Multiple Image Characterization Techniques for Enhanced Facial Expression Recognition

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Abstract— this paper describes an enhanced facial expression recognition system. In the first step, the face localization is done using a simplified method, then the facial components are extracted and described by three feature vectors: the Zernike moments, the spectral components' distribution through the DCT transform and by LBP features. The different feature vectors are used separately then combined to train back-propagation neural networks which are used in the facial expression recognition step. A subset feature selection algorithm was applied to these combined feature vectors in order to make dimensionality reduction and to improve the facial expression recognition process. Experiments performed on the JAFFE database along with comparisons to other methods have affirmed the validity and the good performances of the proposed approach.

Keywords—face detection; expression recognition; DCT transform; Zernike moments; LBP; MIFS; NMIFS.

1 Introduction

Facial expression recognition is still a hard research area with many challenges to meet. This is mainly due to several semantic concepts related to, the amalgam between the terms 'expression' and 'emotion' ; the latter one being only a semantic interpretation of the former as the term 'happiness' to 'smile'[1]. So a facial expression is a simple physiological activity of one or more parts of the face (eyes, nose, mouth, eyebrows,...) [2], while an emotion is our semantic interpretation to this activity. This problem is still difficult to disentangle especially as our mathematical models do not have the ability to create the semantic dimension in the representation of our environment.

Another serious constraint which is also pointed out is the cultural background related to the ethnicity of the person [3], [4]. Technical problems related to the acquisition devices and variation in illumination conditions also make the problem harder [5]. Most researches have been turned towards the study and classification of the six basic facial expressions (universally recognized) summarized on Fig 1.

Developed methods can be classified according to several criteria. Taking into account the way how to characterize the face, methods are "motion extraction" [8] or "deformation extraction" [9]. According to classification techniques, methods are "spatial methods" [10] or "spatiotemporal methods" [11]. Facial expression recognition methods can also be classified according to the way how to consider the face; as a single entity which will lead to "global process" or as a set of features (eyes, nose and mouth) which have to be extracted before performing characterization step.

Fig. 1 : Example of Basic facial expressions from the JAFFE database

In the present work, a multi-feature representation with a subset feature selection was done on the face features (eyes, nose and mouth) instead of the whole face. This choice is justified by psychological [12].

Thus, three different representations were computed. The first one aims to extract the geometric information, while the second one exploits the well known LBP technique to resume the statistical luminance information and the last one computes the spectral source model of the face by the DCT transform. Finally, combined feature vectors were used to recognize the six basic facial expressions.

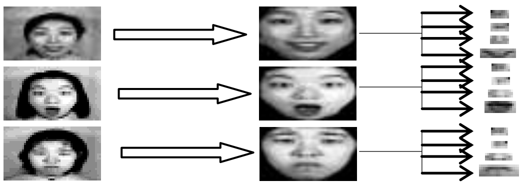
The paper is structured as follows: Section 2 outlines the facial feature extraction. Section describes the various characterization methods. Then, Section 4 presents the subset feature selection procedure based on mutual information. Experimental results are given in section 5. Finally, a general conclusion is given.

2 Facial components detection

Face expression recognition can be done on different information supports like images with single face, multi-face images, video, etc. Abstracting the semantic information, processed by human brain; a face in an image remains a common object with specific geometric and color characteristics so we need to isolate the target which will be subject to the expression processing (“face”). Face detection is one of the most studied problems in computer vision [13]. However, we are interested in face features of the face itself since Psychologists have demonstrated that the eyes, eyebrows, mouth and nose are the areas of the face on which appear the overall facial expressions [12]. So, important processing time will be avoided by characterizing facial components instead of the whole face.

Facial components detection was widely studied and different techniques were developed beginning by Yuille et al. [14] until recent works as Jongju Shin et al. [15]. In our work we made use of the well known and efficient method developed by viola and Jones [16] based on the evaluation of Haar-like features through the compilation of the integral image then the huge number of obtained features is processed by an AdaBoost algorithm [17] to focus on the main important features only. At the last stage, a structure of complex classifiers is used to enhance the speed of the election process by focusing attention on promising regions of the image.

To perform efficient facial components detection, the previous technique was used for both face detection and facial features localization. Fig. 2 gives some examples.



(a) (b) (c)

Fig. 2 : Examples of processed images from JAFEE database (a) original image, (b) detected face and (c) detected facial features

Face detection and facial features detection were performed with high rated results. Indeed, 95% of True Positive rate (TPR) was obtained for face detection and up to 88.7% of TPR average rate for all facial features. This is due not only to the technique's efficiency but also to the simplicity of the database which is composed by images containing a unique person with the same gender in frontal pose.

3 Face features' characterization

In pattern recognition, the dimensionality problem is one of the most difficult constraints that rises when we try to directly process the acquired environmental information [18]. So we have to find an alternative representation of the processed information object; like face features in our case. Instead of the matrix of pixels, we have to find a reduced representative vector which compact the information needed for our processing task. This is what we call a characterization phase.

In the present work, we tried to exploit different ways to perform this characterization in order to enrich the representative feature vector. Three different types of information are used ; Zernike moments, to compact image's geometric characteristics; LBP method which is considered as the most significant way to characterize texture information of the image and DCT transform to obtain its spectral components distribution.

3.1 Face features' characterization by Zernike moments

Zernike moments form part of the general theory of the geometrical moments. They were introduced initially by F. Zernike [19]. At the difference of the general geometrical moments, those of Zernike are built on a set of orthogonal polynomials which were used as the basic elements of the construction of an orthogonal base given by the equation (1)

$$\mathrm{V}_{\mathrm{n,m}}(\mathrm{x},\mathrm{y}) = \mathrm{V}_{\mathrm{n,m}}(\rho,\theta) = \mathrm{R}_{n,m}(\rho).\mathbf{e}^{\mathrm{j.m}.\theta} \qquad (1)$$

$$\begin{cases} \mathrm{R}_{\mathrm{n,m}}(\rho) = \displaystyle\sum_{k=|m|}^{n} \frac{(-1)^{(n-k)/2}.(n+k)!}{(\frac{n-k}{2})!(\frac{k+m}{2})!(\frac{k-m}{2})!}.\rho^{k} \\ \rho = \sqrt{x^2+y^2} \quad \text{and} \quad \theta = arctg(y/x) \end{cases} \qquad (2)$$

with: $n \geq 0$, $m \neq 0$, $|m| < n$, $n - |m| < n$ and (n-k) even.

$R_{n,m}(\rho)$ is the orthogonal radial polynomial, n is the order of the moment and m the factor of repetition (the smoothness of the required details) at this order. ρ and θ are respectively the radius and the angle of treated point of the function.

To implement it, we use the fast algorithm developed by G. Amayeh et all [20] and given in (3) for face characterization through Zernike moments and a trained back-propagation neural network for the classification step.

$$Z_{n,m} = \frac{n+1}{\pi} \sum_{x^2+y^2 \le 1} \sum \left(\sum_{k=|m|}^{n} \beta_{n,m,k} \cdot \rho^{k} \right) \cdot e^{-j.m.\theta} \cdot f(x_j, y_i)$$

$$= \frac{n+1}{\pi} \sum_{k=|m|}^{n} \beta_{n,m,k} \cdot \left(\sum_{x^2+y^2 \le 1} \sum e^{-j.m.\theta} \cdot \rho^{k} \cdot f(x_j, y_i) \right) = \frac{n+1}{\pi} \sum_{k=|m|}^{n} \beta_{n,m,k} \cdot X_{m,k} \qquad (3)$$

Zernike moments are known for their capacity to compress the geometric information of the image into a vector of reduced dimensions depending on the parameters m and n (see equations 1, 2 and 3). The obtained feature vector compacts the geometric characteristics of the image such as the surface, the vertical symmetry and distribution centers masses in the horizontal and vertical directions and other image characteristics which deal with information required for such type of classification problem.

In Fig. 3 we give some samples of Zernike moments feature vectors for two different expressions for images of JAFFE database.

Each curve is a concatenation of four zernike moments feature vectors of the four regions containing principal components of the face (the two eyes, the noze and the mouth). There are many apparent differences between the curves representing images of different persons. This justifies the different research that has been conducted on the use of characterization by such attributes for recognizing faces and facial expressions. [21], [22].

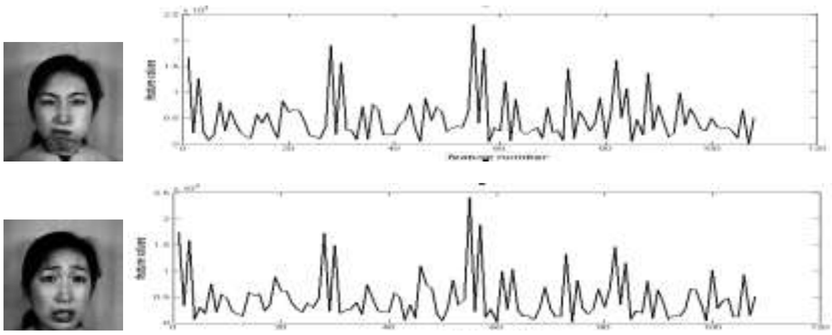


Fig. 3: Zernike moments feature vectors for 2 different expressions (Anger and fear) from images of JAFFE database

3.2 Face features' characterization by LBP

Initially introduced by Ojala et al. [23] for image texture analysis, the LBP was rapidly adopted as an efficient tool for image analysis in general and pattern recognition in particular [23], [24], [25]. The success of this method in image analysis and representation generates a multitude of extended versions adapted to the encountered problems.

Fig. 4, gives a representative scheme of the compiling process in the Basic LBP method. The most important extensions of basic LBP were the extension of the operator to use neighborhood of different sizes, to capture dominant features at different scales and the definition of "uniform patterns" used to reduce the representative feature vectors

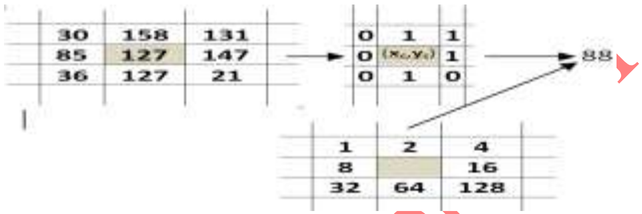


Figure 4: Basic LBP value for the central pixel (xc,yc)

On figure 5, we give a sample of LBP feature vectors compiled for some faces from JAFFE database.

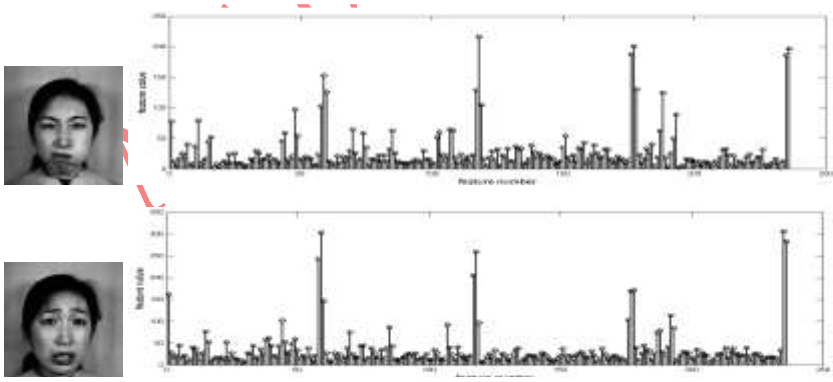


Fig. 5: LBP feature vectors for 2 different expressions (Anger and fear) from images of JAFFE database

This type of characterisation was largely used by researchers for facial expression recognition [26], [27] especially for its capacity to encapsulate the texture information of the image, its robustness to monotonic gray-scale changes caused by illumination variations and its computational simplicity.

3.3 Face features' characterization by DCT

The idea here is to exploit another type of information brought by the image. Indeed, spectral components distribution is an important characteristic of physical signals like speech, image, etc. It was largely used in different types of signal processing domains; like communication, medicine, human-machine interaction, and so on. Despite the existence of several methods for spectral analysis, the DCT seems to be the most preferred and most used by the researchers [28]. This is due to the fact that it concentrates the most important visual information on a set of few coefficients which explains why it was largely used for image and video compression. In addition it leads to real coefficients.

2D-DCT mathematical formulation is given on Equation 4.

$$\begin{cases} X_C(k_1,k_2) \triangleq \sum_{n_1=0}^{N_1-1}\sum_{n_2=0}^{N_2-1} 4x(n_1,n_2)\cos\frac{\pi k_1}{2N_1}(2n_1+1)\cos\frac{\pi k_2}{2N_2}(2n_2+1), \\ \text{where:} \\ (k_1,k_2)\in[0,N_1-1]x[0,N_2-1];\, Otherwise,\, X_C(k_1,k_2)\triangleq 0. \end{cases} \tag{4}$$

However, different ways can be used such as using FFT algorithm or optimized DCT algorithms to enhance DCT coefficients compilation.

In many applications which use DCT transform, like in image and video compression, researchers exploit the fact that most of the energy at the spectral domain is localized at the low frequencies for dimensionality reduction. Here, it was not the case due to the fact that we are working on the face features where the energy at the high frequencies is predominant especially in the case of the eyes region (see Fig. 6).

Fig.6: DCT transforms for different face features

So, we restored to use modified feature vectors by concatenating matrices lines and sorting feature values (see Fig. 7). These vectors will be then truncated eliminating monotone parts.

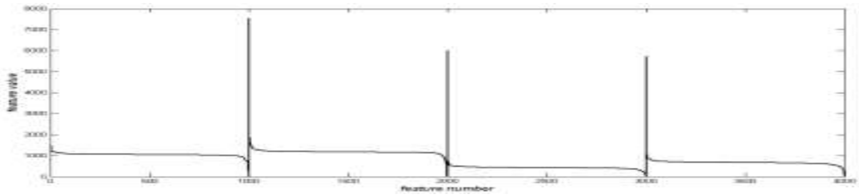


Fig. 7: Original concatenated feature vectors

Examples of applying this type of characterization to images from JAFEE database is given on Fig. 8

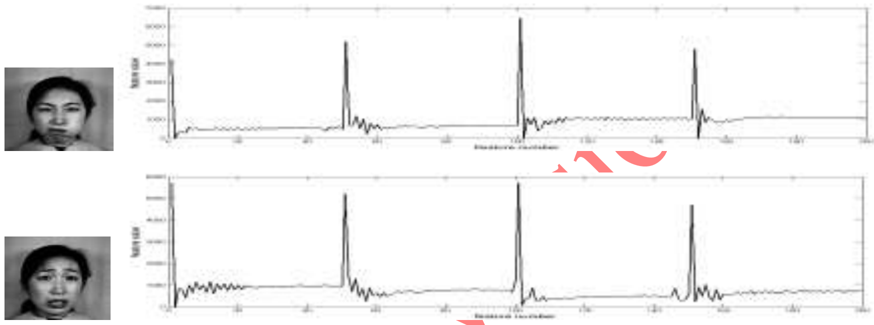


Fig. 8: DCT feature vectors for 2 different expressions (Anger and) from images of JAFFE database

4 Mutual information feature selection

Feature vectors described previously will be used separately, and then combined in a common feature vector. However, due to the rising of dimensionality problem in our classification process, we propose here to introduce a selective tool to compact the combined feature vectors in order to improve the classification performance, optimize the computational cost and reduce the classifier complexity.

The extraction of a compact feature set, which can still capture most of the useful information inherent in the original signal, is thus very important. Suitable feature extraction methods highlight the important discriminating characteristics of the data, while simultaneously ignoring the irrelevant attributes. This type of process can be implemented in two different ways; feature selection or feature extraction [29]. Feature selection algorithms can be classified into filters and wrappers; the formers being used as a preprocessing operation before classification step while last ones are used as part of the classification process. In this work, the dimensionality reduction is performed by an efficient feature selection method called Normalized Mutual Information Feature Selection(NMIFS) [29]; a filter feature selection type.

Consider two discrete random variables x and y, with alphabets X and Y, respectively. The MI between x and y with a joint probability mass function p(x,y) and marginal probabilities p(x) and p(y) is defined as follows:

$$\mathrm{I(x, y)} = \sum_{x \in X} \sum_{y \in Y} P(x, y).\log(\frac{P(x, y)}{P(x).P(y)}) \tag{5}$$

So, given an initial F set with n features, find subset S in F with k features that maximizes the mutual information I(C,S) between the class variable C , and the subset of selected features S. Different methods were developed to solve this problem. In the case of NMIFS, ones define the normalized mutual information between f_i and f_s , $NI(f_i , f_s)$ as the mutual information normalized by the minimum entropy of both features like given in (6).

$$\mathrm{N}I(f_i, f_s) = \frac{I(f_i, f_s)}{\min(H(f_i), H(f_s))} \tag{6}$$

Redundancy measure between the ith feature and the subset of selected features S={ f_s } with $s=1,2,\ldots,|S|$ will be given by (7)

$$\frac{1}{|S|} \sum_{f_s \in S} \mathrm{N}I(f_i, f_s) \tag{7}$$

Where $|S|$, denotes the cardinality of the selected features set S.

Thus, the selection criterion will be to select the feature that maximizes the measure G given by (8).

$$G = I(C, f_i) - \frac{1}{|S|} \sum_{f_s \in S} \mathrm{N}I(f_i, f_s) \tag{8}$$

5 Experimental results

Several classifiers have been proposed and used in facial expression recognition systems to handle the issues of non-linearity, dimensionality and generalization, and three main classification can be distinguished, namely, the HMM (Hidden Markov Models) [30], the SVM (Support Vector Machines) [31] and the feedforward neural networks (FFNN) [32].

In this work, the recognition step is carried out by three feed-forward neural network; each one uses a vector type, as explained previously. Also, the training process is done on combined feature vectors directly and after applying the subset feature selection based on mutual information. To check the validity of the proposed approach, experimental studies were carried out on the well known facial expression JAFFE database [33].

By taking 2 images in random for each person with each expression, a training dataset of 140 couples (Fi, T) examples is formed. The Zernike moments were computed with couple values (m=10, n=5) which seems to give the best results. A DCT feature vector of 50 coefficients was computed for each face's component, and for LBP we used LBP histogram in (8,1) neighborhood. All recorded results were obtained through a FFNN with 25 units in hidden layer, 7 units for the output layer and a number of units adapted to the feature vector used in input layer. "Purelin" was used as transfer function for input and output layers while "Tansig" function was used for hidden one. The training function was "Traingda".

The obtained results will be detailed in the following subsections.

5.1 Individual feature vectors

This section reports the recognition performance using the three different types of features separately. The training images were chosen randomly and reported results are the average of 10 experiments. More accurate results were obtained, (a Global TPR about 90.79 for Zernike moments, 93. 52 for LBP and 88.62 for DCT transform) when we choose manually the images to be used for training and testing the neural networks. This is due to the fact that there are several images where the expressions are not very apparent and it's even difficult for humans to process them correctly.

Table 1 Global TPR for Zernike moments, LBP and DCT with and without applying NMIFS

Feature vectors / **Expression**	**Global TPR %**					
	Zernike	***LBP***	***DCT***	***NMIFS+ Zernike***	***NMIFS+ LBP***	***NMIFS+ DCT***
Neutral	**88.5**	**90**	**83**	**89.23**	**90**	**85**
Happiness	**90**	**92**	**81**	**90**	**93**	**85**
Surprise	**85**	**91**	**87**	**87**	**93**	**87**
Anger	**78**	**83**	**67**	**77.5**	**83.5**	**70**
Disgust	**80**	**81**	**78**	**82**	**83**	**78**
Fear	**73**	**79**	**81**	**74.6**	**79**	**80**
Sadness	**81.5**	**78**	**83**	**83**	**78**	**83.5**
Global TPR %	**82.29**	**84.85**	**80.00**	**83.35**	**85.64**	**81.21**

5.2 combined feature vectors:

Table 2 reports the results recorded using combined feature vectors.

Table 2 Global TPR recorded for combined feature vectors

Feature Vectors / **Expression**	**Global TPR %**			
	Zernike-LBP	***LBP-DCT***	***Zernike-AR***	***Zernike-LBP-AR***
Neutral	**83**	**81**	**75**	**78**
Happiness	**83.5**	**83**	**70**	**77.5**
Surprise	**79**	**81**	**78**	**75**
Anger	**72**	**76**	**61**	**71**
Disgust	**78**	**73**	**76**	**69**
Fear	**67**	**72**	**72**	**72**
Sadness	**75**	**77**	**78**	**71**
Global TPR %	**76.79**	**75.28**	**77.57**	**73.36**

It is clear when using the whole features that not only there is no improvement but the degradation is well apparent. This will be due in one hand to the great number of features which makes the neural networks converge to local minima instead of global one and in another hand to divergent directions of the feature's influences on the decision of class's membership.

5.3 Combined feature vectors with NMIFS

NMIFS was used to retain the strongly relevant features. In addition to the enhancement of facial expression recognition results, the classifiers converge faster due to the reduction of its complexity. For all the reduced combined feature vectors, we found that the Zernike moment features are preponderant against other types of features while DCT features are the less preponderant.

Table 3 Global TPR recorded for combine feature vectors processed with NMIFS

Feature vectors / Expression	Global TPR %			
	NMIFS+ (Zernike-LBP)	*NMIFS+ (LBP-DCT)*	*NMIFS+ (Zernike-DCT)*	*NMIFS+ (Zernike-LBP-DCT)*
Neutral	**93.50**	**94.25**	**92.00**	**95.00**
Happiness	**94.78**	**95.38**	**93.00**	**96.37**
Surprise	**94.40**	**95.00**	**94.20**	**95.82**
Anger	**88.70**	**89.00**	**84.36**	**93.65**
Disgust	**91.47**	**91.00**	**90.52**	**92.85**
Fear	**85.35**	**85.35**	**83.00**	**89.00**
Sadness	**88.39**	**89.40**	**89.25**	**92.50**
Global TPR %	**90.94**	**91.34**	**89.48**	**93.59**

5.4 Comparison with other techniques

Finally, a comparison with common techniques is also given to demonstrate the validity of the proposed approach. The comparison was done on the same database (JAFFE) and according to the same measurement strategy, namely Leave-One-Image-Out (LOIO) [34], [35] and [36]. Table 4 summarizes the results.

Table 4 Global rates' comparison between the proposed technique and former techniques

Applied technique	Global rate
R.S. El-Sayed et al. [38]	**90.00 %**
S. Zhang et al. [39]	**90.70 %**
R. Hablani et al. [40]	**94.44%**
Proposed technique	**93.59 %**

It is clear that the proposed technique outperforms the former techniques except the one presented in [36]. However, its main advantage is still the reduced feature vectors which lead to the construction of simplified, fast and accurate classifiers. In the case of the Neural one used in this study, the number of internal parameters became at the ratio of one to five and it converges three times faster.

6 Conclusion

Facial expression recognition using three different types of characterization feature vectors to train neural network classifiers were studied in this paper. The characterization step was done on faces' components instead of the whole face. First, we found that uniform LBP feature vectors provide better results compared to those obtained using Zernike or DCT transform. Training classifiers using combined feature vectors was also studied and worse results were reported. We also demonstrate that the introduction of a feature selection technique, as a post-processing operation before the classification step, on single and combined feature vectors permits not only a significant enhancement of the classification results but also an improvement of the neural networks classifiers' speed and simplicity. The present technique needs deepest study concerning the appropriate way of combining the different parameters and the best classifier architecture.

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