Human Emotion Classification Using Fuzzy and PCA Approach

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Abstract. The emotion recognition system has been a significant field in human-computer interaction. It is a considerably challenging field to generate an intelligent computer that is able to identify and understand human emotions for various vital purposes, e.g. security, society, entertainment. Many research studies have been carried out in order to produce an accurate and effective emotion recognition system. Emotion recognition methods can be classified into different categories along a number of dimensions: speech emotion recognition vs. facial emotion recognition; machine learning method vs. statistic method. Facial expression method can also be classified based on input data to a sequence video or static image. This report focuses on different types of human facial expressions, like different types of sad, happiness, and surprise moments. This is carried out by trying to extract unique facial expression feature among emotions using Fuzzy and the Principal Component Analysis (PCA) approach.

Keywords: facial expression recognition, face recognition, emotion recognition.

1 Introduction

Over the past decades, human-computer interaction together with computer vision has been an important field in computer study. It is concerned with the relationship of direct communication between the computer and human beings. Much research has been conducted on improving and developing the interaction between humans and the computer. Interested researchers worked on this area for different reasons. One of the significant factors that contributed to increasing and developing the interaction between the computer and humans is studying the computers' ability to distinguish emotions for humans. With emotion recognition systems, the computer will be able to assess the human expressions depending on their affective state in the same way that human's senses do. The intelligent computers will be able to understand, interpret and respond to human intentions, emotions and moods.

The emotion recognition applications have demonstrated their capabilities in different areas of life; for instance, in security and surveillance, they can predict the offender or criminal's behavior by analyzing the images of their faces that are

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captured by the control-camcorder. Furthermore, the emotion recognition system has been used in communication to make the answer machine more interactive with people. The emotion recognition system has had a considerable impact on the game and entertainment field besides its use to increase the efficiency of robots for specific tasks such as me-caring services, military tasks, medical robots, and manufacturing servicing. Generally, the intelligent computer with the emotion recognition system has been used to improve our daily lives. Scientists restrict the emotions of people in seven different feelings: Anger, Disgust, Fear, Happiness, Neutral, sad, and surprise. Generally, scientists have analyzed the human emotions and realized that Human emotion recognition can be achieved by analyzing the facial expressions.

Review of Existing System

It is an established fact that human to computer interaction will prove more naturally if the machines are able to distinguish and react to human non-verbal communication such as emotions. While numerous techniques have been studied to detect human emotions based on facial expressions or speech, there have been few research studies on combining two or more methods to enhance the exactness and potency of the emotion recognition system. Furthermore, the detection of accurate human emotions is of vital importance for efficient human-computer interaction. Numerous researches have explored this phenomenon which comprises 2D features, yet they are receptive to head pose, clutter, and variations in the lighting conditions. Researchers have applied various techniques to enhancing the interaction between humans and computers through the use of emotion recognition. The Principal Component Analysis (pca) and the Haar-like features been used for the classification of emotions. Overall, there are several techniques that have been used for the recognition of human emotions. These studies have provided support through such applications. The existing Emotion detection systems are not much accurate due to the following reasons 1.variation in lighting conditions. 2. Expression of emotion varies from time to time. We built a System that can give a better performance over the existing systems in various luminous conditions and also deals with the problem of varying time to time expressions.

2 Process Flow of Proposed System

Our system uses Viola Jones Face Detection algorithm for detecting the faces and build a system that would give the most efficient results when compared to the existing systems for recognizing the faces.

When a person's image is captured using camera, a face is detected and is stored in a temporary folder. The Eigen vectors of captured face are obtained and Eigen values are computed from them.

The principle components from above Eigen values are analyzed and saved into the database for further use. Now the image is processed for detecting the emotion. During this process the stored Eigen values of the face detected are compared against the training database values which are the average eigenfaces of different expression from training dataset. As we are taking average eigenfaces for a same expression so that it can identify different type of smile, sad, anger and surprise expression.

2.1 Face Detection and Tracking

Face detection is the first stage which is desired to be automated. In most of the research, face is already cropped and the analysis starts with feature extraction and tracking. In the rest, automated face detectors are used. These can be classified mainly into two classes: vision-based detection and detection using infrared (IR) cameras

There are also free face detection software available to researchers for usage and improvement. Most popular of these is the face detector of Open Source Computer Vision Library (OpenCV), which depends on Haar-like wavelet-based object detection proposed by Viola and Jones [6].

2.2 Fuzzy and PCA Approach

We have extended the concept of PCA for better results and named it as Fuzzy PCA. Instead of comparing with the obtained values with a single set; we defined a new set of values for each of the emotions by calculating the average of different expressions of different persons and obtained the mean value for each of the expressions. Then we calculated the deviations of the obtained values that change the data into a new coordinate system such that the variance is put in order from the greatest to the least. Each variance is the eigenvalue of the covariance matrix and has an eigenvector (or characteristic vector) associated with it. These vectors in this case are known as the principal components that will be used to analyze the data because they are simply a linear combination of the data in the original matrix [4].

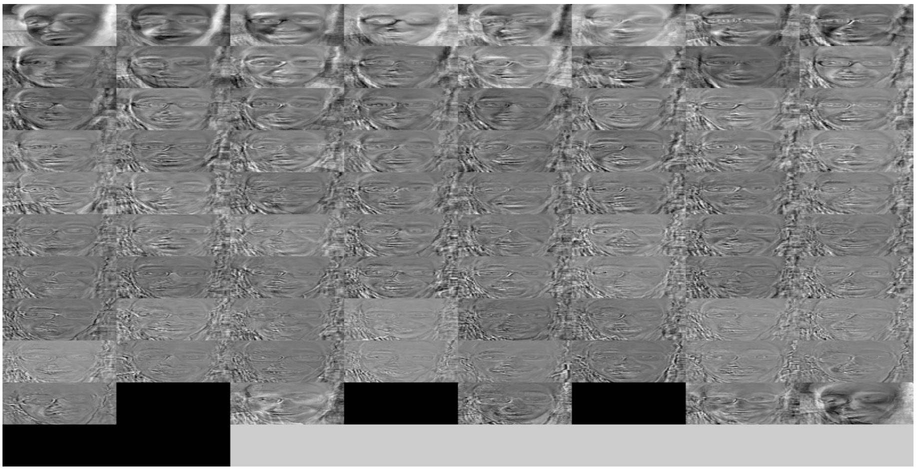

Fig. 1. Eigenfaces of different expression

2.3 PCA Analysis for Average Eigenfaces

A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector. Let's suppose we have M vectors of size N (= rows of image × columns of image) representing a set of sampled images. pj's represent the pixel values[6].

$$xi = [p1 \ldots.. pN]T \,;\; i = 1, \ldots.., M$$

The images are mean centered by subtracting the mean image from each image vector. Let m represent the mean image. m=1/M$\sum_{i=1}^{M} x_i$ And let wi be defined as mean centered image $wi = xi - m$, Our aim is to find a set of ei's which have the largest possible projection onto each of the wi's.

We wish to find a set of M orthonormal vectors ei for which the quantity $\lambda_{i=1/M\sum_{n=1}^{M}(e_i^T wn)^2}$ is maximized with the orthonormality constraint $e_i^T e_k$=δ_{lk}[6].

It has been shown that the e_i's and λ_i's are given by the eigenvectors and eigenvalues of the covariance matrix $C= WWT$.

where W is a matrix composed of the column vectors wi placed side by side. The size of C is $N \times N$ which could be enormous. For example, images of size 64 × 64 create the covariance matrix of size 4096×4096. It is not practical to solve for the eigenvectors of C directly. A common theorem in linear algebra states that the vectors ei and scalars λ_i can be obtained by solving for the eigenvectors and eigenvalues of the $M\times M$ matrix $W^T W$. Let di and μ_i be the eigenvectors and eigenvalues of $W^T W$, respectively.

$$W^T W\, di = \mu i\; di$$

By multiplying left to both sides by W

$$WW^T\,(Wdi) = \mu i\,(Wdi)$$

which means that the first M - 1 eigenvectors ei and eigenvalues λ_i of WW^T are given by Wdi and μi , respectively. Wdi needs to be normalized in order to be equal to ei. Since we only sum up a finite number of image vectors, M, the rank of the covariance matrix cannot exceed M – 1 (The -1 come from the subtraction of the mean vector m). The eigenvectors corresponding to nonzero eigenvalues of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted from high to low according to their corresponding eigenvalues[6][7]. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first 5% to 10% of the dimensions. A facial image can be projected onto M' (<<M) dimensions by computing Ω= $[v1v2 \ldots\ldots vM']^T$.

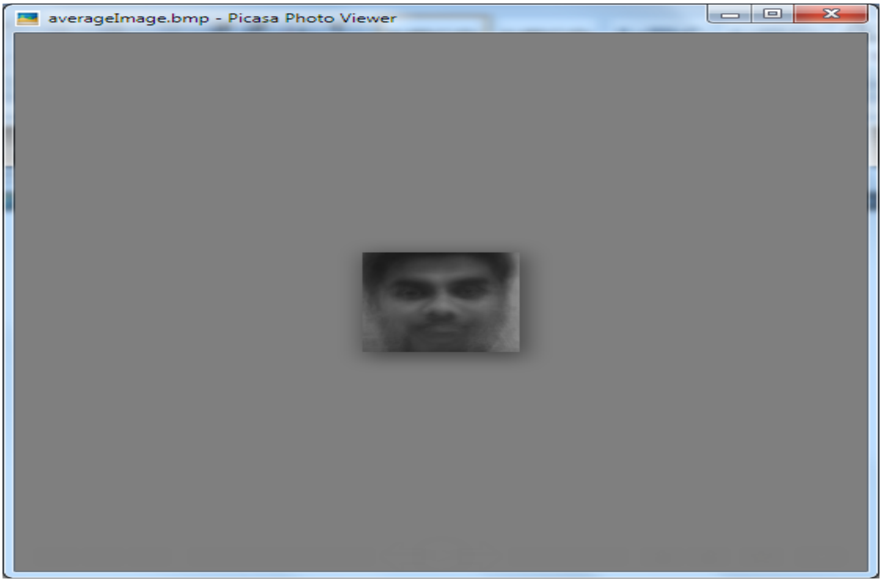

Fig. 2. Average Eigenfaces

2.4 Face Recognition

Once the eigenfaces have been computed, several types of decision can be made depending on the application.

1. Identification where the labels of individuals must be obtained.
2. Recognition of a person, where it must be decided if the individual has already been seen.
3. Categorization where the face must be assigned to a certain class.

PCA computes the basis of a space which is represented by its training vectors. These basis vectors, actually eigenvectors, computed by PCA are in the direction of the largest variance of the training vectors. Each eigenface can be viewed a feature. When particular face is projected onto the face space, its vector into the face space describe the importance of each of those features in the face. The face is expressed in the face space by its eigenface coefficients (or weights), Can handle a large input vector, facial image, only by taking its small weight vector in the face space. This means that can reconstruct the original face with some error, since the dimensionality of the image space is much larger than that of face space. In this report, consider face identification only. Each face in the training set is transformed into the face space and its components are stored in memory. The face space has to be populated with these known faces. An input face is given to the system, and then it is projected onto the face space. The system computes its distance from all the stored faces. However, two issues should be carefully considered:

1. What if the image presented to the system is not a face?
2. What if the face presented to the system has not already learned, i.e., not stored as a known face?

The first defect is easily avoided since the first eigenface is a good face filter which can test whether each image is highly correlated with itself. The images with a low correlation can be rejected. Or these two issues are altogether addressed by categorizing following four different regions:

1. Near face space and near stored face => known faces.
2. Near face space but not near a known face => unknown faces.
3. Distant from face space and near a face class => non-faces.
4. Distant from face space and not near a known class => non-faces.

Since a face is well represented by the face space, its reconstruction should be similar to the original; hence the reconstruction error will be small. Non-face images will have a large reconstruction error which is larger than some threshold θ^r.The distance ϵ_k determines whether the input face is near a known face.

3 Expression Recognition Accuracy

Table 1.

Detected Emotion	**Actual Emotion**			
	Happy	Sad	Anger	Surprise
Happy	97%	0	0	0
Sad	0	63%	12.5%	0
Anger	0	20%	75%	0
Surprise	0	0	0	100%
Confused or Neutral	0	15%	12.5%	0

4 Face Recognition Speed

The speed and accuracy of detection stage of the application was analyzed so that the algorithm providing the best performance could be used in the final implementation. The detection time for our algorithm was compared across 200 sample frames.

5 Conclusion

We were able to overcome many of the challenges of detecting facial expressions in real time by correctly identifying faces through a laptop camera input. Our future work includes development of a model that characterizes the further improvements of proposed system. Our system gives a better approximation in various luminous conditions. Here we accessed the face tracking device and processed the frames obtained from it. As a part of future enhancement we would try to work on the Auto exposure algorithms of the face tracking device so that we can have control over device exposures itself. So that whatever may be the lightening conditions we try to capture those exposures that would give more information about the facial features. The result of doing so is that we can have the better input and hence we can get further more efficient results. In addition, we would like to seek more efficient ways to perform the comparisons of input image with the training image so as to reduce the time taken for comparisons. Thus we can make our project more robust and reliable.

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