Subjective Age Prediction of Face Images 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 analyzed by the variation on the range of the age groups. The efficiency of the system can be confirmed through the experimental results.**

***Index Terms*—Age prediction, feature extraction, principal component analysis, age group, geometric feature.**

I. Introduction

Face aging modeling and face aging simulation have attracted growing research interest from psychology, graphics, and lately computer vision.

As humans, we have a knack for prediction another person's age quite accurately just by glancing at their face. Although age prediction may seem relatively simple to us, computers have a much more difficult time performing the task. Principal Component Analysis (PCA), also known as KarhunenLoeve expansion, is a classical 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 efficiently represent pictures of human faces. They argued that any face image could be reconstructed approximately as a weighted sum of a small collection of images that define a facial basis (eigenimages), and a mean image of the face.

Within this context, Turk and Pent land [3] presented the well-known Eigenfaces method for face recognition in 1991. Since then, PCA has been widely investigated 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 eigenfaces are used for representation.

Zhao and Yang [5] tried to account for the arbitrary effects of illumination in PCA-based vision systems by generating an analytically closed-form formula of the covariance matrix for the case with a special lighting condition and then generalizing to an arbitrary illumination via an illumination equation. However, Wiskott et al. [6] pointed out that PCA could not capture even the simplest invariance unless this information is explicitly provided in the training data. They proposed a technique known as elastic bunch graph matching to overcome the weaknesses of PCA.

Kwon and Lobo [7] first worked on the age classification problem. They referred to cranio facial research, theatrical makeup, plastic surgery, and perception to find out the features that change with age increasing. They classified gray-scale facial images into three age groups: babies, young adults and senior adults. First, they applied deformable templates [8] and snakes [9] to locate primary features (such as eyes, noses, mouth, etc.) from a facial image, and judged if it is an infant by the ratios of the distances between primary features. Then, they used snakes to locate wrinkles on specific areas of a face to analyse the facial image being young or old.

Kwon and Lobo declared that their result was promising. However, their data set includes only 47 images, and the infant identification rate is below 68%. Besides, since the methods they used for location, such as deformable templates and snakes, are computationally expensive, the system might not be suitable for real time processing.

Another related work is age estimation, which selects discriminative features to estimate face age. Primary studies on age estimation coarsely divided human faces into groups based on facial landmarks and wrinkles.

Most recent approaches considered the continuous and temporal property of face age and formulated age estimation as a regression problem. Researchers explored different features, including AAM coefficients, image intensities features designed heuristically, and adopted various regression methods, such as quadratic function, piecewise linear regression, multiperceptron projection, etc. differently from the aforementioned methods, Geng et al. [25] defined an aging sequence as an aging pattern and estimated age by projecting a face instance onto appropriate position of a proper pattern [10].

M. D. Malkauthekar and S. D. Sapkal [26] Presented experimental analysis of classification of facial images. Facial images of different expressions and angles of two classes and three classes are used for classification. For two classes and three classes results are compared by Fisher Discriminant method and Euclidian distance is used for matching. G. MallikarjunaRao et al., [27] presented a Neural Netwrok-based upright invariant frontal face detection system to classify the gender based on facial information. The reliability is depends on Pixel based and geometric facial features. The robustness of classification is depends on pi-sigma neural network and the cyclic shift invariance techniques.

Zong X. Lin et al., [28] proposed fast vertical pose invariant face recognition module for intelligent robot guard. The vertical pose angle is evaluated by the height difference

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between the center of the eyes and the auriculocephalicsulcus of the pinna; earpiece rests on if glasses are worn. The vertical pose angle is derived by the arcsine function of the height difference over the earpiece length. Gabor Wavelet Transform (GWT) is adopted for feature extraction core of the original face recognition module.

Anil Kumar Sao and B. Yegnannarayna [29] proposed analytic phase based representation for face recognition to address the issue of illumination variation using trigonometric functions. To decide the weights to the projected coefficients in template matching eigenvalues are used.

Jing Wu et al., [30] proposed gender classification using Shape from Shading (SFS). Linear Discriminant Analysis (LDA) is used based on the Principal Geodesic Analysis parameters to discriminate female and male genders of the test faces. SFS technique is used to improve the performance analysis of classification in gray scale face images.

II. Proposed Method

The proposed age prediction method consists of four steps.

A. Preprocessing

Input images are affected by the type of camera, illumination conditions, background information the images need to be normalized before feature detection 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 automatic age prediction.

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 annotated 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 prediction. Depending upon the output from the age result, the appearance parameters are fed into the corresponding age prediction. Features from face images are extracted using Active AAM.

Kwon and Lobo did researches on age classification first. They consulted studies in cranio-facial research, art ant theatrical makeup, plastic surgery and found with the growth of a people, the shape of head turns from circle to oval. So they put forward utilizing the proportion of distance between organs to decide whether a facial image belongs to child or adult.

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 models are suitable.

Let us consider the PCA procedure in a training set of M face images. Let a face image be represented as a two dimensional N by N array of intensity values, or a vector of dimension N^2. Then PCA tends to find aM-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lower dimensional ($M << M << N2$). 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 describe the contribution of each vector. By comparing a set of weights for the unknown 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:

$$S = \sum_{i=1}^{M} (xi - \mu).(xi - \mu)' \quad (1)$$

where μ is the mean of all images in the training set and x_i is the i^{th}face image represented as a vector i. 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. A facial image can be projected onto $M'(<< M)$dimensions by computing

$$\Omega = [v_1 v_2 ... v_{M'}]^T \quad (2)$$

The vectors are also images, so called, eigenimages, or eigenfaces .They can be viewed as images and indeed look like faces. Face space forms a cluster in image space and PCA gives suitable representation.

D. Euclidean Distance

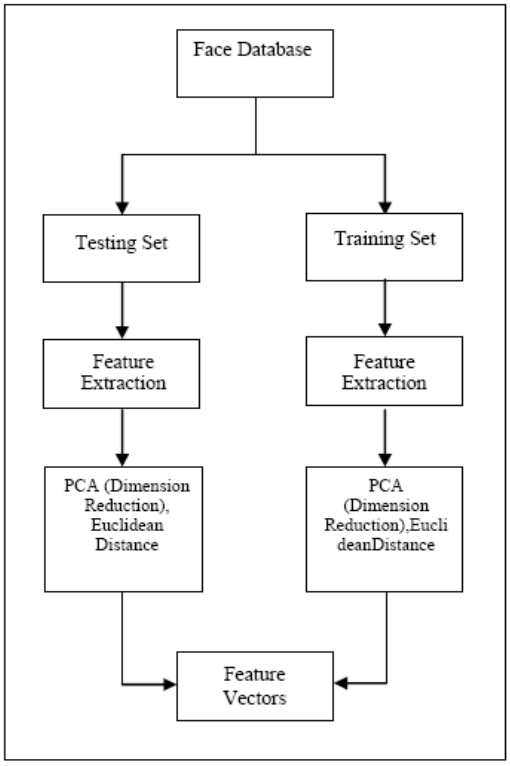

Fig. 1. Flowchart of the human face age prediction system

While the simple Euclidean distance measure seems to be enough, research does suggest that different distance measures may affect the performance 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 improvement of accuracy. However, systems become more complex and the improvement is not often guaranteed [12]. Thus the Euclidean Distance was identified as the maximal means of classification for the system.

A novel competitive nearness approach was implemented 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 considered to be the age result. And the age range label was assigned based on the label of the aging group.

Fig. 1 shows the flow of the proposed age prediction steps.

III. Experimental 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 approach described above, to derive the Training Feature Vector. Secondly, gather the testing images: images were selected 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 minimum Euclidean distance of the Testing feature vector from the average distance of the seven Training feature vectors was computed. The class with the minimum distance was defined as the age result. Thus the image was labeled with the age group of that particular class. The performance 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.

Fig. 2 shows the experimental data for age prediction. Table I shows the training and testing data taken for experimentation. The reasonable age prediction result was described in Table II and the minimum Euclidean distance with every test image and the average Euclidean distance of each training class.

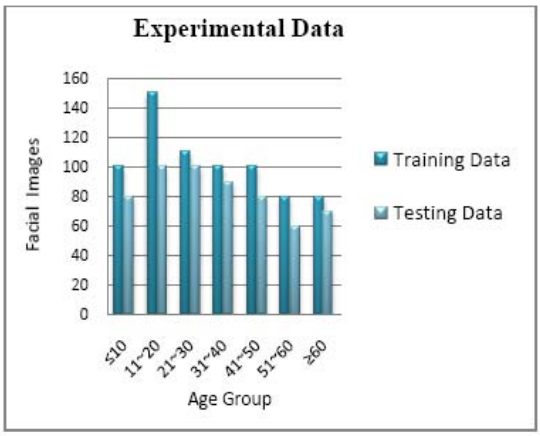

Fig. 2. The experimental data for age prediction

TABLE I: Reasonable age Prediction result

Subjects	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Minimum	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		

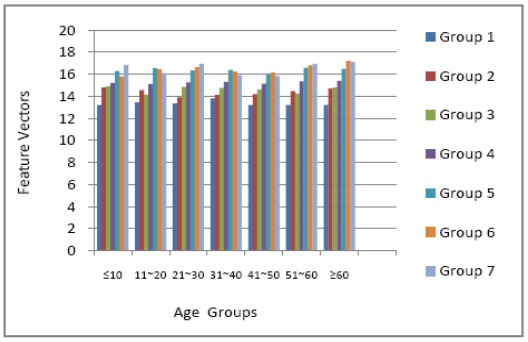

Fig. 3. Performances of subjective age prediction

IV. Conclusion

In this paper, we proposed automatic age estimation of aging effects on face images. As mentioned in the above section, the age group labeling is based on the training data and testing data 720 and 580 images respectively. For group1, group2 and group7, the correct 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 experimental images is 92.5%. It could be concluded that the system's performance is 92.5% in age prediction. The process of the system is divided into three phases: location, feature extraction, and age estimation. We have to work on finding the feature points more accurately.

TABLE III. The Tendency of Incorrect Prediction by Individual Difference

Age Prediction	A person with roundness outline, A person with keen outline, A real age differs from an impression (A baby face, A face which looks old), Wearing of glasses, Disappearance of wrinkles and modification of eyebrows by makeup.

The tendency of incorrect prediction by individual difference such as (a real age differs from an impression,

wearing of glasses, disappearance of wrinkles and modification of eyebrows by makeup, etc.). In addition, as shown in Table III, the tendency of incorrect prediction caused by individual difference of appearance was also seen.

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