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Analysis of Human age Prediction with Multi-Linear PCA

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Abstract - Automatic age estimation from facial images has recently emerged as a technology with multiple interesting applications. Electronic Customer Relationship Management (ECRM), Security Control and Surveillance Monitoring and Health care systems are some of the applications for age estimation. The human faces exhibit remarkable changes as age of person's changes. As age of person changes the appearance of the face also changes, these changes are in shape of the facial parts (eyes, nose, mouth, and chin), the texture of the facial parts (wrinkles).Thus, with the changes in the age of person, the pixel intensities of the facial image are also going to vary at various parts. These characteristics are seems to be common at particular age level, e.g. childhood, teen age, young, adult and old age. These characteristics of the facial image can be used as feature for any recognition system. An age estimation approach can be carried out in three stages, pre-processing, feature extraction and feature matching.

Index Terms --- Multi-linear principal component analysis, True positive factor, Support Vector Machine, Active Appearance Model, Artificial Neural Networks, Gabor filter, graphical user interface.

1. Introduction

This chapter illustrates the complete details about the earlier approaches proposed on age estimation. An automatic face image age estimation system is composed of two parts: face feature extraction and age estimation. The purpose of face feature extraction is to obtain all possible feature variations in all orientations, directions, lighting conditions and facial expressions. Because, these variant factors may lead to changes in color, luminance, shadows and contours of images.

Overall, there are three categories of feature extraction for human facial age estimation in the proposed literature. The first category is statistical-based approaches. XinGeng et al. [2][3] proposed the Aging pattern Subspace(AGES) method for automatic age estimation. The idea of AGES is to model the aging pattern, which is defined as a sequence of personal aging face images, by learning are preventative sub-space from EM-like (expectation maximization)iterative learning Principle Component Analysis (PCA).In other major studies [4][5], GuodongGuo et al. compared three typical dimensionality reduction and manifold embedding methods, such as PCA, Locally Linear Embedding (LLE) and Orthogonal Locality Preserving Projections (OLPP). According to the data distribution in OLPP sub-space, they proposed the Locally Adjusted Robust Regression (LARR) method for learning and prediction of human ages. The LARR applies Support Vector Regression (SVR) to obtain a coarse prediction and determine a local adjustment within a limited range of ages centered on the predicted result using the Support Vector Machine (SVM).

2. Methodology

The age estimation process was based on facial features extracted from the input image. 2-D Gabor filter along with Eigen was used to extract the features and multi-linear principal component analysis (MPCA) was used to reduce the dimensionality. To evaluate the performance a facial image database was created with various age persons. This database includes children images, young people images, adult people images and old people images. Under training, 8 samples from children category, 18 sample from young category, 15 sample from adult category and 5 samples from old category are taken. The proposed system completely carried out in two stages, training and testing. Under training, various facial images of various aged persons were trained. For this purpose initially various images are taken one by one, preprocessed, features extracted, MPCA applied for dimensionality reduction and then stored to database under four classes child (1-15), young (16-30), adult (31-59) and old (above 59). In testing stage feature extracted from the input facial image (test image) are compared with the features in training feature database using SVM classifier, the feature of the matched age group is taken as result age of the test image. The testing was done for available (the query image sample present in trained database) and unavailable (the query image sample not present in trained database) case.

3. Conventional Age estimating Approach

The conventional age estimating approach used Eigen method at feature extraction stage and Principal component analysis (PCA) as a dimensionality reduction technique

3.1 Principle Component Analysis

Until G. Bors and M. Gibbous [56] applied the Karhunen-Loeve Transform to faces, face recognition systems utilized either feature-based technique, template matching or neural networks to perform the recognition. The groundbreaking work of Kirby and Sirovich not only resulted in a technique that efficiently represents pictures of faces using Principal

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Component Analysis (PCA), but also laid the foundation for the development of the "Eigen face" technique of Turk and Pent land [57], which has now become a de facto standard and a common performance benchmark in face recognition. Starting with a collection of original face images, PCA aims to determine a set of orthogonal vectors that optimally represent the distribution of the data. Any face images can then be theoretically reconstructed by projections onto the new coordinate system. In search of a technique that extracts the most relevant information in a face image to form the basis vectors, Turk and Pentland proposed the Eigen face approach, which effectively captures the variations within an ensemble of face images.Mathematically, the Eigen face approach uses PCA to calculate the principal components and vectors that best account for the distribution of a set of faces within the entire image space. Considering an image as being a point in a very high dimensional space, these principal components are essentially the eigenvectors of the covariance matrix of this set of face images, which Turk and pent land termed the Eigen face. Each individual face can then be represented exactly by a linear combination of Eigen faces, or approximately, by a subset of "best" Eigen faces – those that account for the most variance within the face database characterized by its eigen values, as depicted in Figure.1

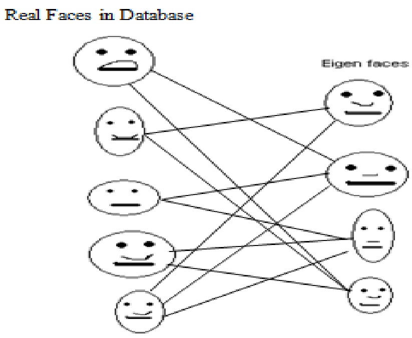

Fig.1 Faces are Linear Combinations of Eigen faces.

3.2 Feature Extraction Using 2D-Gabor Filter and Eigen approach.

The Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image. Gabor filters have been widely used in pattern analysis applications. To visualize a Gabor function selects the option “Gabor Function” under “Output Image”. The Gabor function for the specified values of parameters “wavelength”, “orientation”, “phase offset”, “aspect ratio”, and “bandwidth” will be calculated and displayed as an intensity map image in the output window. (Light and dark gray colors correspond to positive and negative function values, respectively). The image in the output window has the same size as the input image: select, for instance, input image octagon.jpg to get an output of size 100 by 100. If lists of values are specified under “orientation(s)” and “phase offset(s)”, only the first values in these lists will be used.

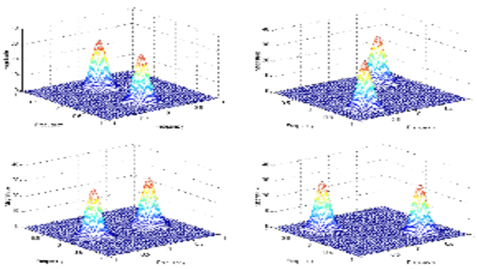

Fig.2 Plot of frequency response of the Gabor filter for different values of u0, v0 corresponding to four orientations - 0, 45, 90 and 135

4. Results

The input facial image goes through preprocessing stage, preprocessing stage is as follows:1) The input color image is read from the database,2) Then it is resized into a uniform dimensions, further it is cropped for facial region,3) converted in to the gray scale,4) Further histogram equalization is applied to gray level image to highlight the different part and wrinkle on facial image.

The Gabor feature representation of an image I(x, y) is the convolution of the image with the Gabor filter bank g (x,y, θ, Φ) .The Gabor filter is used for edge detection, in this paper the Gabor filter is used for the Edge-Based Feature Extraction. The edge-based facial feature include the eyes, eyebrows, nose and mouth, these feature from facial image are extracted using the edge detection properties of the Gabor filter, besides this the wrinkle and skin texture is also extracted which is used to classify the people at old age following figure shows how the eye, eyebrows, mouth& nose are detected using

5. Conclusion

The proposed an adaptive age estimating approach based on Gabor filter and Multi-linear Principal Component analysis (MPCA). In this work, the age of human beings was tried to predict based on their facial images, because, the facial images features varies with age of the persons. The proposed work completely focused towards the varying nature of pixel intensities of facial images. The proposed approach extracts the all possible variations from facial images with Gabor filter. By applying the Gabor filter on various orientations, respective variations are obtained. At each and every orientation, only few features are dominating in nature. When the Gabor filter was applied on image, the respective dominant features are obtained.

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