FACIAL EXPRESSION RECOGNITION USING PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

Facial expressions play an important role in human communication. The contours of the mouth, eyes and eyebrows play an important role in classification. Eigen faces are used to classify facial expression. It has been assumed that, facial expression can be classified into some discreet classes (like happiness, sadness, disgust, fear, anger and surprise) whereas absence of any expression is the “Neutral” expression. Intensity of a particular expression can be identified by the level of its “dissimilarity” from the Neutral expression.

**Keywords** - Principal component, edge detection, feature extraction, segmentation

I. INTRODUCTION

For developing a facial expression recognition system, it is important to realize that there are many possibilities that exist to represent a facial expression. Facial expressions can be represented through: Pictures, Video, Cartoons, Smiley, Facial characteristic points, Active Action Units.

Firstly, the train images are utilized to create a low dimensional face space. This is done by performing Principal Component Analysis (PCA) in the training image set and taking the principal components (i.e. Eigen vectors with greater Eigen values). In this process, projected versions of all the train images are also created. Secondly, the test images also are projected on the face space-as a result, all the test images are represented in terms of the selected principal components. Thirdly, the Euclidian distances of a projected test image from all the projected train images which is the most similar to the test image. The test image is assumed to fall in the same class that the closest train image belongs to. Fourthly, in order to determine the intensity of a particular expression, its Euclidian distance from the mean of the projected neutral images is calculated. The more the distance-according to the assumption-the far it is from the neutral expression. As a result, it can be recognized as a stronger the expression.

II. BASIC PRINCIPLE (PCA)

Principal Components Analysis (PCA) ia a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA ia a powerful tool for analysing data.

If there are a lot of images that are close to each other in the PCA space, it means that the images quite resemble but differ slightly from each other. The directions of these variations is important because it ‘says’ something about in what the images differ. A ‘cloud’ of these images could therefore be spanned by the directions of the variations, which are called the Principal Components.

To characterize the trends exhibited by this data, PCA extracts directions where the cloud is more extended. For instance, if the cloud is shaped like a football, the main direction of the data would be a midline or axis along the length of the football. This is called the first component, or the principal component. PCA will then look for the next direction, orthogonal to the first one, reducing the multidimensional cloud into a two-dimensional space.

Using PCA we find a subset of principal directions (principal components) in a set of training faces. Then we project faces into this principal components space.
and get feature vectors. Comparison is performed by calculating the distance between these vectors. Usually comparison of face images is performed by calculating the Euclidean distance between these feature vectors. Sometimes the angle-based distance is used.

The steps involved in performing PCA on a set of data are:

- Get some data
- Subtract the mean
- Calculating the covariance matrix
- Calculate the eigenvectors and Eigen values of the covariance matrix
- Choosing components and formatting a feature vector
- Deriving the new data set
- Getting the old data back

III. RECOGNITION SYSTEM

Automatic systems for facial expression recognition usually take the form of a sequential configuration of processing steps, which adheres to a classical pattern recognition model. The main steps to proceed:

A. Image Acquisition

Images used for facial expression recognition are static images or image sequences. An image sequence contains potentially more information than a still image, because the former also depicts the temporal dimensionality of input images. 2-D monochrome (grey-scale) facial image sequences are the most popular type of pictures used for automatic expression recognition. However, colour images could become prevalent in future, owing to the increasing availability of low-cost colour image acquisition equipment, and the ability of colour images to convey emotional cues such as blushing.

- STANDARD SIZING

B= imresize (A, [mrows ncols])

This instruction returns image B that has the number of rows and columns specified by [mrows ncols]. Either NUMROWS or NUMCOLS, in which case imresize computer the number of rows or column automatically to preserve the image aspect ratio.

- EDGE FINDING

BW= edge (I)

It takes a gray scale or a binary image I as its input, and returns a binary image BW of the same size as I, with 1’s where the function finds edges in 1 and 0’s elsewhere. By default, edge uses the Sobel method to detect edges but the following provides a complete list of all the edge-finding methods supported by this function:

- Sobel method
- Prewitt method
- Roberts method

These methods find edges using the sobel, prewitt or roberts approximation to the derivative. It returns edges at those points where the gradient of I is maximum.
LIGHTING COMPENSATION

\[ J = \text{imadjust}(I, [\text{low}_\text{in}; \text{high}_\text{in}], [\text{low}_\text{out}; \text{high}_\text{out}]) \]

This instruction maps the values in I to new values in J such that values between low_in and high_in map to values between low_out and high_out. Values below low_in and above high_in are clipped; that is, values below low_in map to low_out, and those above high_in map to high_out.

C. Feature Extraction:

Feature extraction converts pixel data into a higher-level representation of shape, motion, color, texture, and spatial configuration of the face or its components. The extracted representation is used for subsequent expression categorization. Feature extraction generally reduces the dimensionality of the input space. The reduction procedure should (ideally) retain essential information possessing high discrimination power and high stability. Such dimensionality reduction may mitigate the ‘curse of dimensionality’. Geometric, kinetic, and statistical- or spectral-transform-based features are often used as alternative representation of the facial expression prior to classification.

PERFORMING PCA

\[ [\text{Coeff}, \text{Score}, \text{latent}, \text{tsquare}] = \text{princomp}(X) \]

X is n by p data matrix. Rows of X correspond to observations and columns to variables.

- Coeff: Coeff is a p-by-p matrix, each column containing coefficients for one principal component. The columns are in order of decreasing component variance.
- Score: Representation of X is principal comp. Space rows of score correspond to observation, columns to components.
- Latent: Eigen values of the covariance matrix of X. It is the variance of Score

D. Classification:

Expression categorization is performed by a classifier, which often consists of models of pattern distribution, coupled to a decision procedure. A wide range of classifiers, covering parametric as well as non-parametric techniques, has been applied to the automatic expression recognition problem. The two main types of classes used in facial expression recognition are action units (AUs), and the prototypic facial expressions defined by Ekman.

The 6 prototypic expressions relate to the emotional states of happiness, sadness, surprise, anger, fear, and disgust. However, it has been noted that the variation in complexity and meaning of expressions covers far more than these six expression categories.

E. Post-processing:

Post-processing aims to improve recognition accuracy, by exploiting domain knowledge to correct classification errors, or by coupling together several levels of a classification hierarchy, for example.

IV. RESULTS

<table>
<thead>
<tr>
<th>s/t</th>
<th>Anger</th>
<th>Fear</th>
<th>Surprise</th>
<th>Sadness</th>
<th>Joy</th>
<th>Disgust</th>
</tr>
</thead>
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<td>0</td>
<td>0</td>
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<td>0</td>
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<tr>
<td>Fear</td>
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<td>200</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
<td>Surprise</td>
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<td>0</td>
<td>200</td>
<td>0</td>
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<td>0</td>
</tr>
<tr>
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</tr>
<tr>
<td>Joy</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
</tr>
<tr>
<td>Disgust</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>198</td>
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</tbody>
</table>
V. CONCLUSIONS

Principal Components Analysis is a method that reduces data dimensionality by performing a covariance analysis between factors. Thus Facial expression recognition or cognitive assessment can be done by comparing the principal components of default image or slice with the new/any respective subject.

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