International Journal of Scientific Research & Engineering Technology (IJSET)
Vol.6 pp.14-20

Shape and Appearance Fusion: ART and PCA Using SVM

Imène TALEB #1, Madani OULD MAAMAR *2, Abdelaziz OUAMRI#3

Electronics Department, Faculty of Electrical Engineering, University of Science and Technology ORAN – Mohamed Boudiaf – USTO-MB, B.P. 1505 .El Mnaouer, Oran, 31000, Algeria.

1imene.taleb@univ-usto.dz

3 ouamri@yahoo.com *

2madani.ouldmammar@univ-mosta.dz

Abstract— **This paper presents a novel facial expression recognition (FER), based on Fusion of Angular Radial Transform (ART), Principal component Analysis (PCA) and Support Vector Machine (SVM), to recognize the facial expression recognition. Principal Component Analysis is an extraction method based on statistical features which were extracted the global greyscale features of the whole image. The PCA is a holistic appearance method, where the extracted features are sensitive to the environment. So a hybrid method is proposed in this paper, which combines the PCA with ART. Angular Radial Transform (ART) as a regional based shape descriptor. It belongs to the broad Zernike moment family. The coefficients are then used as input to a support vector machine (SVM) to recognize facial expression. Experiments are performed using the standard Japanese Female Expression (JAFFE) and Cohn-Kanade databases.**

Keywords— **facial expression recognition (FER), Fusion, Angular Radial Transform (ART), Principal Component Analysis (PCA),Support Vector Machine (SVM), Japanese Female Expression (JAFFE), Cohn-Kanade.**

I. INTRODUCTION

The automated recognition of facial expressions has been studied with much interest in the past 20 years [1]. Quality works was make, but the field still under active research due to the complexity of the problem. In fact, where human understand such pattern even in complexes situations, machines still sensitive even to simple variation like light, rotation and resolution.

According to the Facial Action Coding System (FACS)[2], six basic facial expression have to be considered: Happy, Sad, Fear, Anger, Disgust and Surprise, plus the Neutral expression. To extract features of such expression many methods are used.

The method introduced in this paper evaluates experimentally, an approach based on a fusion of PCA and ART methods.So the hybrid method combines the PCA as holistic descriptor with ART as shape descriptor. In general, there are two approaches to represent the face and consequently the facial features to perform facial expression analysis: the geometric feature-based methods and appearance-based methods [3].

The geometric facial feature-based methods present the shape, texture and/or location information of prominent components (including mouth, eyes, eyebrows and nose) [4].The appearance-based methods, on the other hand, using image filters such as Gabor wavelets, generate the facial feature for either the whole-face or specific regions in a face image[4].

Tian and al, developed an Automatic Face Analysis system to analyze facial expressions based on both permanent facial features (brows, eyes, mouth) and transient facial features (deepening of facial furrows) in a nearly frontal-view face image sequence[5]. Bourel and al present a new approach using local spatio-temporal vectors obtained from the Extended Kalman Tracker for the recognition of facial expressions from videos sequences in the presence of occlusions [6]. In [7] [8] the Hidden Markov Models are used to recognize different patterns of facial animation parameter evolution and automatically segmenting and recognizing human facial expression from video sequences.

Gabor wavelets [9] are widely used to extract the facial appearance changes as a set of multi scale and multi orientation coefficients. The Gabor filter may be applied to specific locations on a face [9] or to the whole face image [10]. Different Classifiers was trained in the purpose of the facial expression recognition such as neural networks [11, 12], support vector machines [13], linear discriminant analysis [14], principal component analysis [14], rule- based classifiers [15].

In this paper, the ART descriptor, the MPEG-7 International Standard, is adopted. Known to be invariant to both scale and rotation, ART was largely used in Logo and shape recognition, and prove efficiency and accuracy. One can consider it as belonging to the mathematic moment set as Zernike moment. Characterized by a set of orthogonal function basics, ART extract a set of coefficients that describe shape information [16]. Combined with Appearance Model such PCA, making a features-based fusion, we show that such mixed features is suitable to increase the performance of the whole recognition system.

The experiments as will be shown in the last section, shows that combination of appearance based method PCA and shape based descriptor ART, two complementary features information, increased the facial expression recognition rate more than used separately.

ISSN 2356-5608

II. THE FERS PROPOSED

The facial expression recognition system is composed of two subsystems: one for information extraction and one for information classification.

A. Preprocessing

There are many factors in captured image, such as contrast, brightness, image size, which affect the accuracy, robustness and instantaneity of facial expression recognition accuracy. So the aim of the pre-processing is to obtain images which have normalized intensity, uniform size. The preprocessing procedure should also eliminate the effects of illumination and lighting. In pre-processing module images are resized from [256x256] to [72x72].

The preprocessing procedure of our FER system performs the following five steps in converting a TIFF JAFFE image to a normalized pure expression image for feature extraction: 1). detecting facial feature points manually including eyes, nose and mouth; 2). rotating to line up the eye coordinates; 3) locating and cropping the face region using a rectangle according to face model as shown in Fig.2

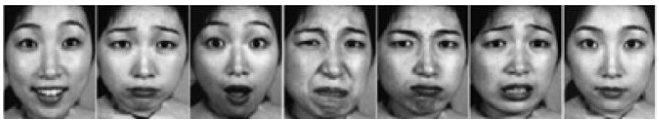

Fig. 1 A JAFFE face images (pre-processing)

B. Features space

In the following, we will introduce the mathematical basis of Angular Radial Transform, and Principal Component Analysis. Both methods are used to extract representative shape and appearance Features information. These characteristics will be assessed separately and then a fusion of the two characteristics will be refined and evaluated as a single feature, containing both the appearance and shape information of the face expression.

1) Angular Radial Transform (ART)

The MPEG-7 standard comitee has proposed a region base shape descriptor: the Angular Radial Transform (ART). This shape descriptor has many properties: compacting size, robustness to noise and scaling, invariance to rotation, ability to describe complex objects. These properties and the evaluation made during the MPEG-7 standardization process make the ART a unanimously recognized efficient descriptor [16]. ART belongs to the broad Zernike moment family. A set of orthogonal moment basis is defined on a unit disk in polar coordinates (ρ,θ) .The basis functions $V_{nm}(\rho,\theta)$ are separable along the angular and radial directions [17], and are defined as :

$$F_{nm} = \int_0^{2\pi}\int_0^1 V_{nm}(\rho,\theta).f(\rho,\theta)\rho d\rho d\theta$$

$$V_{nm}(\rho,\theta) = \frac{1}{2\pi}\exp(jm\theta)\, Rn(\rho)$$

3.3

$$R_n(\rho) = \begin{cases} 1 & n = 0 \\ 2\cos(n\pi\rho) & n \neq 0 \end{cases}$$

In order to achieve rotation invariance, an exponential function is used for the angular basis function. The radial basis function is defined by a cosine function.

The ART transform of a function $f_{nm}(\rho,\theta)$ is the inner product of the basis $V_{nm}(\rho,\theta)$ and the function over the unit disk. The transform coefficients corresponding to the basis $V_{nm}(\rho,\theta)$ is C_{nm}, which is expressed as[16] :

$$C_{nm} = \int\int V_{nm}(\rho,\theta).f(\rho,\theta)\rho d\theta d$$

Hence the reconstructed function is a linear combination of the basis function:

$$f(\rho,\theta) = \Sigma_n\Sigma_m C_{nm}.V(\rho,\theta)$$

C_{nm} is a complex number, where $f_{nm}(\rho,\theta)$ is the image intensity function in polar coordinates and $V_{nm}(\rho,\theta)$ is the ART basis function of order n and m. The vector with components C_{nm} will be the feature vector.

2) Principal Component Analysis (PCA)

PCA is one of the most widely used methods in image recognition and compression [18]. PCA reduce the feature dimension while preserving as much information as possible and perform decorrelation. Also it preserves the reconstruction error as well as variance.

Find the best projection direction which represents the original data in the sense of least mean-squares. The dimension of feature space, which decides the size of data, can be reduced by PCA.

The strategy of the Eigenfaces method consists of extracting the characteristic features on the face and representing the face in question as a linear combination of the so called “eigenfaces“ obtained from the feature extraction process [19].

The principal components of the faces in the training set are calculated. Recognition is achieved using the projection of the face into the space formed by the eigenfaces.

ISSN 2356-5608

International Journal of Scientific Research & Engineering Technology (IJSET)
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3) Fusion (ART/ PCA)

Multi-biometrics try to consolidate information from multiple sources in three distinct levels: i/ feature extraction level; ii/ match score level; and iii/ decision level. Since the feature set contains richer information about the raw biometric data, fusion at the feature level is expected to provide better recognition results.

For enhancing the performance and accuracy of face recognition, we use the multi-algorithmic concepts, where a combination of different facial expression recognition algorithms is used. We implemented two well known face recognition algorithms, they are following: i/ Principal Component Analysis, and ii/ Angular Radial Transformation.

Two kind of fusion one can made at the feature level, “serial fusion”, and the parallel fusion, where both features have to be at the same dimension, and will be fused together to make a complex value number, where the real part represent an information from the first features, and the imaginary part, represented by the second features. The fusion features, the complex one, can be used as a complex features for classification. The second pattern of fusion, that consist of concatenating the different features of interest. f1 and f2 are features from two different spaces, a simple concatenation o of the form[m*f1;n*f2] can be used as a new features and used to be learn in the classifier. In our case normalize f1 and f2 in such way that the sum of each of their element is equal to one, and take the value of n and m as equal to one.

Our contribution, in this paper is the fusion (concatenation) of two kinds of features of the same face, one related to the shape (ART features), the other related to the global appearance (PCA features) as depicted in figure 3:

Let $A_i = \{a_{i,1}, a_{i,2},..., a_{i,n}\}$ and $P_i = \{p_{i,1}, p_{i,2},..., p_{i,m}\}$ represent the normalized feature vector of the face from ART and from PCA of a user, respectively. The normalized vectors result from transformation to the individual feature values (via normalization schemes like min-max, z-score ...). The fused feature vector $X_i = \{x_{i,1}, x_{i,2},..., x_{i,d}\} \in R^d$ can be obtained by concatenating the two feature vectors A_i and P_i.

In MPEG-7, 12 angular and three radial functions are used (n<3,m<12) [16], these values which lead to acceptable approximation of $f(\rho,\Theta)$ will be used in the rest of the paper.

For Art features, 35 coefficients are extracted for each face shape and 40 features extracted by the PCA, the features of appearance are then concatenated and classified by SVM. This combination has the advantage of being much less slower than geometrical methods, which generally require manual effort for detection, or a significant calculation for the detection of each facial area.

4) Classification tools

Support Vector Margin Classifier

Consider the problem of separating the set of training vectors belonging to two classes, given a set of training data $(x_1, y_1),..., (x_m, y_m)$ where $x_i \in R^N$ is a feature vector and $y_i \in \{1, +1\}$ its class label.

Assume:

1/ that the two classes can be separated by a hyper-plane $\mathbf{w}.\mathbf{x} + b = 0$,

2/ no knowledge about the data distribution is available. From the point of view of statistical learning theory, of all the boundaries determined by **w** and b, the one that maximizes the margin is preferable (due to a bound on its expected generalization error). The optimal values for **w** and b can be found by solving the following constrained minimization problem:

$$\min_{\mathbf{w}} \quad E(\mathbf{w}) = \frac{1}{2} \parallel \mathbf{w} \parallel^2$$
$$\text{s.t.} \quad y_i\left[(\mathbf{w}\cdot\mathbf{x}_i) + b\right] \geq 1 \qquad i = 1,\ldots,m$$

Solving it requires the construction of a so-called dual problem, using Lagrange multipliers α_i (i = 1,..., m), and results in a classification function:

$$f(\mathbf{x}) = \operatorname{sign}\left(\sum_{i=1}^{m} \alpha_i y_i \left(\mathbf{x}_i \cdot \mathbf{x}\right) + b\right)$$

Most of the α_i take the value of zero; those x_i with nonzero α_i are the “support vectors”.

SVMs have been successfully employed for a number of classification tasks such as genetic analysis [20] and face detection [21].

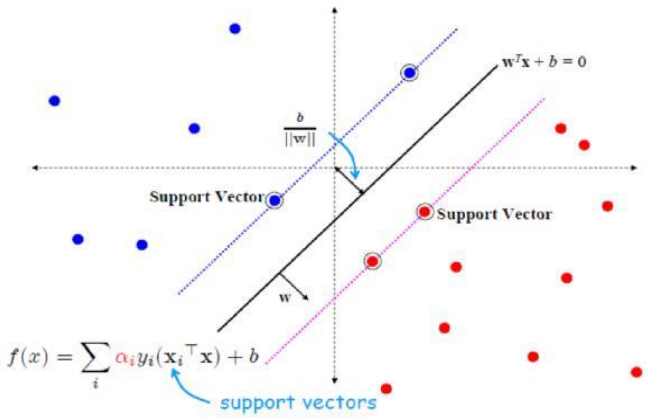

Fig. 2 SVM presentation

ISSN 2356-5608

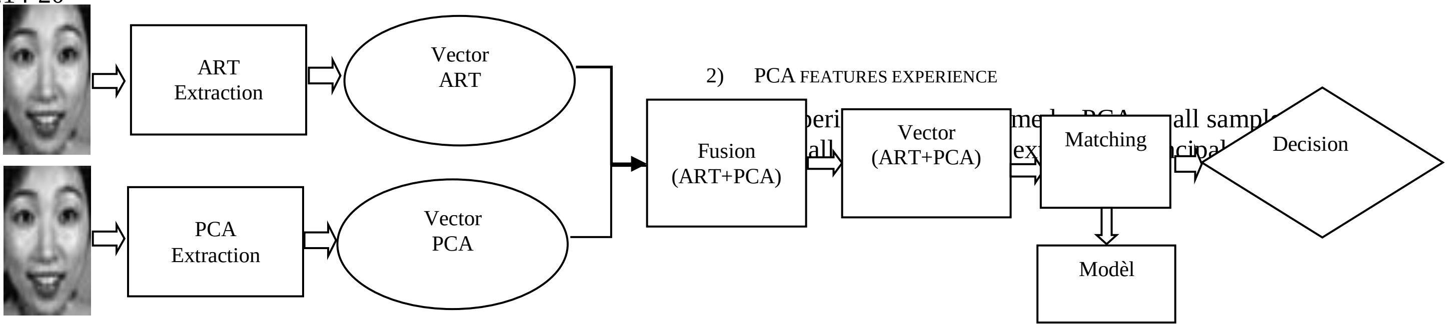

Fig. 3 The block diagram of Feature Level Fusion

III. Experimental Results

After presenting the mathematical model of ART and PCA, the following gives more detail on the experiences and the obtained results:

1) Images databases

To evaluate the proposed features fusion of ART and PCA, experiments was performed on two different databases: JAFFE (for Japanese Female Facial Expression [22]) and Cohn-Kanade (CK) [23]. The former is a collection of 210 different gray level pictures each one of size 72x72 taken from 10 persons (female) exposed 3 times for each expressions. The latter is composed of 486 sequences from 97 subjects of size 128x128. Each sequence begins and ends with neutral expression, while the middle of the sequence contain the large intensity of a given expression. In both databases, one can observe that the expression is forced and not authentic, leading to some wrong or confused -labeled pictures. This is a major problem in all kind of collected database under a not natural environment.

Fig. 4 Samples of Facial expressions JAFFE

Fig. 5. Samples of Facial expressions Cohn-Kanade database

2) PCA features experience

and form the basis on which features are extracted for each image sample. The recognition rate obtained is improved using a second approach: consider the construction of 7 PCA subspace, each one constructed from only sample of a known class. For an input image, feature are extracted considering each one of the 7 sub PCA, and are used in an SVM using the OVA (One Versus All) approach. This is how we used PCA in this paper.

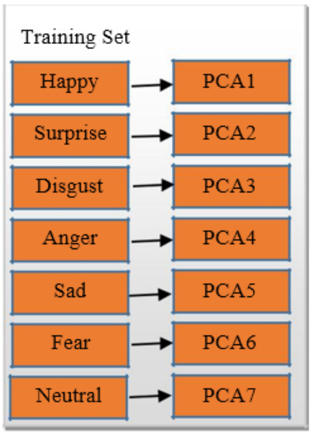

Fig. 6 PCA Block diagram

3) ART features experience

ART is generally applied on binary images of a known dark object, drawed on a completely white background. Other works used ART on gray level image. In this work, we combined two kind of image: original gray level image and all orientations gradient image on [0,π [. Combined with ART and Binary ART equal to sign (ART_Features). In both function, parameter m<4, and n<3 was used to do extraction as shown in figure 7. Figure shows an example of such extraction the coefficient obtained was introduced on a SVM classifier to learn a multiclass system.

ISSN 2356-5608

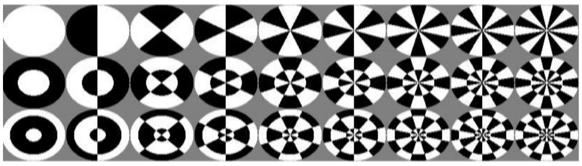

Fig. 7. Binary ART functions

4) ART & PCA Features Fusion

Generally, two approaches are used to in features fusion level: Serial and/or parallel. Facial expression information can be extracted from appearance and shape pattern. PCA is conducted to extract the appearance information, when ART is used to consider the shape or region information. Fusion of both features in a simple weighted concatenation gives a improvement in the rate recognition.

Two approach are used to perform a multiclass recognition with a simple binary classifier (as SVM): OVA (One Versus One) and OVO (One Versus One). In OVA, classifiers are built to recognize sample among C different Class. The Ci classifier is constructed over training set composed of example of the Class i as the positive class, and all the rest of the training samples are considered as Negative Class. The con here is to learn classifier that focused more on negative-sample, when the amount of negative samples are more important. Moreover, a decision that considered a sample as belonging to negative class is not a relevant information. In the OVO approach, the distribution of positive and negative example are more uniform helping the classifier to consider as much positive example then negative, and both negative and positive example are relevant. The drawback is the construction of C*(C-1) classifer. That leads in our case to the construction of 42 classifier. In addition, two classifier constructed on Ci and Cj class can gives a false response considering an example on a Cj class. Fusion of the decision is constructed over a voting technique to decide to which class a sample belong when it is introduced on all these set of classifier. To combine the advantage of the both approach, and avoid constructing an important set of classifier, a third approach is used in this paper: Error Correcting Code for classification. In this approach, a code word is used to combine a subset of class as a positive Class, and the other subset as a negative class. In the table below, one can find how we can combine 15 binary classifier in a problem of 10 class. A test sample is introduced on all the classifier. All the output are extracted from which we construct the output word. The output word is compared to the different code word in a simple hamming distance, to decide to which class the sample belong.

IV. RESULS AND ANALYSIS

PCA based

The average recognition rate (RR) for JAFFE test samples with PCA is 92,71% and 91.22% for CK database . Table 1 reveals the comparison of the recognition rate for every expression with PCA methods with training set of 140 images and test set of 70 images. The Accuracy rate of the neutral and anger using PCA Algorithm is higher than other expressions for 70 test samples for JAFFE database. The recognition rate of the disgust and fear with PCA Algorithm is higher than other expressions for 70 test images for CK database. Table 1 demonstrates the system results of the testing 70 images using PCA method.

TABLE I
ACCURACY RATES OF VARIOUS FACIAL EXPRESSIONS USING PCA (JAFFE AND CK DATABASES)

FE	RR-PCA % (JAFEE)	RR-PCA % (CK)
Neutral	97.77	87.14
Anger	97.60	91.43
Disgust	92.17	94.29
Fear	84.00	94.29
Happy	83.00	90.00
Sad	83.00	90.00
Surprise	96.12	91.43
RR	92.71	91.22

ART based

The average recognition rate JAFFE test samples with ART are 82, 51% for JAFFE database and 88.57% for CK database. Table 2 reveals the comparison of the recognition rate for every expression with ART method (35 coefficients) with training set of 140 images and test set of 70 images. The Accuracy rate of the surprised expression using ART Algorithm for JAFFE and CK databases is higher than other expressions for 70 test samples.

TABLE III
ACCURACY RATES OF VARIOUS FACIAL EXPRESSIONS USING ART (JAFFE AND CK DATABASES)

FE	RR-ART % (JAFEE)	RR-ART % (CK)
Neutral	80.33	81.43
Anger	86.00	88.57
Disgust	70.00	90.00
Fear	73.00	90.00
Happy	88.57	87.14
Sad	83.77	88.57
Surprise	96.00	94.29
RR	**82.52**	**88.57**

ISSN 2356-5608

TABLE IIIII
ACCURACY RATES OF VARIOUS FACIAL EXPRESSIONS USING PCA+ART (JAFFE AND CK DATABASES)

FE	RR-PCA+ART% (JAFEE)	RR-PCA+ART% (CK)
Neutral	98.84	94.29
Anger	99.17	93.00
Disgust	97.33	99.10
Fear	93.66	95.00
Happy	97.17	97.14
Sad	92.33	92.00
Surprise	98.12	97.12
RR	96.66	95.37

Table 3 show the performances of recognition of the proposed system on JAFFE and CK databases respectively. We observe the following:

1. For the JAFFE database, neutral, happy, anger and surprise expressions are easily to recognized, while fear, and sad expressions are not.
2. For the CK database, surprise, disgust, neutral and happy expressions are easy to recognize while anger and sad expressions are not.
3. Figure.8 shows clearly the increase recognition rate for JAFEE and CK databases under the fusion approach.

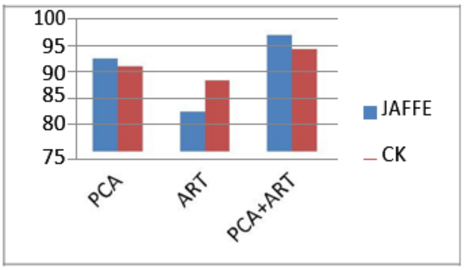

Fig. 8 Result of contrast
(JAFFE And CK databases)

TABLE IV
COMPARISON WITH DIFFERENT APPROACHES ON THE JAFFE DATABASE

Methods	Subject	Images	Classes	(%)
Radial encoded jets [24]	10	213	7	89,67
LDNG [25]	10	213	7	90,6
Gabor texture and CBP[26]	10	210	7	71,43
BDBN[27]	10	213	7	93
LBP+HOG[28]	10	213	7	87,6
ART+PCA	10	213	7	96.66

Table 4 shows the comparisons with some other published approaches (local and global methods) applied to the JAFFE database.

Although the overall results are promising, the results presented in the tables 1, 2 and 3 indicate that there is a spread of the classification results across different expressions. This suggests that different facial expressions could need different sizes of training sets to enhance the obtained results.

V. CONCLUSIONS

The paper has presented a fusion region based descriptor ART and holistic based PCA and SVM is used for the expression classification and hence recognition. The proposed solution leads to a system capable of classifying the six basic universal emotions, with an average accuracy of more than 96% for JAFFE and 95.37% for CK.

One of the limitations of the proposed system is that it only allows recognition for static images. Therefore, in perspective a significant enhancement would be achieved considering the temporal component of expressions, hence analyzing video input as well.

ACKNOWLEDGMENT

This work was supported by signal and image laboratory, electronic department of university of sciences and technologies Mohamed boudiaf, Oran.

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