Facial Expression Recognition Using Neural Network Trained with Zernike Moments

Mohammed Saaidia Dept. Génie-Electrique Université M.C.M Souk-Ahras Souk-Ahras, Algeria mohamed.saaidia@univ-soukahras.dz

Abstract—Neural network classifying method is used in this work to perform facial expression recognition. The processed expressions were the six most pertinent facial expressions and the neutral one. This operation was implemented in three steps. First, a neural network, trained using Zernike moments, was applied to the set of the well known Yale and JAFFE database images to perform face detection. In the second step, detected faces are processed to perform the characterization phase through computed vectors of Zernike moments. At last step, a back propagation neural network was trained to distinguish between the seven emotion's states of a presented face. Finally, method performances were evaluated on the well known JAFEE and YALE database.

Keywords-face detection; face expression recognition; image analysis; patern recognition

I. INTRODUCTION

The first works on this human phenomenon were initiated by psychologists who have studied the individual and social importance. They showed that it plays an essential role in coordinating human conversation [1] through the multitudes of information it conveys. Moreover, Mehrabian [2] showed that the textual content of a message is limited to only 7% of its overall impact, while the tone of the speaker's voice participates by 38% and facial expressions by 55 %. Recognition of any facial expression is linked to several semantic concepts that make this problem difficult to manage given the relativism that generates on solutions found. Thus, it is quickly pointed to distinguish between 'expression' and 'emotion'. Indeed, this last term is only a semantic interpretation of the first as the term 'happy' to 'smile'. A facial expression can be the result of an emotion or not (for example simulated expression). So a facial expression is simply a physiological activity of one or more parts of the face (eyes, nose, mouth, eyebrows,...) while an emotion is our semantic interpretation to this activity. However, given the difficulties still encountered in this area, we can still ignore this subtlety. The significant advances in several related fields such as image processing, pattern recognition, detection and face recognition, allowed to take of the studies of this phenomenon from the field of human psychology to the automatic analysis, classification, synthesis, and even expressive animation [3]. T The different works that have been carried out to date were all oriented to the study and classification of facial expressions

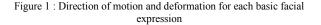
Narima Zermi and Messaoud Ramdani

Dept. Electronique Université B.M Annaba Annaba, Algeria narima.naili@univ-annaba.dz

called basic expressions (universally recognized); six in all and are summarized on Figure 1:



angry disgust happiness fear surprise sadness



Multitude of methods which were developed, can be classified according to the parameterization step in the recognition process or to the classification one [4].

According to the first step, methods are "based motion extraction" [5], [6] or "based deformation extraction" [7], [8]. According to the classification step, methods can be "spatial methods"[9], [10], or "spatiotemporal methods" [11], [12]. Method proposed here, is a "spatial model based motion extraction" one.

Another way to perform classification task is the way to characterize the face. Some methods process the face globally although some other methods extract face futures before performing characterization.

So, the recognition of facial expression can be approached in several ways. In this work, we propose to exploit the geometrical moments, especially those of Zernike, to perform facial expression recognition. This type of characterization was fully used in face recognition [13], [14]. The encouraging results obtained in these works allow to state that if this kind of characterization (by Zernike moments) enables efficient classification in inter-persons classification so we can pretend to better results in intrapersons classification problem like facial expressions recognition.

In second section of this paper we will present and explain the way to perform face detection and characterization. In third section, method implementation is explained. Experimental results are presented and discussed in fourth section. Section five will be reserved to the conclusions and future possible enhancements.

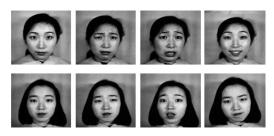


Figure 8: Example of two subjects from JAFFE database with three different expressions for each one. Up: Neutral, Disgusted, Afraid and Happy. Down: Neutral, Sad, surprised and Angry.

II. NEURAL NETWORK CLASSIFIER

The second element of our classification system is the analysis and decision part. In the field of pattern recognition and especially that of the facial expression recognition, several types of classifiers have been proposed and used. It is based on the use of three main theories of classification, namely, the HMM (Hidden Markov Models) [20], [21], the SVM (Support Vector Machines) [22] and neural networks [23], [24]. These three systems can cope with the challenges of real classification problems that are non-linearity, dimensionality and generalization. Neural networks have proven effective in many areas of practice shape recognition such as handwriting recognition, speech analysis or robot control.

III. EXPERIMENTAL RESULTS

In order to check the validity of our proposed method, experimental studies were carried out on the well known Yale and JAFFE images databases [25][26]. Yale database contains 4 recordings of 15 subjects taken for three different expressions (Happy, Sad and Surprise) and the neutral expression. Instead, JAFFE database contains only female subjects with the six well known and most studied expressions (Happy, Fear, Sad, Surprise, Disgust and Anger) in addition to the neutral expression. Figure 7 and figure 8 give examples of images with different expressions from the two databases.

Experiences were carried out separately on each database. To obtain the training database for Yale images we have take randomly 10 images of different people, each one with 4 different recordings, so that it gives us 40 couples (Zi,Ci) and (Zn,m, T) examples for training the neural networks. For JAFFE database we took randomly 2 images for each person with each expression so we obtain a training database with 80 couples (Zi,Ci) and (Zn,m, T) examples.

Obtained results will be detailed in the following subsections.

A. General results

Table I and table II give the results obtained applaying the previously described method to Yale and JAFFE database with a randomly chosen parameters m and n.

TABLE I. RESULTS OBTAINED FOR 'YALE' DATABASE.

real Expression Detected Expression	Neutral	Hap.	Surp.	Angry	TPR %	FPR %
Neutral	4	1	1	2	40	40
Happy	1	7	1	1	70	30
Surprise	2	2	6	1	60	50
Angry	3	0	2	6	60	50
	Global TPR				57.5	

TABLE II. RESULTS OBTAINED FOR 'JAFFE' DATABASE.

Expression real Expression Detected	Neutral	Hap.	Surp.	Angry	TPR %	FPR %
Neutral	8	0	0	2	80	20
Нарру	0	9	1	0	90	10
Surprise	0	2	7	2	70	40
Angry	1	0	1	8	80	20
	Global TPR				80	

B. Sensitivity to m and n parameters

As already indicated, the values of parameters n and m not only influences the number of elements of the feature vector but, more importantly, it influences the discriminative ability between different expressions of the same face. This remark pushed us to study the influence of these parameters on the quality of the classification process. Table III and table IV report the recorded results for different values of the couple (m,n).

TABLE III. RESULTS OBTAINED FOR 'YALE' DATABASE.

Expression	Re	Global			
Couples (n,m)	Neutral	Нар.	Surp.	Angr y	TPR %
(3,1)	10	30	20	10	17.50
(4,2)	10	30	20	10	17.50
(4,3)	10	30	30	10	20.00
(5,1)	10	30	20	20	20.00
(6,3)	10	30	30	20	22.50
(6,5)	20	40	40	20	30.00
(9,5)	40	60	60	50	52.50
(10,5)	40	70	60	60	57.50
(12,5)	60	70	70	70	67.50
(12,7)	60	80	70	70	70.00
(12,10)	70	80	70	70	72.50
(12,11)	60	80	80	70	72.50
(15,11)	60	80	70	60	67.50
(17,11)	40	70	70	50	57.50
(20,11)	20	60	60	30	42.50

Expression		Globa l TPR			
Couples (n,m)	Neutral	Hap.	Surp.	Angry	%
(3,1)	50	50	43	50	48,25
(4,2)	50	55	47	53	51.25
(4,3)	50	57	51	53	52.75
(5,1)	63	63	60	60	61.50
(6,3)	70	75	68	69	70.50
(6,5)	71	83	68	71	73,25
(9,5)	80	90	73	78	80.25
(10,5)	80	90	70	80	80.00
(12,5)	85	92	73	86	84.00
(12,7)	90	92	73	89	86.00
(12,10)	92	95	81	90	89.50
(12,11)	87	92	78	90	86.75
(15,11)	87	92	78	83	85.00
(17,11)	71	87	70	78	76.50
(20,11)	61	76	63	70	67.50

TABLE IV. RESULTS OBTAINED FOR 'JAFFE' DATABASE.

IV. COCLUSION

Facial expression recognition method was proposed. Recognition process was achieved in two principal steps; face detection and face expression recognition. The study was especially focused on the second step. Arguments were presented to justify characterization choices and the way to implement proposed method was detailed. Practical study was carried out on the well known Yale and JAFFE database. Recorded results were presented and commented.

More detailed studies have to be achieved to explore all classifier parameters and to improve method performances.

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