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IMAGE SEQUENCES BASED FACIAL EXPRESSION RECOGNITION USING SUPPORT VECTOR MACHINE

J. Kamalakumari[1], Dr. M. Vanitha[2]
[1]Research Scholar, Department of Computer Science,
JJ College of Arts and Science (Autonomous), Pudukkottai
Email id –rameshkamala@hotmail.com
[2]Assistant Professor, Department of Computer Applications, Alagappa University, Karaikudi
Email id –mvanitharavi@gmail.com

Abstract: This paper demonstrates the application of Support Vector Machine techniques to judge emotions in facial images. Natural changes in the face are difficult to identify and needs a proper classification algorithm to distinguish these changes. Even small changes result in a large number of relevant input functions. Automatic recognition of facial expression can be addressed by face positions, removal of facial features and learning methods. This paper demonstrates the use of SVM in facial image recognition and produces performance equal to that of neural networks.

Keywords: Classification, Facial Recognition, Support vector Machine.

I. INTRODUCTION

A persons image of the face plays a significant role in social communication, as it is an index of human emotions and feelings. According to Mehrabian [1], nonverbal part like the face in social interaction is the most informative channel. Facial expressions contribute to fifty five percent, verbal seven percent and vocal thirty four percentage respectively in communications. Thus facial expressions are a subject of research study in many areas of science like psychology, behavioral science, medicine and computer science.

Relevant studies in computer science explore ways of automating face detection and segmentation processes. Several methods have been proposed for extracting facial features from facial images. A pertinent problem in extraction techniques is in providing full representation of expressions, which is dynamic and changes often. In 1978, Ekman et.al [2] introduced a system (Facial Action Coding System) called a FACS for recognizing facial expression. FACS analyzed muscle contractions (S) in a face and its relationship in developing relations. Facial muscle contraction results in an action is marked as an action unit (AU). FACS analyzed facial expressions based on the observed decompositions in action units. There are at least 46 AU for facial expressions that change. Twelve of these AU's are related to the eye, gaze and orientation of the head. Though Action Units describe facial motions, but lack in providing information on the messages they represent.

Manipulation of facial expressions through action units can be analyzed at the semantic level, to find the meaning of a particular action. According to the Ekman's theory [2], there are six basic emotional expressions namely pleasure, sadness, anger, fear, disgust and surprise, on a face that are universal irrespective of cultures and races. Systems that automatically analyze facial movements are commonly referred to as Facial Expression Recognition System (FERS). The main system components are face detection, feature extraction and recognition of expressions.

II. LITERATURE REVIEW

Archana Vijayan et al. noted that hormone replacement therapy (HRT), causes a change in the physical appearance of the body and face and thus affects facial recognition systems. Existing facial recognition system studies have shown that the eye is constant due to changes in Thyrotropin Releasing Hormone (TRH), thus facial recognition is based on the characteristics of the eye. The face and eye alignment is detected first. The face image is converted to binary representation and face recognition is performed using SVM classifications. Segmentation detects the face and eye regions. Parallel relationships are preserved and transformed to maintain the collinearity and distance ratio of the points. SVM classification was found to be more accurate in facial recognition than other similar measures. Eye Week provided a degree of reliability and robustness to automatic face recognition by subjecting the experiment to change through a hormone therapy [1].

Muzammil Abdulrahman et al., conducted a Japanese Female Facial Expressions (JAFFE) research using Mevlana University Facial Expression (MUFE) database. They used Support Vector Machine (SVM) classifiers. All experiments were performed with JAFFE on MUFE data and their results showed that PCA + SVM had an average recognition rate of 87% and 77%, respectively. The study investigated on the MUFE facial expression recognition feature, where PCA and LBP were used as feature extraction techniques. The results showed that both PCA and LBP sorters increased the accuracy of SVM classification in a Euclidean distance L2. In overall performances, they found that students faces generated more facial expressions than [2] professional actors.

K. Venkata Narayana et al. combined Principal Component Analysis PCA and SVM for face recognition is their work. They used wavelet transforms as a pre-processing measure before applying PCA for feature extraction. SVm was then used to classify on an Indian face database. Their method achieved better performance in face recognition when compared to applications of only PCA for face recognition. Though, PCA and SVM combined face recognition can be influenced by variations in face images like lighting, expression and pose, they concluded that their method could result in a better recognition rate [3].

Navin Prakash et al. in their study on facial recognition using Support Vector Machine (SVM) developed an algorithm. They mentioned the advantages and solution to the disadvantages of using an SVM classifier in facial recognition. SVM classifier's success in training and learning algorithms are better in face recognition. They concluded that SVM can be extended in many ways or combined with other classifiers in different ways to achieve better results. In reality SVM's achieve lesser results as they are less sensitive to outliers and noisy samples. An extension of SVM called Fuzzy SVMs (FSVMs) can help achieve better face recognition as FSVM methods assign different fuzzy membership values for different sample points to reproduce different status in their own classes, while less significant data like outliers and noise are allotted lower membership values, thus increasing the recognition rate [4].

Puja et al. in their study considered technical conditions, complex backgrounds and different positions of the face. They observed, that algorithms yielded different accuracy for different conditions. Their algorithm detected faces in images, where the skin color was taken as the screening tool. It successfully identified faces in a certain range of people like Indians who have a specific color. Their experimental results at the training stage showed that the face classifier SVM-LBP edge could separate mismatched examples of faces in the training data. They used an implicit surface with a built-in weight setting. The efficiency of the results were calculated based on the generalization of training set values like total number of false detections and error detection. The generalized value of the precision SVM-LBP was found to be higher than other related results. It can be concluded that SVM-LBP combination is good for edge detection than skin fusion [5].

III. PROBLEM STATEMENT

Expressions play a vital role in our day-to-day communications. For over a decade many studies have focused on developing accurate and reliable systems to identify facial expressions (FERs). These systems can be found in many applications like daily communication, personality development, child based recognitions, neuroscience, psychology, access control and monitoring. The use of electronic products in environmental telemedicine and healthy human behavior studies has been on the upswing. FER systems can recognize facial expressions and spontaneous facial expressions. Artificial expressions are expressions produced by people when they are asked to do so, while expressions that people show in spontaneity are spontaneous facial expressions. Spontaneous facial expressions can be observed on a day-to-day basis like people in conversations or while watching movies. Recognizing faces with illumination has proved to be a much deeper problem. Although many researches have been conducted in facial recognition, recognition in low intensity is difficult to identify and very few expressions are recognized, thus leaving abundant scope for further investigation.

III.A. Proposed Work

Many previous studies on facial recognition, focused on geometrical features like face appearances based on eye, mouth or other parts. Faces reflect the appearance or texture in wrinkles, bumps, grooves, etc. Combining both geometric and appearance is a better choice for facial recognitions as they represent abstractly changing facial expressions. Linear discriminant analysis (LDA) has been widely employed in FER systems. However, LDA is a linear technique that is limited in flexibility when applied to more complex datasets. Annotation can runs in two modes namely manual and automatic. In a manual mode, the reference point is set manually, while in automatic mode the reference point is based on the Constrained Local Model (CLM) of the automatic tool position. LDA is mainly used to overcome deficiencies due to lighting. The LDA can also be used for dimension reduction. SVM classifier is used for classification as they provide a higher recognition rate when compared to other methods. The block diagram of the proposed system is depicted in Figure 1.

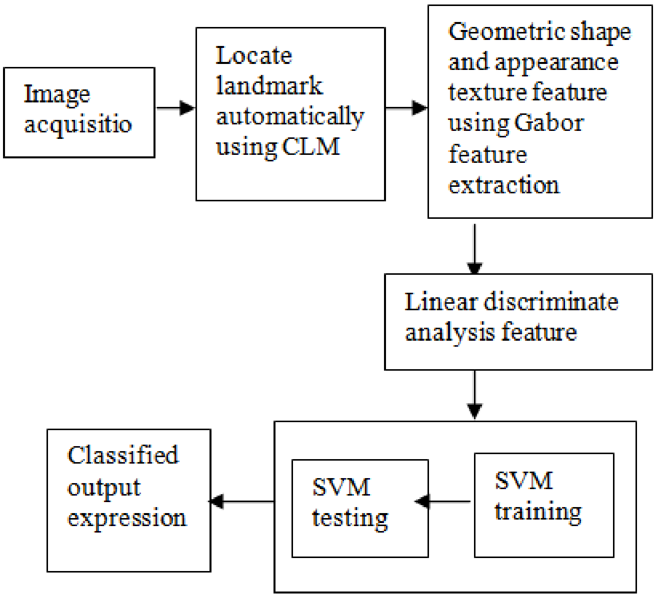

Fig. 1- block diagram of the proposed system

III.B. Objective of the proposed system

- To develop an automated system for facial expression recognition system.
- To improve the Recognition in terms of Recognition Rate and Accuracy.
- To identify the facial expressions correctly by applying LDP with Gabor feature extraction and SVM classification techniques.

III.C. Performance metric

The following performance metrics were used in the present study

TP = True positive, FP = False Positive

Precision = $\frac{TP}{(TP+FP)}$

Accuracy = $\frac{(TP+TN)}{Total\ population}$

Recognition Rate = $\frac{No\ of\ facial\ expression\ recognized}{No\ of\ facial\ expression\ given}$

IV. EXPERIMENTAL RESULTS

IV.A.Data Collection

The database of Cohn-played [8] is used to identify facial expressions in six basic facial expressions namely anger, disgust, fear, pleasure, sadness and wonder. The database is marked with Faus according to [9] into a facial expression to determine the appropriate ground condition for facial expressions. All subjects were considered to form an experimental database.

The most commonly used method of SVM generalization namely cross validation is used [10] with leave, in order to maximize the use of available data and produce better classification accuracy. The term leave is used to form a set of variance test data on a set of methods. This study uses 20% leaves. More specifically, all the sequences of the images in the database are divided into six categories, where each category corresponds to one of the six basic recognized facial expressions. The neutral state is not considered as a class because the system tries to recognize the facial expression from fully expressed neutral state. Twenty percent faces in the data were taken each group and five groups were formed by choosing randomly. A group of samples for each class were considered for the test group, while the rest of the data set formed the training set. After classification, a set new samples were added to the current training set, while removing old samples (20% of each category) to form a new set of tests. The remaining samples set up the new training set. The accuracy obtained for each facial expression was averaged over all facial expressions, providing information about specific expressions. Confusion matrix is used in a manner, where, the confounding matrix is a matrix containing information about the actual class label (in columns) and the labels obtained by the classification (in rank). The diagonal confused matrix entry is then the rate of the facial expression that is correctly classified, while the diagonal term corresponds to the false sort rate. Abbreviations used are faith, Hassan, express anger, disgust, fear, happiness, sadness and surprise, respectively.

IV.B. Support Vector Machines

Support vector machine classifier hyperplane, based on statistical learning theory isused based to ensure higher performance margins. A kernel function is used to efficiently map the input data to the size of the feature space that cannot be linearly segmented while applying linear methods. Results were displayed on even singular availability of training data, thus making it a dynamic and interactive method to identify facial expressions with well-expressed classification accuracy. Subtle differences are separated from individual expressions such as "anger" or based on the displacement in the data "disgusted". SVM becomes a preferred classification technique for varied expressions. Further, the choice of appropriate kernel functions allows the SVM classification to further refine and optimize specific areas of facial expression recognition. Table 1 lists Evolution Measures of Facial Expression during Detection

TABLE I. Evolution Measures of Facial Expression Detection

Emotion	Happy	Sad	Anger	Disgust	Fear	Surprise	Overall
Happy	-	72.5	61.8	97.1	93.8	97.1	88.46
Sad	72.5	-	63.2	94.9	88.8	99.1	83.7
Anger	61.8	63.2	-	90.9	66.7	99.7	76.46
Disgust	97.1	94.9	90.9	-	96.8	97.1	95.36
Fear	93.8	88.8	66.7	96.8	-	99.8	89.18
Surprise	97.1	99.1	99.7	97.1	99.8	-	98.56
					Total Accuracy		88.62

IV.C. Evaluation and Result

The expression of the facial expression of the Cohen-Play AU database is used for evaluation of speech recognition of still images, while on-site meetings are based on the identification of spontaneous expression to evaluate the images in Table 1 the initial implementation appropriately identifies the representation of the test in 78% with subsequent improvements, including the selection of training data for the increasing awareness of the accuracy of 87.9% of the kernel function, as shown in Table 1. Incorporating new improvements to the movement of the head or performing automatic selection of the SVM model is likely to produce even better performance and further improve the suitability for building interfaces based on SVM for recognition of express emotions and social intelligence.

V. CONCLUSION

Face recognition is one of several techniques to identify people. There are several ways that can be used for this purpose. Substantial research remains to be done in making person recognition technology work reliably. This paper has proposed and demonstrated the uses of combining LDP and SVM in facial expression. LDP is used for reduction of dimensions and to overcome problems due to illumination, while SVM classifier is used for classification. Thus it is concluded that LDP and SVM can help better accuracy in FERs.

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