Effectiveness of Eigenspaces for Facial Expressions Recognition

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***Abstract*— Making Computer Systems to recognize and infer facial expressions from the user image is a challenging research topic. A method of facial expression recognition, based on Eigenspaces is presented in this paper. In our approach we identify the user's facial expressions from the input images, using a method that was modified from eigenface recognition. We have evaluated our method in terms of recognition accuracy using two well known Facial Expressions databases, Cohn- Kanade facial expression database and Japanese Female Facial Expression database. The experimental results show the effectiveness of our scheme.**

***Index Terms*— Facial Expression Recognition, Facial Expressions, Human Computer Interaction, Eigenspaces, PCA.**

I. Introduction

The human face provides one of the most powerful, versatile and natural means of communication, during social interaction. According to Meharabian [1], Facial Expressions provide important communicative cues, which constitute 55 percent of the effect of a communicated message; hence recognition of facial expressions became a major modality in Human Computer Interaction. For example, in a Human-Computer Interface if the Computer can sense and understand the users' intentions from their facial expressions, it might be possible for the system to assist them by giving suggestion and proposals according to sensed situation.

The possibility of making Computers to recognize facial expressions and use the information in Human Computer Interaction has gained significant research interest over the last few years. This has given rise to a number of automatic methods to recognize facial expressions in images or video [2-7].

In our previous paper [8], we have suggested the usage of Eigenspaces in recognition of facial expressions. In this paper, we have extended the set of Facial expressions from three expressions to six universal expressions (Fig.1) and established the effectiveness of the algorithm on two standard Facial expressions databases Cohn-Kanade database and JAFFE. The well-known Eigenface identification technique [9] was modified and used for recognizing facial expressions. Our goal is to use dimensionality techniques on a large and varied dataset to learn a reasonable space for expressions and recognize the facial expressions of the user. The novelty of our approach is its performance in classification, robustness and lack of preprocessing of images.

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II. Facial Expressions

Mehrabian [1] indicated that only 7% of message is due to linguistic language, 38% is due to paralanguage and 55 % of message is communicated by facial expressions. This implies that the facial expression is a major modality in human face-to-face communication. Thus we can imagine that, when designing the Human Computer Interfaces (HCI), the facial expressions seems to be a major factor for improving the communicability of message, even in human-machine communication.

Recognition of human facial expression by computer is a key to develop such technology. In recent years, much research has been done on machine recognition of human facial expressions [10- 14].

Cross-cultural psychological research on facial expressions indicates that there may be a small set of facial expressions that are universal. This was first suggested by Charles Darwin in his pioneering work on "The Origin of Species". Psychologists Paul Ekman and Wallace Friesen [15, 16] conducted the first methodologically sound studies, and concluded that the emotions "Happiness, Anger, Sadness, Disgust, Surprise and Fear" are shown and interpreted in all human cultures in the same way. Fig 1 shows the universal expressions.

Fig.1 Six universal expressions from Cohn-Kanade database and JAFFE database. **Top row**: Sad, Anger, Disgust. **Bottom row**: Fear, Happy, Surprise

III. Related works

In recent years, the research of developing automatic facial expression recognition systems has attracted a lot of attention from many different fields. A more recent and complete overview can be found in [7, 17]. The approaches to facial expression recognition can be, roughly divided into two classes: geometrical feature-based approaches and appearance-based approaches [18]. The geometrical feature-based approaches rely on the geometric facial features, which represent the shapes and locations of facial components such as eyebrows, eyes, nose, mouth etc. As for the appearance-based approaches, the whole-face or specific regions in a face image are used for the feature extraction via optical flow or some kinds of filters.

Many of the previous works [19, 20] on facial expression recognition are based on the existence of six universal expressions (anger, disgust, fear, joy, sorrow and surprise). These universal expressions are based on the psychological results of Ekman[16] and the Facial Action Coding System (FACS), developed by Ekman and Friesen [15], which codes expressions as a combination of 46 facial movements called Action Units.

The combination of these action units result in a large set of possible facial expressions. For example, smile expression is considered to be a combination of "pulling lip corners (AU12 + 13) and/or mouth opening (AU25 + 27) with upper lip raiser (AU10) and bit of furrow deepening (AU11)." However, this is only one type of a smile; there are many variations of the above motions, each having a different intensity of actuation. Despite its limitations, this method is the most widely used method for measuring human facial motion for both human and machine perception.

Conventional methods extract features of facial organs, such as eyes and a mouth, in gray or color images of front faces and recognize the expressions from changes in their shapes or their geometrical relationships by different facial expressions [6, 21-23]. However, estimation of their precise positions and shape attributes in real images is difficult, because of the wide variety of the face features, skin color/brightness, illumination conditions and geometrical variations such as head orientations. As a result, many of the systems need human assistance such as attaching marks on the subject's face or specifying windows covering each organ in the image.

Neural networks seem promising for recognizing facial expressions [24 - 26], but the methods using Neural Networks assumes locations of facial organs are to be provided as its input. Another idea is to estimate the movement of muscles from optical flow to recognize facial expression [27-29]. Its success depends on the reliability of optical flow estimation from image sequences, and its accurate estimation seems difficult because of the complexity of facial images. Moreover, the method should compensate the flow vectors for the head movements of which estimation is not easy. The above systems work under many restricted conditions. One of the conditions is, the neutral expression of the subject is given first as control, the human operator specifies the windows covering the organs of the input face, or the marks are attached on the subject's face.

The success of facial expressions recognition system depends heavily on how well the movement of the key features points, like eyeballs and mouth corner, are tracked on the human face. To facilitate the tracking process, in the current practice the face of the human performer is painted with color make-up or attached with some small illuminative balls [30]. However, the artificial attachment is intrusive to humans, possibly jeopardizing the quality of the human act.

To eliminate such restrictions and to take the advantage of similarity measure between face and facial expression, we have proposed a method in [8] to recognize facial expressions from the whole face, rather than from changes in the shape of the facial organs such as eyes and a mouth, or their geometrical relationships. In other words, the expressions can be recognized without extracting the individual facial features. The idea is similar as the face identification method proposed by Turk and Pentland in [9] and method used in Frank and Noth [31], but the characteristics of the problem domain are quite different. Our system was designed to recognize the expression of an unknown subject from a single front view of his/her face.

IV. PROPOSED METHOD

In the proposed method, facial expressions of the human face are identified from the input image using Eigenspaces method. The method is modified from the well-known Eigenface identification technique, but here it is used for recognizing facial expression not identity of the person.

To illustrate the feasibility of using Eigenspace for facial expression recognition, the PCA reconstruction method was modified and the modified PCA reconstruction method was shown in Fig. 2. 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, we divided the training set into six classes according to universal expressions as shown in Fig. 1 and computed the Eigenspaces of each class. For a test face image, we first project it onto the Eigenspace of each class independently and then derive reconstructed image from each Eigenspace. By measuring the similarity (mean square error) between input image and the reconstructed image of each class, we can identify the class of input image whose reconstructed image is most similar to the input one.

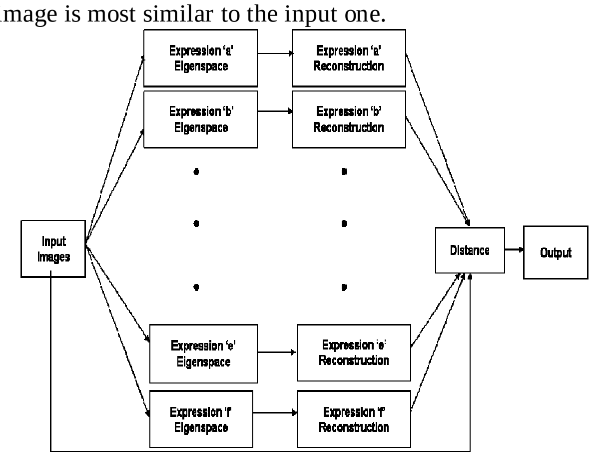

Fig.2 Proposed PCA reconstruction

V. EIGENSPACES FOR FACIAL EXPRESSION RECOGNITION

When using Eigenspaces for facial expression recognition of unknown faces, one possibility is to calculate one Eigenspaces for each facial expression from a labeled database of different persons. The classification procedure corresponds to that of face recognition: Project a new image to each Eigenspaces and select the Eigenspaces, which best describes the input image. This is accomplished by calculating the residual description error. However, the problem with facial expression classification is that the person, whose facial expression needs to be classified, is unrecognized. Each person uses a different smile. Nevertheless, each smile of each person should be classified as smile.

In order to deal with this fact, we have modified the concept of the Eigenface method so that a separate subspace is formed for each facial expression of the human being, instead of having a single subspace for all expressions as in the original eigenface method. In other words, all six universal facial expressions will have their own expression space as a subspace of the image space as shown in figure 2.

With the expression subspaces available, we could then proceed for recognition of expression in any given image. Like the images for obtaining the expression subspaces, the new image is first turned to the corresponding column vector. We then take the expression subspaces, one at a time, and measure the distances between the new image vector and the subspaces. Whichever expression space having the shortest distance to the input image, the corresponding expression will be designated as the facial expression contained in the input image. A major difference of our approach from the original eigenface method is that, while in the original eigenface method it is the distance, in the same subspace, between the input image vector and the cluster center of each face identity is used for comparison, here it is the distance between the input image vector and the vector space of each facial expression that is used.

VI. RESULTS AND ANALYSIS

We have tested our method on the Cohn-Kanade facial expression database [32]. The database contains 97 university students with all six expressions (Happiness, Sad, Surprise, Fear, Anger and Disgust). From the database we have collected 90 images for training (fifteen for each expression). We have used one expression of one student for training. For testing we have taken 360 images (sixty for each expression) other than used for the training. The results are presented in form of confusion matrices. (Columns represent the emotion selected by our method for samples belonging to the emotion of each row). The cell values show how often a certain error (confusion) occurred.

The confusion matrices obtained with testing sets of Cohn-Kanade FE Database are given in table 1. In our earlier work [8], we have reported the effectiveness of this scheme for three expressions only (happiness, sad and surprised). In the present paper, we are extending the set of expressions to all six universal expressions. We have also increased the training images from 10 to 15 for each expression and expression subspaces are increased from three expressions to six expressions. We have also increased the testing images from 25 to 60.The accuracy rates are increased by 8 % for Happiness and by 23, 25 % in case of surprised and sad respectively when compared with our previous results. One of the reasons for this increase in recognition rate is that there is a clear correlation between performance and the total number of samples, more the number of samples the better the performance.

An analysis of the Confusion matrix for Cohn-Kanade FE Database (Table 1) suggests that the best-recognized category is Surprise 83 % followed by Happiness 80% even though Happiness and Surprise were often confused for each other. The system was confused and recognized happiness as surprise five times and in the same way recognized surprised as happiness six times. Possible reason might be, in both cases the mouth is widely opened.

Out of all expressions, Fear was the most confused expression, which was confused with all other expressions. According to Zhang [34], the expressers who are posing for expressions found that it is most difficult to pose fear expressions accurately. Further human has more difficulty in recognizing fear. According to Adolphs et.al. [35], there is evidence supporting this hypothesis that fear expressions are processed differently from the other basic facial expressions.

Another important observation to note is sad, anger and disgust are the three expressions, which are highly confused among each other. Approximately, eleven times they were confused with the other two expressions, which is very high. Even from the universal expressions shown in Fig. 1 we can observe all this three expressions are very close to each other. The difference between such expressions is hard to discriminate.

Further, we have also used JAFFE database [33] to test the effectiveness of the proposed method for facial expression recognition. JAFFE database contains 213 images of seven facial expressions (six basic expressions and neutral expression also) posed by ten Japanese female models. For training, we have used thirty expressions (five for each expression) and for testing, we have taken thirty images for each expression. We have used all expressions leaving neutral expression. The confusion matrices for JAFFE are given in table 2. Analysis of the confusion matrix of JAFFE (Table 2) suggests that the system was again maximum confused between Happy and surprised. In case of surprised it has six expressions classified as happy, this is the single largest confusion when compared with other expressions confusions.

VII. CONCLUSION AND FUTURE WORK

When analyzing facial expressions, we humans always consider context information of the situation, knowledge about the observed person, speech, voice, hand and body gestures. In a similar way, an automatic system would need to obtain and combine information from different cues. For a reliable expressions interpretation in human computer interaction, facial expression recognition therefore can only be considered, one part or module of a holistic approach.

Although humans recognize facial expressions virtually without effort or delay, reliable expression recognition by machine is still a big challenge. Compared with the facial expression recognition method based on the video sequence, the one based on the static image is more difficult due to the lack of temporal information. The main contribution of this paper is to investigate the facial expression recognition based on the static image and to propose a new recognition method using Eigenspaces. The proposed system was tested using Cohn-Kanade Facial Expression database and JAFFE database. The experimental results show the effectiveness of method proposed in this paper. As facial expressions plays important role in human-to-human communication, our future work is to develop a facial expression recognition system, which combines body gestures of the user with user facial expressions.

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Table 1: Confusion matrix for Cohn-Kanade FE Database

Expressions	Happiness	Fear	Surprise	Sad	Anger	Disgust	Accuracy rate
Happiness	**48**	5	5	0	2	0	80 %
Fear	3	**47**	2	3	2	3	78 %
Surprise	6	2	**50**	1	1	0	83 %
Sad	0	3	0	**46**	6	5	77 %
Anger	0	5	0	6	**45**	4	75 %
Disgust	2	4	0	5	6	**43**	72 %

Table 2: Confusion matrix for JAFFE Database

Expressions	Happiness	Fear	Surprise	Sad	Anger	Disgust	Accuracy rate
Happiness	**25**	2	3	0	0	0	83%
Fear	2	**23**	0	2	1	2	77%
Surprise	6	0	**24**	0	0	0	80 %
Sad	0	0	0	**22**	4	4	73 %
Anger	0	2	0	3	**21**	4	70%
Disgust	0	3	0	3	4	**20**	67%

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