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Automatic Age Estimation Using PCA

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ABSTRACT

This paper details with the subjective age prediction of face images using Principal Component Analysis (PCA). The face database is built by the seven individual age groups which are divided from the adult facial images between 10 to 60 years old. An age prediction algorithm is developed for examining the age of individual. Age prediction is concerned with the use of a training set to train a model that can predict the age of the facial images. The facial feature is extracted based on the geometric feature based method and principal component analysis (PCA) method. The accuracy of the system is analysed by the variation on the range of the age groups. The efficiency of the system can be confirmed through the experimental result.

Keywords: **Key: Age prediction, feature extraction, principal component analysis, age group, geometric feature.**

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I. INTRODUCTION

Face aging making and face aging simulation have attracted rising research interest from psychology, graphics, and lately computer vision. As humans, we have a knack for guess another person's age quite accurately just by glancing at their face. Although age prediction may seem relatively simple to us, computers have a considerable more difficult time performing the task.

Principal Component Analysis (PCA), also known as KarhunenLoeve expansion, is a typical feature extraction and data representation technique widely used in the areas of pattern recognition and computer vision. Sirovich and Kirby [1], [2] first used PCA to proficiently represent pictures of human faces. They argued that any face image could be renovated nearly as a weighted sum of a small collection of images that define a facial basis (Eigen images), and a mean image of the face. Within this context, Turk and Pent land [3] presented the well-known Eigen faces method for face recognition in 1991.

Since then, PCA has been widely examined and has become one of the most successful approaches in face recognition. Penev and Sirovich [4] discussed the problem of the dimensionality of the "face space" when Eigen faces are used for representation. Zhao and Yang [5] tried to account for the random effects of illumination in PCA-based vision systems by generating.

II. PROPOSED METHOD

A .Preprocessing

Input images are affected by the type of camera, brightness conditions, background information the images need to be normalized before feature recognition and extraction. The steps of pre-processing are: Step1. For each image select the facial regions of importance (ROI). The region containing the eyes, nose and mouth was manually cropped, since these features are necessary for involuntary age estimation. Step2. Normalize all the cropped regions of importance to a size of 64*64 pixels. Step3. The face database has a collection of colored images so finally the normalized color images were converted to grey scale.

B. Feature Extraction

Face interpreted images are read from the database followed by feature extraction using Active Appearance Model (AAM). AAM converts face images into appearance parameters, contains both shape and texture information. This is the given as input for training the age estimation. Depending upon the output from the age result, the appearance constraints are fed into the corresponding age prediction. Features from face images are extracted using Active AAM. Kwon and Lobo did examines on age classification first. They consulted studies in cranio-facial research, art and the atrical makeup, plastic surgery and found with the growth of a people, the shape of head turns from circle to oval.

C. Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) can do prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, applications having linear copies are suitable. Let us consider the PCA method in a training set of *M* face images. Let a face image be characterized as a two dimensional *N* by *N* array of intensity values, or a vector of dimension *N*2. Then PCA tends to find a *M*-dimensional subspace whose basis vectors correspond to the extreme variance direction in the original image space. This new subspace is normally lower dimensional (*M*<< *M* << *N*2). New basis vectors define a subspace of face images called face space. All images of known faces are projected onto the face space to find sets of weights that define the contribution of each vector. By comparing a set of weights for the unidentified face to sets of weights of known faces, the face can be identified. PCA basis vectors are defined as eigenvectors of the scatter matrix S defined as: where μ is the mean of all images in the training set and *xi* is the *I th* face image represented as a vector *i*. The eigenvector linked with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigen vector that finds the least modification. A facial image can be projected onto *M ′*(<< *M*)dimensions by computing

D. Euclidean Distance

While the simple Euclidean distance amount seems to be enough, research does advise that different distance measures may affect the presentation of system. Thus an appropriate distance measure has to be chosen to reflect the nature of the problem being solved [12]. More complex classifiers, e.g. Support Vector Machine could also be used for development of accuracy. However, systems become more complex and the development is not often guaranteed [12]. Thus the Euclidean Distance was identified as the maximal means of classification for the system. A novel modest nearness approach was executed using the average class distance. The average for each of the seven training class was calculated. Then for any test input image, the distance to these seven classes' average sets were computed. The class which had the least distance was measured to be the age result. And the age range label was allocated based on the label of the aging group. Fig. 1 shows the flow of the proposed age prediction steps.

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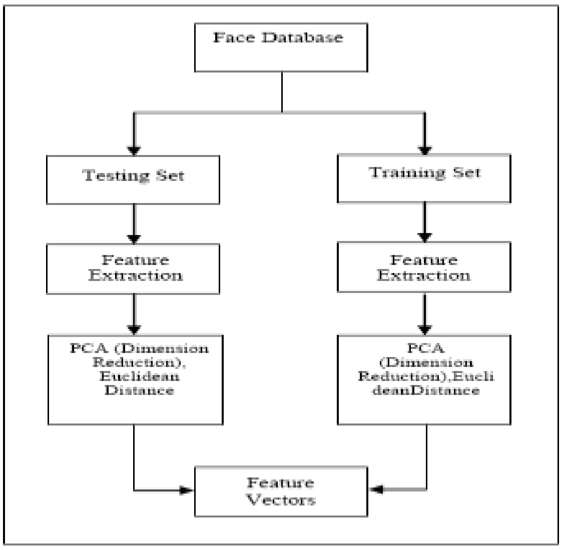

Fig. 1. Flowchart of the human face age prediction system

Result

Firstly, train the system: images were selected for each class from the face database. The system was trained within these images using the PCA method distinct above, to derive the Training Feature Vector. Secondly, gather the testing images: images were designated for each class from the face database. The images were processed for classification by using the PCA approach described above, to derive the Testing Feature Vector. Finally, prediction: the smallest Euclidean distance of the Testing feature vector from the average distance of the seven Training feature vectors was added. The class with the smallest distance was distinct as the age result. Thus the image was labeled with the age group of that particular class. The presentation of age prediction is the age range and not the exact age of the human face. Hence, the percentage of accuracy achieved during the experiments was tabulated, charted and presented.

Table I: Reasonable Age Prediction Result

Subjects	Group1	Group2	Group3	Group4	Group 5	Group6	Group7	Mini-mum	Result
	13.20	14.80	14.90	15.20	16.30	15.80	16.85	13.20	≤ 10
	13.45	14.56	14.15	15.10	16.55	16.45	16.10	14.56	11~20
	13.35	13.90	14.85	15.25	16.35	16.63	16.95	14.85	21~30
	13.80	14.12	14.75	15.30	16.40	16.25	15.90	14.75	31~40
	13.30	14.20	14.60	15.15	16.00	16.15	15.85	16.00	41~50
	13.50	14.45	14.25	15.35	16.60	16.80	16.95	16.80	51~60
	13.10	14.70	14.80	15.40	16.50	17.20	17.10	17.10	≥ 60
Average	66.90	72.58	74.25	76.00	82.10	81.85	81.95		

III. CONCLUSION

In this paper, we proposed automatic age estimation of aging effects on face images. As declared in the above section, the age group arrangement is based on the training data and testing data 720 and 540 images respectively. For group1,group2 and group7, the right rates are 100%, however, for group3 the total correct rate is 90.5% (since the correct rates for group4, group5, and group6 are 91.5%, 93.5% and 94.5% respectively). Thus, the overall prediction rate for all the 1300 trial images is 89.5%. It could be decided that the system's presentation is 90.5% in age prediction. The process of the system is divided into three phases: location, feature extraction, and age estimation. We have to work on assumption the feature points more accurately.

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