Facial Expression Recognition using Eigenfaces and SVM

Prof. Lalita B. Patil
Assistant Professor
Dept of Electronics and Telecommunication,
MGMCET, Kamothe, Navi Mumbai
(Maharashtra), INDIA.

Prof.V.R.Bhosale
Assistant Professor
Dept.ofComputer Engineering,
MGMCET,Kamothe, Navi Mumbai
(Maharashtra), INDIA

Abstract - A challenging research topic is to make the Computer Systems to recognize facial expressions from the face image. A method of facial expression recognition, based on Eigenfaces is presented in this work. Here the facial expressions of input images is recognised using eigenface and SVM. Evaluation was done for this method in terms of identification, correctness using Cohn-Kanade facial expression database and JAFFE database. The results show the effectiveness of proposed method. Security systems, monitoring systems and biometrics have become indispensable in the recent times and a major emphasis has been placed on to the development of effective and robust algorithms in the allied fields like acoustic finger print, retina scanning, finger print analysis and face expression recognition. Indeed, there is an emerging need for such algorithms which is cost effective and easy-to-use in this scenario. It has become imperative that efficient algorithms are developed to cater to the needs of expression recognition system. This paper proposes an intelligent approach to identify the facial expressions through eigenfaces which manipulates with the Eigenvalues and SVM for the identification. From the experiment, it is found that the proposed scheme furnishes 94% expression recognition rate with an overwhelming average time of less than 4 second.

Keywords - Feature vector, eigenfaces, eigenvalues, eigenvector, Support Vector Machine

I. INTRODUCTION

Among the most challenging tasks for visual form analysis and object recognition understands how people process and recognize each other's face, and the development of corresponding computational models for automated face expression recognition. An automated facial expression recognition system includes several related face processing tasks, such as detection of a pattern as a face, face tracking in a video sequence, face verification, and face recognition. Facial expressions are the facial changes in response to a person's internal emotional states, intentions or social communications. Facial expression analysis has been an active research topic for scientists since the work of Darwin. After that much progress has been made to build computer systems to understand and use this natural form of human communication. A facial expression analyzer system should have numerous capabilities to perform well on different conditions. In other words, any ethnicity or outlook variance should be handled by the system. Automation of facial feature extraction and expression classification are vital during acquisition, there may be misleading or missing data, therefore inaccurate facial expression data is also a problem.

II. PROPOSED ALGORITHM

A Literature survey-

Over the last decade, facial expression analysis has become an active research area that finds potential applications in areas such as more engaging human—computer interfaces, talking heads, image retrieval and human emotion analysis. Facial expressions reflect not only emotions, but other mental activities, social interaction and physiological signals.

In this survey, we introduce the most prominent automatic facial expression analysis methods and systems presented in the literature. Facial expression classification methods are discussed with respect to issues such as face normalization, facial expression dynamics and facial expression intensity, but also with regard to their robustness towards environmental changes. Human beings naturally and intuitively use facial expression as an important and powerful modality to communicate their emotions and to interact socially. There has been continued research interest in enabling computer systems to recognize expressions and to use the emotive information embedded in them in human-machine interfaces. This paper presents the application of the machine learning system of support vector machines (SVMs) to the recognition and classification of facial expressions in still images. The emotions considered in this project are anger, fear, surprise, joy and disgust.

B Implementation flow -

The patterns which can be observed in all the images of emotions recognition are the presence of some objects. These characteristic features are called eigenfaces in the facial recognition domain. The higher the eigen value, the more characteristic features of a face does the particular eigenvector describe.

The eigenfaces is well known method for face recognition. Sirovich and Kirby[1] had efficiently representing human faces using principle component analysis. M.A Turk and Alex P. Pentland[2] developed the near real-time eigenfaces systems for face recognition using eigenfaces and Euclidean distance.. The research is focused to develop the computational model of emotion recognition that is fast, simple and accurate in different environments. Therefore, in this paper we develop a technique to extract features from an intensity image of human frontal face to represent the features using eigenfaces and then it is demonstrated that the features vectors obtained from the eigenfaces can easily be used with SVM for emotion recognition.

C. Calculation of eigen faces -

The basic idea of eigenfaces is that all face images are similar in all configurations and they can be described in its basic face images. Based on this idea, the eigenfaces procedures are as follows:

a: We assume the training sets of images are G1,G2 ,_,Gm with each image is I (x, y) . Convert each image into set of vectors and

new full-size matrix (m * p) , where m is the number of training images and p is x * y

b: Find the mean face by:

$$\Psi = \frac{1}{m}\sum_{i=1}^{m}\Gamma_i \qquad (1)$$

c: Calculated the mean-subtracted face:

$$\Phi_i = \Gamma_i - \Psi, i = 1, 2, \ldots, m \qquad (2)$$

and a set of matrix is obtained with

$A = [\Phi_1, \Phi_2, \ldots, \Phi_m]$ is the mean-subtracted matrix vector with its size *Amp*

d: By implementing the matrix transformations, the vectors matrix is reduced by:

$$Cmm = Amp \ x \ ATpm \qquad (3)$$

Where C is the covariance matrix and T is transpose matrix.

e: Find the eigenvectors, V_{mm} and eigenvalues, λ_m from the C matrix using Jacobi method and ordered the eigenvectors by highest

eigenvalues. Jacobi's method is chosen because its accuracy and reliability than other method.

f: Apply the eigenvectors matrix, V_{mm} and adjusted matrix, Φ_m. These vectors determine linear combinations of the training set

images to form the eigenfaces, U_k by:

$$U_k = \sum_{n=1}^{m} \Phi_n V_{kn}, k = 1,2\ldots,m \quad (4)$$

Instead of using m eigenfaces, m' < m which we consider the image provided for training are more than 1 for each individuals or

class. m' is the total class used.

g: Based on the eigenfaces, each image has its face vector by:

$$W_k = U_k^T \left(\Gamma - \Psi\right), k = 1,2,\ldots,m' \quad (5)$$

and mean subtracted vector of size (p´1) and eigenfaces is $U_{pm,'}$. The weights form a feature vector:

$$\Omega^T = [w_1, w_2, \ldots, w_{m'}]$$

h: A face can reconstructed by using its feature,

Ω^T vector and previous eigenfaces, $U_{m'}$ as :

$$\Gamma' = \Psi + \Phi_f \quad (6)$$

$$\text{where } \Phi_f = \sum_{i=1}^{m'} w_i U_i .$$

The experiments have been conducted using *Cohn-Kanade and JAFFE* image database. Figure 2. shows the mean image after the transformation of training images. The eigenfaces result has been obtained From the Figure 3. Each training session shows the variations of eigenfaces. Fig. 3 used 40 images (5 classes with 8 images per-class). The eigenfaces above shows exactly. If the experiments conducted using more images, the eigenfaces becomes more whitening. Means, lesser images make the eigenfaces become darker and indistinct. We have found that 40 images were sufficient for a very good description of face images.

Figure 1. Image Database

Above figure shown some examples of the JAFFE and *Cohn-Kanade* face database .

Figure 2. Mean Image ,Ψ

The eigenfaces used for each training images and unknown images to determine its weight vectors to describe class identity (equation 5). These features are used for classification and recognize the emotions.

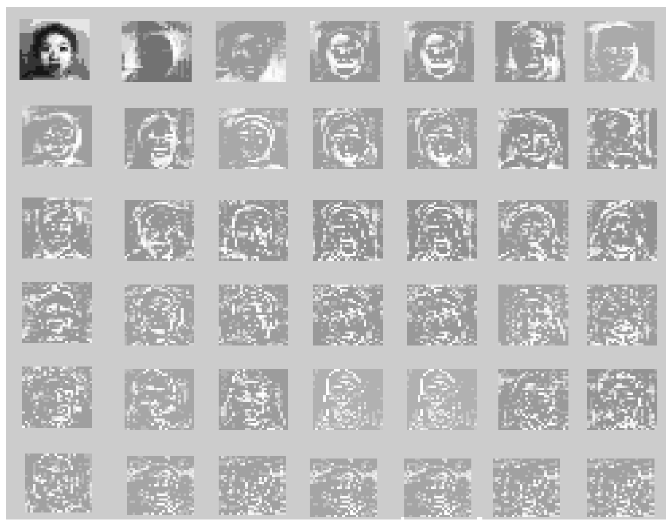

Figure 3. The Eigenfaces of Images in Database

The project follows following flow for the implementation. Though there are many approaches handling the challenges posed by expressions variations, we have developed an intelligent system which handles the drawbacks exhibited by other approaches. It is less sensitive to illumination, pose and expressions variations, cost-effective and easy-to use. Image acquisition is the process, which reads the image and stores the pixel values in the array format. This process is little complex in the object oriented context because the image size is varied and the array size is dynamically changed depending upon the size of the image and the image that are stored in files. In characteristics extraction, the features of the input images which may be noisy are characterized by differing lighting and pose conditions. They follow patterns such as eyes, nose, mouth, lips, and chin that are observed in a human face. These characteristic features are the eigenfaces, which are calculated for the training set as well as for the test image by finding the eigenvectors of the face. The eigenface has the special characteristics over that of a mean face from the training set and the original image can be reconstructed from the training set by combining the eigenfaces. Follow patterns such as eyes, nose, mouth, lips, and chin that are observed in a human face. These characteristic features are the eigenfaces, which are relative importance of a feature in the image, weights are assigned for the eigenfaces. The eigenfaces will have a certain weight so that an image can be reconstructed by summing up all the weights. The weights for the unknown image are calculated and compared with the weights of the images in database which are already determined.

Once the weights are assigned, the similarity of the features from the test image to those of the database images are ought to be determined. This is accomplished by finding the Euclidean distance of the weight vector of the test image and the images from the database. If the weights of the test image differ too much from the weights of the database images, then the database image is found to be a non-match. Evidently, if a database image matches the test image then it is understood that it have similar features at similar degrees.

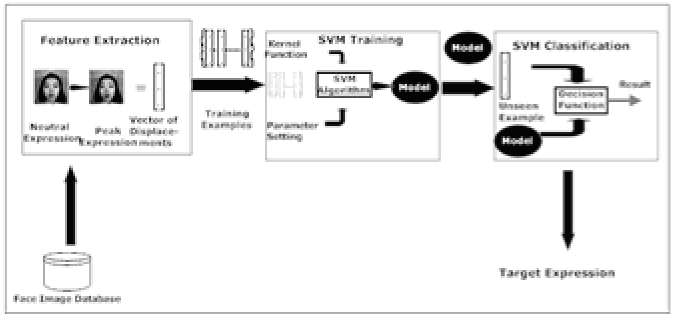

Figure 4. Face Reorganization System

In the proposed method, facial expressions of the human face are identified from the input image using Eigenfaces method. The method is modified from the famous Eigenface identification technique. If the input image is similar to some expression training set, the reconstructed image will have less distortion than the image reconstructed from other eigenvectors of training expressions. Based on this idea, the training set is divided into five classes according to universal expressions as shown in Figure. 1 and computed the Eigenfaces of each class. For a test face image, they first project it onto the Eigenface of each class independently and then derive reconstructed image from each Eigenface.

By measuring the similarity between input image and the reconstructed image of each class, they can identify the class of input image whose reconstructed image is most similar to the input image using SVM.

D Support vector machine(SVM) -

Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. A support vector machine constructs a hyper plane or set of hyper planes in a high-dimensional space, which can be used for classification, regression or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general larger the margin the lower the generalization error of the classifier. Support Vector Machines are a maximal margin hyper plane classification method that relies on results from statistical learning theory to guarantee high generalization performance. Kernel functions are employed to efficiently map input data which may not be linearly separable to a high dimensional feature space where linear methods can then be applied.
SVMs exhibit good classification accuracy even when only a modest amount of training data is available, making them particularly suitable to a dynamic, interactive approach to expression recognition. The often subtle differences distinguishing separate expressions such as ‘anger’ or ‘disgust’ in our displacement-based data as well as the wide range of possible variations in a particular expression when performed by different subjects led us to the adoption of SVMs as the classifier of choice. Selection of an appropriate kernel function allowed further adjustment and optimization of the SVM classifier to our particular domain of facial expression recognition.
Support vector machines have previously been successfully employed in a variety of classification applications including identity and text recognition as well as DNA micro array data analysis’s can be explained below.

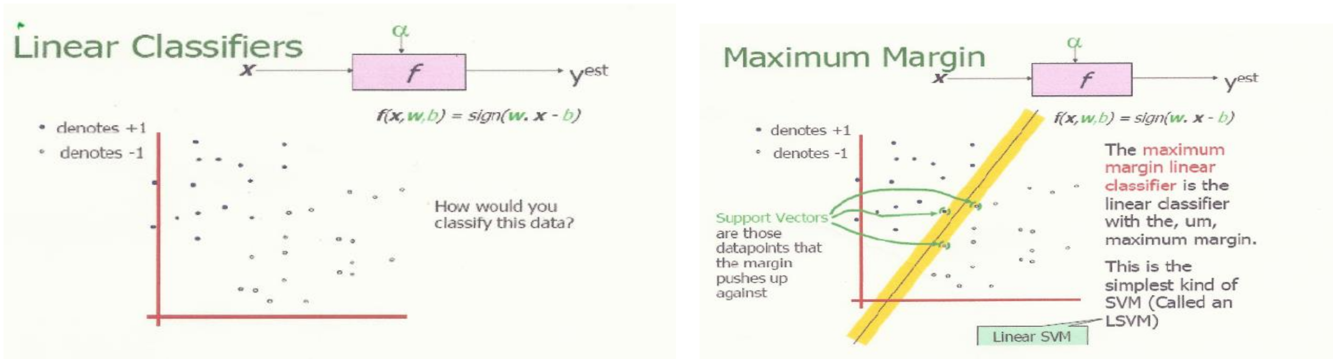

Figure 5. SVM Classification

E Module description -

- The input image is taken from the Image database created with emotions of different faces of students database.
- It is pre-processed and computed Eigenfaces.
- Features are extracted from Eigenfaces and feature vectors are formed.
- Feature vectors of database image and unknown input image then applied to the SVM algorithm..
- A model is designed so that we can easily compare.
- After that, the model is trained and the values are trained.
- Finally, the emotion is identified

F Flow chart -

The following flow chart represents flow of the work.

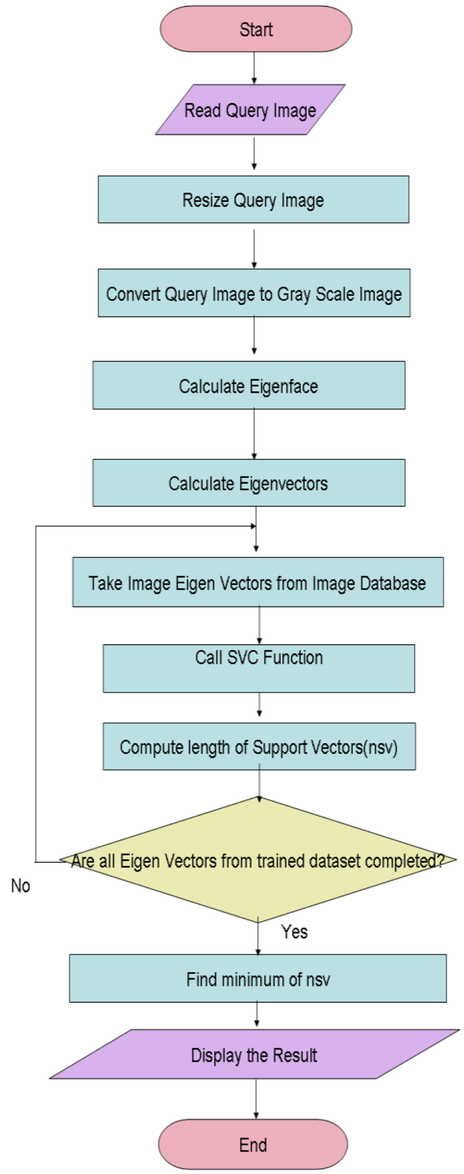

Figure 6. Flow Chart of System

III. EXPERIMENTAL RESULTS

The accuracy of recognition is 100% on trained dataset. With eigenfaces and SVM accuracy of recognition for angry angry - 92.2%, disgust - 90.3%, fear - 83.5%, happy- 91.7% and surprise - 84.8%.

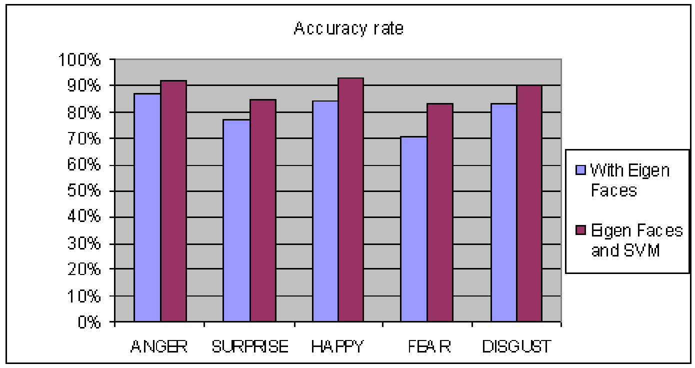

Figure 7. Result Analysis

Without SVM accuracy of recognition for angry - 86.7%, disgust - 83.4%, fear - 70.8 %, happy -84.6% and surprise - 77.2%.

IV.CONCLUSION

Facial Expression provides a key mechanism for understanding and conveying emotions. It focuses to process human facial expressions and synthesizes corresponding facial expressions for face expression estimation. In this study, we used the eigenfaces to represent the features vectors for human faces. The features are extracted from the original image to represents unique identity used as inputs to the SVM to measure similarity in classification and recognition. The eigenfaces has proven the capability to provide the significant features and reduces the input size for SVM. Accuracy rate is improved by using eigenfaces with SVM.In the present time of computer implemented machine civilization, much kind of machine systems or equipments offering services to human beings have been indispensable for leading our daily life, with increasing tendency in future. In fact not only the machine computational speed but also machine intelligence is playing an important role.

REFERENCES

[1] Kirby *et al*., 1990. Application of the Karhunen-Loeve procedure for the characterization of human faces. IEEE Trans. Pattern Analysis and Machine intelligence, 12: 103-108
[2] Turk, M.A. and A.L. Pentland, 1991. Face recognition using eigenfaces. Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition, pp: 586-591.
[3] P. Ekman and W. V. Friesen, “Emotion in the Human Face” ,Prentice-Hall, 1975.
[4] Chapman Stephen [2006], “MATLAB Programming for Engineers”
[5] “A Practical Guide to Support Vector Classification” Chih-Wei Hsu, Chih-Chung Chang, and Chih-Jen Lin Department of Computer Science National Taiwan University, Taipei 106, Taiwan http://www.csie.ntu.edu.tw/~cjlin Initial version: 2003 Last updated: April 15, 2010`
[6] “Face Recognition: A Literature Survey” W. ZHAO Sarnoff Corporation R.CHELLAPPA University of Maryland P. J. PHILLIPS National Institute of Standards and Technology and A. ROSENFELD University of Maryland ACM Computing Surveys, Vol. 35, No. 4, December 2003, pp. 399–458.
[7] “Face Expression Recognition and Analysis: The State of the Art” Vinay Kumar Bettadapura Columbia University.
[8] “Emotion Classification Using Facial Expression” Devi Arumugam Research Scholar, Department of Computer Science, Mother Teresa Women’s University, Kodaikanal, India Dr. S. Purushothaman B.E, M.E., Ph.D(IIT-M) Principal, Sun College of Engineering and Technology, Sun Nagar, Erachakulam, Kanyakumari, India (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 2, No. 7, 2011
[9] “Automatic facial expression analysis: a survey” B. Fasela; Juergen Luettinb Journal of pattern recognition society (Pattern Recognition 36 (2003) 259 – 275). www.elsevier.com/locate/patcog.
[10] “A Practical Guide to Support Vector Classification” Chih-Wei Hsu, Chih-Chung Chang, and Chih-Jen Lin Department of Computer Science National Taiwan University, Taipei 106