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Techniques for Facial Expression Recognition In Computer Graphics

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Abstract—Facial expressions are the means through which people interact with others, conveying their feeling of happiness, sadness, contempt, etc. The expressions convey non-verbal cues, which play an important role in interpersonal relations. We humans having a very essential part in our body 'the brain' which can construe the expressions of others very easily, but, this liberty has not been granted to machines. They need to be explained of what humans are trying to express. This is where the technology of facial expression recognition comes into the picture. Automatic recognition of facial expressions can be an important component of natural HCI interface; it may also be used in behavioral science and in psychological fields. Deducing an effective facial expression from original face is a criticalprerequisite for the success of facial expression recognition. In this paper, we present an overview of different methods used in the field of facial expression recognition; highlighting the major components and the recent advancements in this field.

Key Words—facial expression, expression recognition, methods in recognition, robotics, LDA, neural networks.

I. INTRODUCTION

Afacial expression is a reflection of the state of mind of a person. Facial expressions, and other gestures, convey non-verbal communication cues in face-to-face interactions. These cluesembellish the speech by helping the listener to understand the intended meaning of spoken words.Studies on Facial Expressions and Physiognomy date back to the early Aristotelian era (4th century BC). Physiognomy is the assessment of a person's character or personality from their outer appearance, especially the face. The idea that a person's character can be judged from his face is relatively ancient[1]. Universally seven expressions of emotions are accepted. Figure 1 illustrates all the expressions.

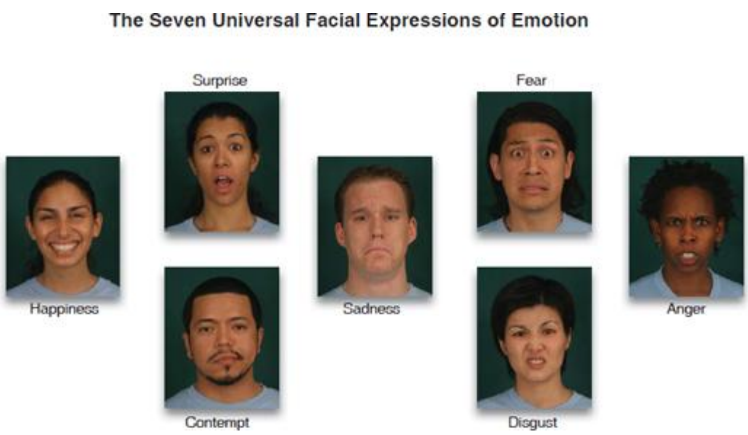

Figure 1.Demonstrating the seven universal expressions of emotion.

The foundational studies on facial expressions that have formed the basis of today's research can be traced back to the 17th century.In 1872, Darwin wrote a treatise that established the general principles of expression and the means of expressions in both humans and animals [2]. He also grouped various kinds of expressions into similar categories. The categorization is as follows:

- low spirits, anxiety, grief, dejection, despair
- joy, high spirits, love, tender feelings, devotion
- reflection, meditation, ill-temper, sulkiness, determination
- hatred, anger
- disdain, contempt, disgust, guilt, pride
- surprise, astonishment, fear, horror
- self-attention, shame, shyness, modesty

II. APPLICATIONS

Facial expression recognition when combined with face acquisition, facial data extraction and representation forms altogether what is known as the facial expression analysis system. With the forward motion of technology in stuff like robotics and blue brain the expression recognition has to cope with the changing environment. For robots to communicate efficiently with homo-sapiens they have to understand the human nature; their mood swings, through expressions. Expression recognition systems will help in creating this intelligent visual interface between the man and the machine.Other than the two main applications, namely robotics and HCI(Human Computer Interaction), expression recognition systems can come in handy in a ton of other arenas like behavioral science, video games, animations,televisions, Educational Software, etc.

Practical real-time applications have also been demonstrated. Bartlett et al. have successfully used their face expression recognition system to develop an animated character that mirrors the expressions of the user (called the *CU Animate*) [2]. They have also been successful in deploying the recognition system on Sony's *Aibo*Robot and ATR's *RoboVie*[2]. Another interesting application has been demonstrated by Anderson and McOwan, called the *'EmotiChat'* [3]. It consists of a chat-room application where users can log in and start chatting. The face expression recognition system is connected to this chat application and it automatically inserts emoticons based on the user's facial expressions. With the technological era approaching, the future of facial expression recognition has a lot of applications and implementations ahead.

III. METHODOLOGIES

Many methods have been applied to facial expression recognition systems such as neural network (NN), supportvector machines (SVM), linear discriminant analysis (LDA), K-nearest neighbor, multinomiallogistic ridge regression (MLR), hidden Markov models (HMM) and others. Here, we would just represent a brief idea about the following methods only:

3.1 Linear Discriminant Analysis (LDA)

This method requires large sets of example databases including various expressions from different test subjects. After labeling all subjects in the training set and havingdefined all the classes, the computationof the scatter matrices is done through the following equations(Equations used from[4]):

$$S_w^{(V)} = \sum_{i=1}^{L} \Pr(C_i)\Sigma_i , \qquad -(1)$$

$$S_b^{(V)} = \sum_{i=1}^{L} \Pr(C_i)(\mu - \mu_i)(\mu - \mu_i)^T. \quad \text{-(2)}$$

Here *Sw*is the within-class scatter matrix showing theaverage scatter summation(*i)*of the sample vectors (*V*) of differentclasses *Ci*around their respective mean, vectors μ_i:

$$\Sigma_i = E[(V - \mu_i) \times (V - \mu_i)^T | C = C_i]. \quad \text{-(3)}$$

Similarly, $S_b$is the between-class scatter matrix, representingthe scatter of the conditional mean, vectors (μ_i)around the overall mean vector µ. Pr*Ci*is the probabilityof the *i*th class. Thediscriminatory power of a representationcan be quantified by using various measures.In this paper we use the separation matrix, which showsthe combination of within- and between-class scatters ofthe feature points in the representation space. The classseparation matrix and a measure of separability can becomputed as

$$S^{(V)} = S_w^{-1} S_b \quad \text{-(4)}$$

$$J_V = \text{sep}(V) = \text{trace}(S^{(V)}) \quad \text{-(5)}$$

JV is our measure of the discrimination power (DP) of agiven representation *V*. As mentioned above, the representationmay correspond to the data in its original form(e.g., a gray-scale image), or it can be based on a set of abstractfeatures computed for a specific task.For example, through this analysis we are able to comparethe DP's of different spatial segments (components)of a face. We can apply the analysis to segments of theface images such as the areas around the eyes, mouth,hair, and chin or combinations of them. Figure 2 shows aseparation analysis for horizontal segments of the faceimages in the database. The results show that the DP'sof all segments are comparable and that the area betweenthe nose and the mouth has more identification informationthan other parts. Figure 3 shows that the DP of thewhole image is significantly larger than the DP's of itsparts.

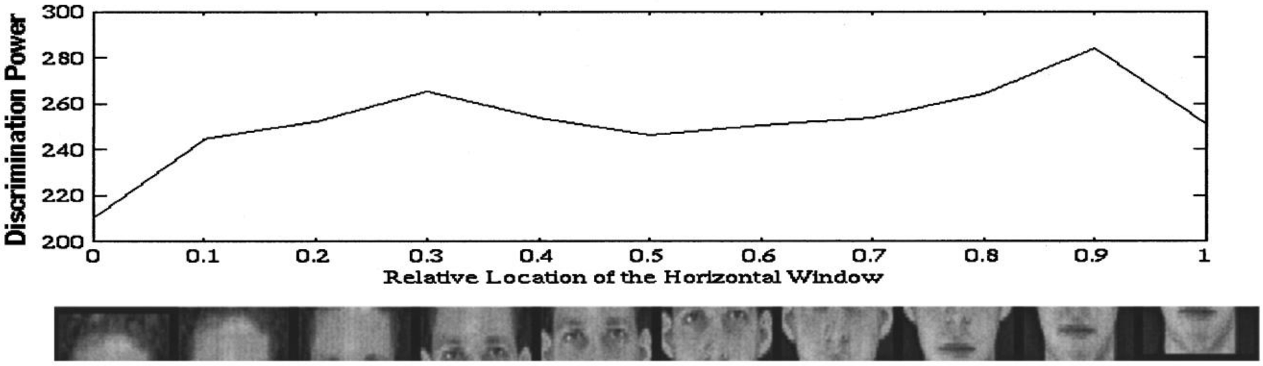

***Figure 2.Variation of the discrimination power of horizontal segments of the face defined by a window of fixed height sliding from top to bottom of the image.*[4]**

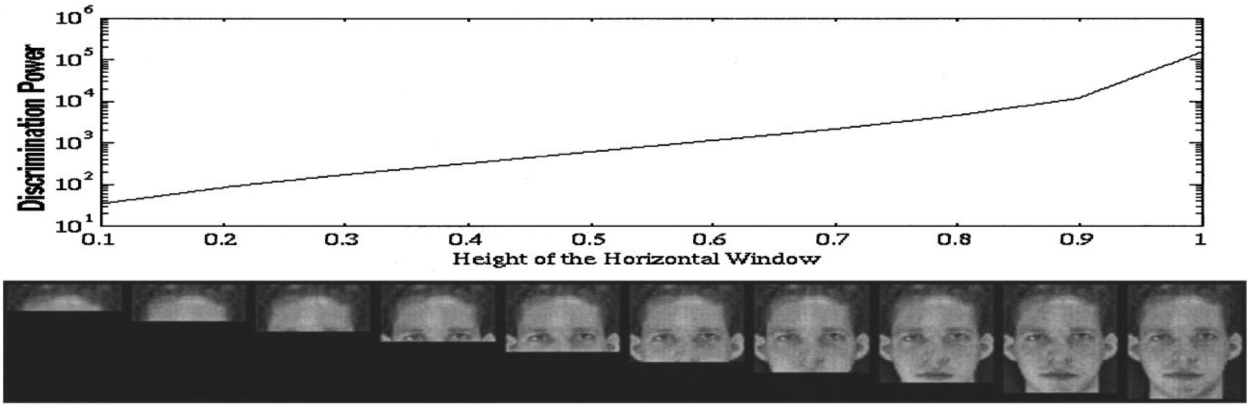

***Figure. 3. Variation of the discrimination power of a horizontal segment of the face that grows in height from top to bottom of the image.*[4]**

3.2 Neural Networks

This network comprises of a 4 layer modular neural structure. The input layer has 192units corresponding to the 24x8 pixels of the area croppedfrom the original images. Every input neuron transmits informationthrough a single hebbian weight, projecting to aspecific neuron in the first hidden layer, selected accordingto a self-organized process[5]. After this one has a reduced image of 48 neurons which still has all the characteristics of the original image. Thewhole network architecture is depicted in figure 4, where atthe top we have a sample input image. Then there are the receptive fields continued by unsupervised compression.This method typically divides the expression sets into different types of happiness, sadness and surprise. There are 3 neurons for neutral face which should be OFF when such a face is detected. Also as happiness and surprise can be easily identified, 3 neurons are enough for that while 4 for sadness. Thestructure of the modules could depend on the emotion theypertain to; in this case wherethey all have thesame type of architecture: one hidden layer fully connectedwith one output unit. There is a difference in the number ofhidden neurons belonging to each module since the recognitionof happy and surprised faces is much easier than therecognition of sad ones, a fact that was previously knownfrom experiments both with humans and computers.

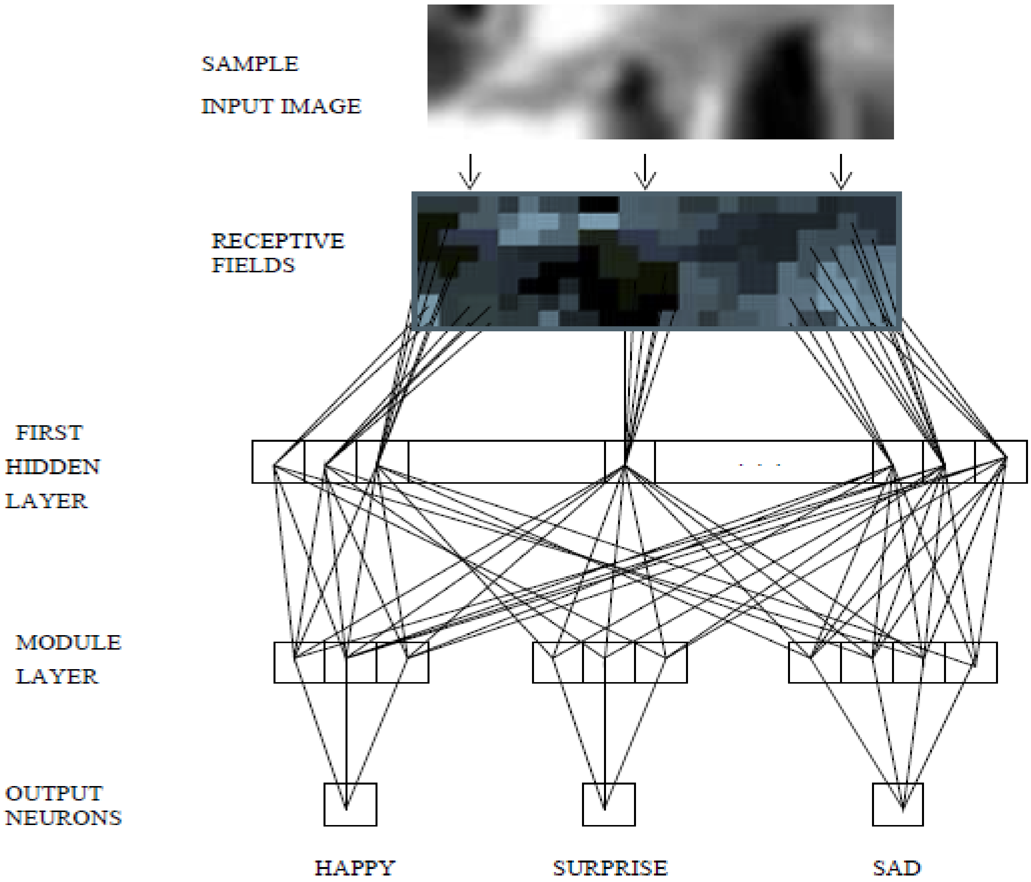

Figure 4. Schematic structure of the network architecture used to perform facial expression recognition **[5]**

Table 1. Generalization error rates for the modules, specialized in happy, sad and surprise faces**.[5]**

Expression Module	Error (SORF-Hebbian)	Error (PCA)	Error (Random)
Happy	0.057	0.082	0.089
Sad	0.044	0.032	0.154
Surprise	0.053	0.053	0.071
Total	0.154	0.167	0.314

IV. CONCLUSION

From all the above mentioned information this becomes axiomatically correct that it is not as easy as we speak; to make machines understand human interpretations. The methods involve a lot of mathematical equations and formulas yet they have not been highly efficient in recognizing the facial expressions accurately. Moreover, we have the essential technology required for this field but there has not been much high research in the direction of this particular field. We can identify the basic emotions quite easily but when it comes to some ambiguous expressions like happiness and surprise, the machine finds it pretty difficult to differentiate. By far LDA when implemented with local binary pattern recognition method shows the most prominent results. LDA mainly deals with mathematical terms and plotting the pixels based on the matrices. The major part of this paper for this method goes to K. Etemad and R. Chellappa and their research work. Also neural networks provide quite a promising future in the coming years. There are other methods too in this field which will strive in the near future, but this field requires a highly contributed and supportive mass for its upbringing.

REFERENCES

[1]R. Highfield, R. Wiseman and R.Jenkins, *"How your looks betray your personality"*, New Scientist, Feb 2009.

[2] VinayBettadapura, " Face Expression Recognition and Analysis: The State of the Art",Arxiv , March 2012.

[3] K. Anderson and P.W. McOwan, "A Real-Time Automated System for Recognition of Human Facial Expressions," *IEEE Trans. Systems, Man, and Cybernetics Part B,*vol. 36, no. 1, pp. 96-105, 2006.

[4] K. Etemad and R. Chellappa, "*Discriminant analysis for recognition of human face images" ,*Journal of Optical Society., August 1997.

[5] Leonardo Franco, Alessandro Treves *"A Neural Network Facial Expression Recognition System using Unsupervised Local Processing",* Researchgate.

