight given in the data training. In our experiments, we used a 2-layer ANN for our classification –hidden layer, and output layer.

II. EXPERIMENTS

In this study, we used the face database as our dataset. The face database contains large gray-scale images in GIF format of few individuals. There are few images for each condition, one per different facial expression or configuration: center-

light, with glasses, happy, left-right, with no glasses, normal, right-light, sad, and sleepy, surprised, and wink. We run each method (with both feature selection and classification) 10 times and study the mean value, standard deviation, and maximum value of accuracy.

A. Polynomial SVM with different degree for PCA

To find how the performance change with the number of Principal Components reduces, we run SVM with different percentage of Principal Components (PC). We found that a SVM decrease with the number of PC reduces. To verify which SVM kernel is best suitable for selected features by PCA, we run SVM with dissimilar parameters many times. We got different degrees of polynomial kernel. Our result shows that with PCA feature selection, if the PC are enough, polynomial kernel with degree 1 i.e. Linear kernel, gives us the better performance, and with the polynomial SVM degree going greater, the classification result get poorer.

B. Comparison of SVM and ANN with PCA

During the comparison of SVM with different kernels, and with ANN. We run each kernel with different number of PCs, which represent 80%, 90%, 95%, and 100% variances. Polynomial kernel of SVM shows nearly same performance as linear which is just a linear kernel. RBF kernel SVM and ANN shows a poorer performance than that of linear and polynomial. The reason of RBF might be that it over-fits the training data too much that it is not applicable for testing data. For ANN, because it is running on multiple class classification, it may stuck on some local minimum during gradient descent back propagation process, which makes the prediction varies a lot (from about 0.1 to more than 0.9). Also it may have some over-fitting if the training of the model is too accurate, which make it not applicable to testing data.

C. Comparison of ICA and PCA with SVM and ANN

For ICA, we need to run PCA to reduce the dimensionality. Since, the dimension of the data is too high,

that makes it difficult to run ICA directly. Therefore we use the weights. That we got for each objects with respect to different Independent Components (ICs) as input for classifiers SVM and ANN [7]. Comparison of ICA and PCA shows that ICA gives a less variance over PCA. This is because the classifier we used can handle complex input. PCA, it just selected the variance of the data, some may be useful, but some may not. For ICA, features are well represented, and this gives a good performance regarding to average accuracy and also with improvements considering variance.

III. CONCLUSION

In this study, we have used PCA and ICA for feature selection and SVM and ANN for classification to do face recognition using face database. Our experiment shows that after PCA for feature selection, simple classifier gives us a better classification output. Here, classification accuracy we got from SVM with linear kernel is better than that from more complex kernels such as polynomial and RBF. So, by comparison of ICA and PCA with different classifiers, linear kernel SVM and ANN, we found that ICA gives a better representation of image features than PCA in terms of variance of accuracy in classification. Comparing linear kernel SVM and ANN, linear kernel SVM gives us a well classification results.

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