



## Efficient Method for Face Recognition from Pose and Expression

*Mrs. J.Savitha*

*Ph. D Research Scholar,  
Karpagam University,  
Coimbatore, Tamilnadu, India.*

*Dr. A.V.Senthil Kumar*

*Department of Computer Applications (PG),  
Hindustan College of Arts and Science,  
Coimbatore, Tamilnadu, India.*

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**Abstract -** *Face recognition is one of the most relevant applications of image analysis. In the last decade, facial expression recognition has attracted more and more interest of researchers in the computer vision community. It's a true challenge to build an automated system which equals human ability to recognize faces. This paper introduces the recognition of facial expression / emotion of human at different levels with the face. Major challenge of face recognition lies in managing with variations in pose, illumination and expression which is not supported in the cases of expression and pose by Principal Component analysis (PCA)[6]. This developmental study set out to determine such an age and find how the ability to recognize emotions changes from birth through adulthood. We present an approach S-PCA to automatic localization of facial feature points which deals with pose and expression. One of the challenges in face recognition is matching the face with the expression & pose of the test face. In this paper, a new approach of S-PCA is used for combining position and emotions of face for recognition is been proposed.*

**Keywords—** *Facial Expression, Face Recognition, Position and Emotions.*

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### I. Introduction

Face recognition is most important in the development for its stuff in the coordination of various fields like commercial, medical or military systems. Face recognitions are used for access control to security purpose or video monitoring in major security or religious places and areas like airports and other highly sensitive. When we view the human face, we see many interesting features. The most interesting fact is the expression of emotion. By seeing their face, identifying & understanding the feeling of the people is amazing. For human, their main opportunity to connect with the outside world is by trying to understand the emotions of the people around them. Over decade, instinctive facial expression recognition systems have become a more and more important in research field. Major part of human communication is done through facial expressions. By interpreting the expression of the face, one can tell the emotional state of another person much faster than by using words. Instinctive facial expression recognition systems can lead to major progress in human-centered human-machine interaction, so that in the future, robots/machines can understand human activities and react positively. Facial expression recognition uses visual information to divide facial motion and facial feature deformations into different abstract classes.

In this paper we present a system able to accurately localize facial expression and pose in real-world frontal face[1] scenarios, which can deal with viewpoint and expression variations with respect to illumination changes and self-occlusions (i.e., points non visible due to severe head rotations). Most existing facial expression recognition systems only work well on near-frontal faces. For using an automatic facial expression recognition system in real-world environments, the capability of dealing with non-frontal[2] poses is essential. Here in this paper, special attention to formulate an efficient expression and pose of human which evaluates matching hypotheses between the recognized face and sample dataset.

### II. Background Study

A number of experiments have explored feature saliency, attempting to discern the relative importance of different features or areas of the face. Although the early of these, generally agreed to the importance of face outline, hair, and eyes — and the relative unimportance of the nose and mouth — there is evidence that these results may be biased by the artifacts of the techniques and face presentations used. Faces grow and develop in a way such that features are mutually constraining. The main motivation of this proposed method is to find out an effective facial representation for face recognition. In fact these growth patterns can be expressed mathematically and used to predict the effects of aging. Such techniques have already been used successfully in the location of missing children years after their disappearance. Faces are complex visual stimuli, not easily described by simple shapes or patterns; yet people have the ability to recognize familiar faces at a glance after years of separation. Emotion recognition using visual cues has been receiving a great deal of attention in the past decade. Most of the existing approaches do recognition on six universal basic emotions because of their stability over culture, age, and availability of such facial expression databases. The choices of features employed for emotion recognition are classified in [3] into two main categories, i.e., geometric features and appearance features.

**Existing Method:** PCA for face recognition is based on the compressing data and on reliably storing and communicating data. It abstracts the appropriate information in a face image and encrypt as efficiently as possible. It identifies the subspace of the image space spanned by the training face image data and de-correlates the pixel values. The orthodox

illustration of a face image is obtained by sticking out it to the group defined by the Principal components[4]. PCA is frequently used in data analysis, and from bioinformatics to computer media. The difficulty of face recognition in different illumination and poses with different rotation angles using PCA [7][9]. Face recognition using PCA, based on frontal face, seek a computational model that briefs face, by extracting most accurate expression appears in the face. The experimentation involved the use of Eigen faces[8] and PCA (Principal Component Analysis).The main aim of most commercial face recognition is to increase the capability of security and surveillance systems.

The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.



Fig 1. Various Expressions of Face

### III. Proposed System

In most face recognition cases it is assumed that frontal faces or captured shots are available for registration to the database, other expression & poses of faces are collected for testing data. Given a face from the testing data set, one needs to check whether the face match in the database. On a positioned and straightened face, various facial feature points such as face, eyes, eye brows, nose, and lips are identified using active shape models[5]. Multi-view expression recognition systems extend frontal face expression recognition approaches in order to process expressive face images or video sequences at different view angles. Although the above mentioned methods can adjust with large enough amount of image variation, in exceptional, such as huge expression/ pose changes, where viewing conditions are so unlike that a more powerful methods should be implemented[10].

#### S-PCA algorithm:

S-PCA is proposed algorithm in which different energy ratios of even/odd symmetrical principal components and their different sensitivities to pattern variations are employed for feature selection. is based on a simple idea of the even-odd decomposition. In this algorithm, eigen faces of the even/odd symmetrical image set are respectively called even/odd eigen faces since they are even or odd symmetrical themselves. And the subspaces which they construct are called even/odd eigen space, which are proved to be mutually orthogonal. S-PCA is built on the fact that PCA can be written as a regression-type optimization problem, with a quadratic penalty; the lasso penalty (via the elastic net) can then be directly integrated into the regression criterion, leading to a modified PCA with sparse loadings.

Step 1: getting data (X) in the ugi.

Write  $X_1, \dots, X_N$  as column vectors, each of which z as  $M$  rows. Place the column vectors into a single matrix  $\mathbf{X}$  of dimensions  $M \times N$ .

Step 2: Find the empirical mean along each dimension

$m = 1, \dots, M$ .

$$U[m] = 1/N \sum_{n=1}^N X[m,n]$$

Step 3: Store mean-subtracted data in the  $M \times N$  matrix  $\mathbf{B}$ .

$$\mathbf{B} = \mathbf{X} - \mathbf{u}\mathbf{h}$$

Where  $\mathbf{h}$  is a  $1 \times N$  row vector of all 1s

$$h[n] = 1 \quad \text{for } n = 1, \dots, N$$

Step 4: find the covariance of the matrix

Find the  $M \times M$  empirical C from the outer product of matrix  $\mathbf{B}$  with itself:

$$C = ((1 / (N - 1)) \mathbf{B} \cdot \mathbf{B}^*)$$

Step 5: Find the eigenvectors and eigen values of the covariance matrix

$$\mathbf{V}^{-1} \mathbf{C} \mathbf{V} = \mathbf{D}$$

Matrix  $\mathbf{D}$  will take the form of an  $M \times M$  diagonal matrix, where

$$D[p,q] = \lambda_m \quad \text{for } p = q = m$$

is the  $m^{\text{th}}$  eigen value of the covariance matrix  $C$ , and

$$D[p,q] = 0 \quad \text{for } q \neq 0$$

**Step 6: Select a subset of the eigenvectors as basis vectors**

Save the first  $L$  columns of  $V$  as the  $M \times L$  matrix  $W$ :

$$W [ p,q] = V [p,q] \quad \text{for } p = 1, \dots, M \quad q=1, \dots, L$$

where

$$1 < L < M$$

$$S = \{ s[m] \} = \{ \sqrt{C[m,m]} \} \quad \text{for } m=1, \dots, M$$

Calculate the  $M \times N$  z-score matrix:

$$Z = ( B / (s.h) ) \quad \text{(Divide element-by-element)}$$

Calculate the vectors and covariance matrix

$$Y = W * Z = KLT \{ X \}$$

$$Y = w * ZB$$

**IV. Experimental Results**

We investigate clustering for the cross-pose case using the vast predefined data. This is a challenging task involving compound recognition decisions across widely varying viewing conditions and a choice of model order. Again, from the 100samples in the database, on each test we select 4 images each of 8 different samples from the last 100faces in the database. Sample image may be either frontal or profile positioned and are taken from any of the four images of the recorded images. The S-PCA algorithm successfully identified most clusters regardless of whether the faces are all frontal, all profile, or a mix of both given in table 1. The number of splits and merges required to move to the correct clustering for this testing is 8, which is not good enough for the experimental average of 7% over 100 repetitions.

Table 1 .Dimension of PCA & S-PCA

S.No	Dimension	PCA	S-PCA
1	Accuracy	96.3	100
2	Time taken	4.35	3.21
3	Error rate	0.985	0.25



Fig 2. Results for 60 frontal and profile images, consisting of four image each of 15 people.

The following chart represents the difference between implementation of PCA algorithm and S-PCA (proposed method) in the face recognition.

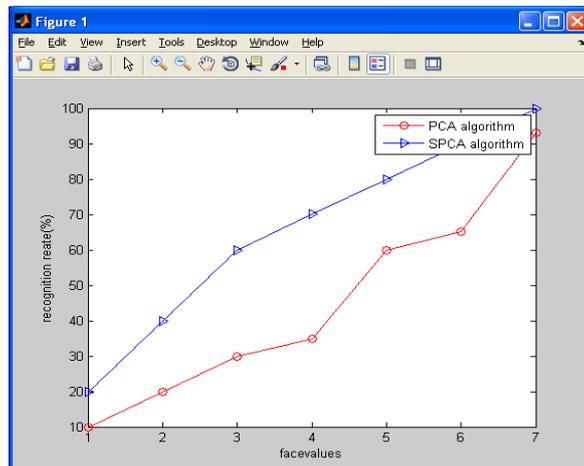


Fig 3. Accuracy Comparison of PCA & S-PCA

## V. Conclusion

In this paper, a multi-view facial expression recognition system was developed with the capability of being applied to real-world situations using S-PCA. Therefore, facial landmarks are found automatically on faces showing pose variations up to profile view. We presented an approach to facial expression & pose working in real-world scenarios. Our tests demonstrate almost real time performances and state-of-the-art results on challenging datasets. The proposed method S-PCA is based on an efficient, and a comparison of the faces in right & left position with emotions which delivers more accuracy and less time consumption.

There are several issues for future work. In future, this face recognition can improve the system by incorporating with other biometric system like speaker recognition, fingerprint, eye iris, retina and voice recognition. Inclusive of map points, e.g. at naso labial furrows, possibly carry information, which is relevant for expression recognition, and should be considered to be utilized. Also, the use of different classifiers, as well as varying the size of training and test sets could be interesting.

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