FACIAL EXPRESSION IDENTIFICATION SYSTEM WITH EUCLIDEAN DISTANCE OF FACIAL EDGES

S. Kherchaoui[1], A. Houacine[2]
LCPTS, Faculty of Electronics Computer Science
USTHB, BP32 El Alia, Bab Ezzouar,
Algiers, Algeria.
[1]ainos04@yahoo.fr
[2]ahouacine@usthb.dz

Abstract— **In this paper we present facial expression recognition system. Identification and classification is performed on the seven basic expressions: happy, surprise, fear, disgust, sad, anger and a neutral state. This system consists of three main parts. The first step is the detection of the face and facial features to extract the face centered region.Next step consists of a normalization of this interest region and edge extraction. At this step we have a face edge image that we use to calculate the Euclidean distance of all pixels that constitute edges. The third step is the classification of different emotional state by the SVM method.**

Keywords-facial expression identification; edge detection; euclidian distance; support vector machine (SVM).

I. INTRODUCTION

Facial expression is a visible manifestation of the affective state, cognitive activity, intention, personality, and psychopathology of a person. Mehrabian [15] reported that facial expressions have an important effect on the person we are talking to; the facial expression of a speaker accounts for about 55% of the effect, 38 % of the latter is conveyed by voice intonation and 7 % by the spoken words.

The detection of the emotional state of a person or the identification of the facial expressions (facial expression recognition FER) is a difficult task. There are many different difficulties due to the variations of the human population expressions and the surrounding contexts for the same individuals. In fact, even the human beings can badly interpret their facial expressions. The information that facial expressions carry can play an important role when humans interact with machines. There are three main tasks to construct a Facial Expression Recognition System, namely face detection, facial feature extraction, and emotion classification.

Several researchers addressed Face detection through several methods such as using neural networks [1, 2] and support vector machines SVM [21], or by exploiting the invariable characteristics like skin color or some particular facial features. The facial feature extraction constitutes an attempt to find the most appropriate image representation for face expression identification and interpretation of their emotional states.

An important milestone in the study of facial expressions and human emotions is the work carried out by the psychologist Paul Ekman and his colleagues since the 1970s. Their work has a meaningful importance and a large influence on the development of the modern automatic facial expression recognition,as it established its universality [11]. They defined seven basic expressions (joy, fear, surprise, disgust, sadness, anger, and neutral expression). Ekman and Freisen [12] have developed Facial Action Coding Systems "FACS" described by 44 units of action coding. These actions do not contain emotions, and their identification is done through other systems.

We can categorize the expression recognition techniques into two main approaches namely the holistic [4] and the geometric approaches [3].

Holistic methods include model based techniques analyzing the entire face, which is then considered as one global pattern without decomposing the face to components. A feature vector, representing the expression information, is obtained after processing the face image. Many transforms have been applied for facial expression feature extraction, like Gabor wavelet [22], curvelets [18], and local binary pattern [17, 19]. A principal component analysis is often used for dimensionality reduction, and multilayer neural networks or support vector machines are widely used for classification [3, 8].

The analytic or geometric feature based methods divide the face into smaller components or sub-section from which the expressions can be identified. Characteristic points are detected, and distances between characteristic points are calculated to form the feature vectors or build a model of appearance [7, 9, 10]. The system presented here can be identified as a holistic approach.

The paper is organized as follows. In section two are described the processing steps involved by our expression identification system, as localization of the face and its features, extraction of facial edges, computation of Euclidian distance map of edge pixels, and classification by SVM. In section three, we present the data used for performance evaluation and present the experimental results. Finally, a conclusion is given in a last section.

II. Facial expression identification system

FER system presented here is divided into three parts:

1. Face and facial features detection.
2. Normalization and features processing.
3. Facial expressions classification by SVM classifier.

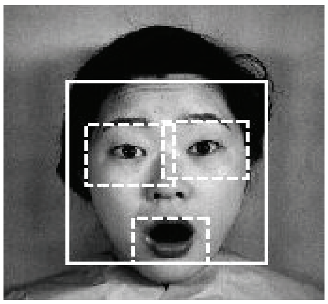

Figure 1. Face and facial features localisation.

A. Face and facial features detection

The system described below is designed to identify seven basic facial expressions which are: joy, fear, surprise, disgust, sadness, anger and neutral expressions. Face and facial feature detection is done according to the Viola and Jones method [4, 16]. The facial features considered are the eyes and the mouth. Their respective regions within the face are localized according to the Viola and Jones detection algorithm [4, 16]. This algorithm provides competitive detection rates in real-time. Although it can be trained to detect a variety of object classes, it was motivated primarily by the problem of face detection.Viola and Jones used the Haar-like features that bear some resemblance to Haar basis functions, previously used in the realm of image-based object detection.

1) Extracting the region of interest

The aim of this part is to limit the region of interest on the face localized, tacking care of including the facial features detected.

We have localized the eyes and the mouth regions; we may then easily determine the boundaries of the region of interest by considering the limits of the eyes and mouth regions as follows:

$$Upper\ Lim = (lim\ left\ eye\ up + lim\ right\ eye\ up)/2$$

$$-(witdh\ left\ eye + witdh\ right\ eye)/2 - cst$$

cst is an experimentally determined value.

$$Left\ lim = left\ lim\ left\ eye.$$

$$Right\ lim = right\ lim\ right\ eye.$$

$$Lower\ lim = lower\ lim\ mouth + (witdh\ mouth/2)$$

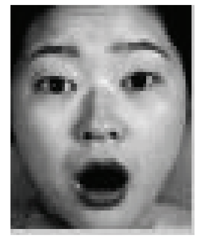

Figure 2. Face region of interest

2) Normalization of face region of interest image

The determined interest region is normalized to size of 60 by 60 pixels. The simple nearest neighbor interpolation is used for this resizing.

B. Face edge extraction

The facial expression changes with the emotion, the face translates this variation by expression wrinkles; as by modification of the feature contours and appearance of particular wrinkles around the mouth and eyes within the face. For this, we apply the Canny edge detector [20] on the face region of interest image. A threshold is selected to localize main facial contours and most of expression wrinkle edges.

a) Canny edge detector

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images [20]. Canny also produced a computational theory of edge detection. Its algorithm runs in five separate steps:

- Smoothing: Blurring of the image to reduce noise.
- Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.
- Non-maximum suppression: Only local maxima should be marked as edges.
- Double thresholding: Potential edges are determined by thresholding.
- Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a strong edge.

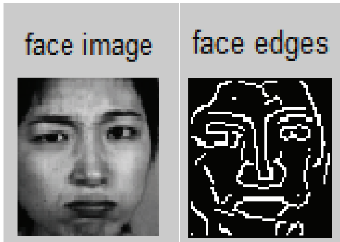

Figure 3. Face edges.

b) Euclidean distance of facial edges image

To each pixel in facial binary edge image, the distance transform assigns a number that is the distance between that pixel and the nearest nonzero (white) pixel of the facial edges. We use the Euclidean distance metric, of facial edges. The matrix of distances is of the same size as the facial edge image. It is converted to a vector by concatenating rows for the classification task.

C. Classification using SVM

Support vector machines SVM is employed in our system to perform the classification task. SVM is a popular technique for classification [6].

SVM performs an implicit mapping of data into a higher dimensional feature space, where linear algebra and geometry can be used to separate data that is only separable with nonlinear rules in the input space. Given a training set of labelled examples $T = \{(x_i, y_i), i = 1 \ldots\ldots l\}$ where $x_i \in R^n$ and $y_i \in \{1, -1\}$ the new test data is classified by the following function:

$$f(x) = sgn(\sum_{i=1}^{l} a_i y_i \, k(x_i, x) + b \qquad (2)$$

Where $k(x_i, x)$ is a kernel function, a_i are Lagrange multipliers of the dual optimization problem, andb is the parameter of the optimal hyperplane. Given a nonlinear mapping ϕ that embeds input data into feature space, kernels have the form of $k(x_i, x) = \langle \phi(x_i).\phi(y_j) \rangle$ the SVM finds a linear separating hyperplane with the maximal margin to separate the training data in feature space.

SVM allows domain-specific selection of the kernel function. Though new kernels are being proposed, the most frequently used kernel functions are the linear, polynomial, and RBF kernels. SVM makes binary decisions.

Multi-class classification here is accomplished by a cascade of binary classifiers together with a voting scheme.

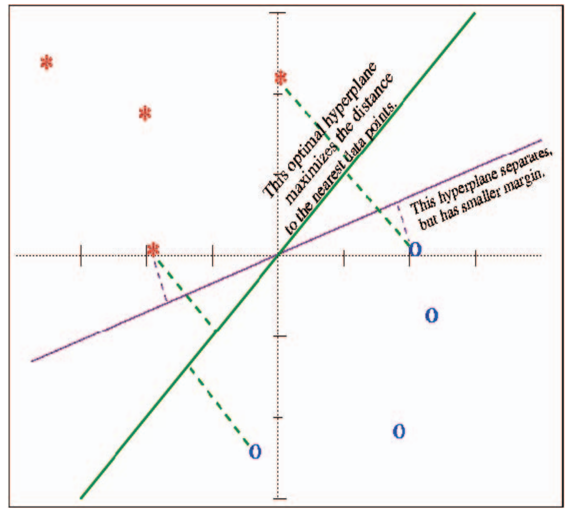

Figure 4. The Optimal hyperplane

The multiclass SVM can be obtained by two methods. The most popular decomposing strategy is the “one against all”, which consists of building one SVM per class, trained to distinguish the samples in a single class from the samples in all remaining classes. Another popular strategy is the “one against one”, which builds one SVM for each pair of classes. For a problem with c classes, c (c-1) /2 SVMs are trained to distinguish the samples of one class from the samples of another class. Usually, classification of an unknown pattern is done according to the maximum voting, where each SVM votes for one class.

For the system presented here we have used the one against one strategy with 21 classifier pairs for the seven considered classes.

III. RESULTS

For training and evaluation of the system we used the JAFFE (Japanese Female Facial Expression) Database [5]. The JAFFE database contains 213 face images with seven facial expressions; six basic expressions plusone neutral. The 213 images represent ten Japanese women hence the name given. We explore the effectiveness of the system presented in this paper by identifying the seven facial expressions.

We used 139 images from JAFFE database for training and 74 images for testing. We have taken two images per emotional state for each subject when available.

TABLE I. RECOGNITION RATE RESULTS

State	Ang.	Disg.	Fear	Hap.	Neut.	Sad.	Surp.
Rate %	90	88.88	91.66	100	91.66	100	90

TABLE II. CONFUSION MATRIX

State	Ang.	Disg.	Fear	Hap.	Neut.	Sad.	Surp.
Ang.	9	1	0	0	0	0	0
Disg.	0	8	1	0	0	0	0
Fear	0	1	11	0	0	0	0
Hap.	0	0	0	11	0	0	0
Neut.	0	0	0	0	11	1	0
Sad.	0	0	0	0	0	10	0
Surp.	0	0	1	0	0	0	9

The correct identification of facial expressions rate is 93.24%. The best rate is for the happy and neutral expression with 100% accuracy.

The facial expression identification system was implemented on matlab 8.1, the tests were carried out on an i5-3210M machine and the execution time is 1.62 seconds.

The proposed method performance is comparable to existing techniques that used the JAFFE database as illustrated in Table II.

TABLE III. COMPARISON

The FER system	**Identification rate**
Curvelet Feature Extraction for Face Recognition and Facial Expression Recognition [18]	94.74%
Application of Complete Local Binary Pattern Method for Facial Expression Recognition [17]	More than 80%
Recognition of Facial Expressions using Local Binary Patternsof Important Facial Parts [19]	More than 94%
Recognizing facial expression: Machine learning and application to spontaneous behaviour [14]	More than 93%

IV. CONCLUSION

We presented a fully automatic recognition system of facial expressions, based on Canny edge detection, Euclidean distance map, and support vector machines.

The system presented in this article gives a very encouraging detection rate associated to a very interesting processing time. Only basic processing tasks are involved leading to an easy implementation. The system thus introduced opens prospects for improvement as the enlargement of the learning data to overcome the limitations of the JAFFE database. Other geometric parameters may be considered and evaluated in the future.The performance of this system depends on the accuracy of the methods for detecting facial features and edge extraction.

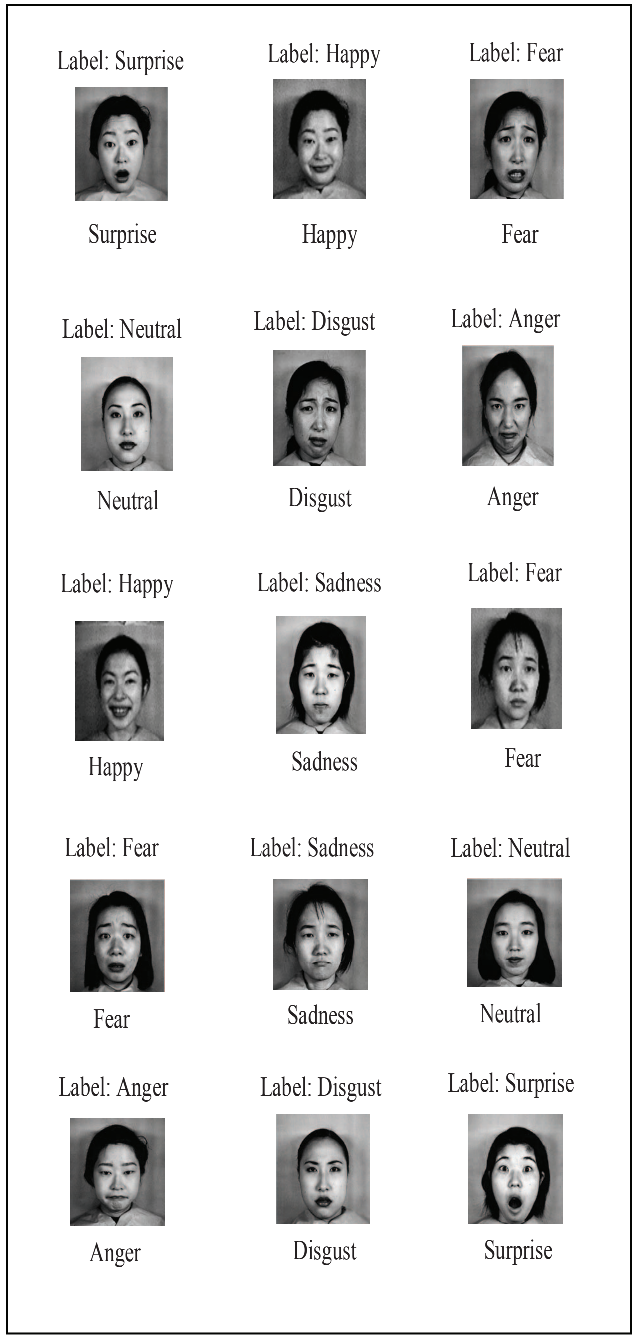

Figure 5. Example of true facial expression identification

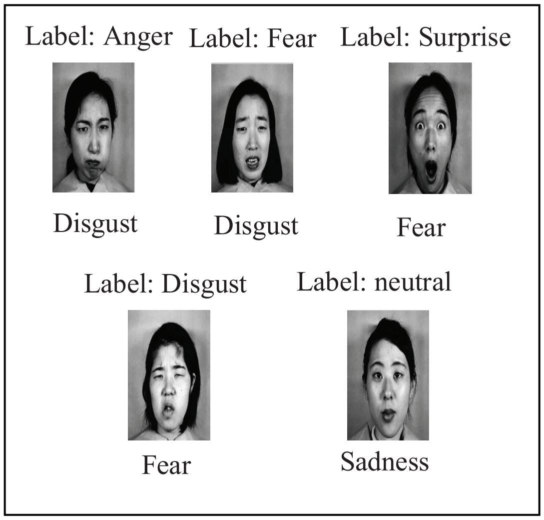

Figure 6. Example of false facial expression identification

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