Automatic Age Prediction of Aging Effects on Face Images

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Abstract

Automatic age prediction system for gray-scale facial images is proposed in this paper. Ten age groups, including, are used in the prediction system. The process of the system is divided into three phases: location, feature extraction, and age prediction. Principal Component Analysis (PCA) was used to reduce dimension and enhance class. Finally Euclidean distance was used to classify the images into one of seven major groups. These groups are: Group1 (0 to 10 years), Group2 (11 to 20 years), Group3 (21 to 30 years), Group4 (31 to 40 years), Group5 (41 to 50 years), Group6 (51 to 60 years) and Group7 (60 over). The proposed system is experimented with 1300 facial images on a Core 2 Duo processor with 2 GB RAM. One half of the images are used for training and the other half for test. It takes 0.2 second to classify an image on an average. The identification rate achieves 95.5% for the training images and 85.5% for the test images, which is roughly close to human's subjective prediction.

Key Words: Age Prediction, Feature Extraction, Principal component Analysis (PCA).

1. Introduction

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 Karhunen Loeve 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 analyze 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.

2. The Proposed Method

The proposed age prediction method consists of four steps.

2.2. Preprocessing

Input images are affected by the type of camera, illumination conditions, background information. So, 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.

2.3. 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.

2.4. Principal Component Analysis (PCA)

Features from face images are extracted using Active Appearance Model (AAM). Let $I = [\, I_1, I_2, \ldots, I_N]$ represents N training set images with landmark points as $x = [\, x_1, x_2, \ldots, x_N]$. Shape variations are obtained by aligning these landmark points and then Principal Components Analysis PCA) is performed on those points. Any shape vector x in the training set can be represented as in Eq. 1.

$$x \approx \bar{x} + V_s b_s, b_s = V_s^T (x - \bar{x}) \qquad (1)$$

where $\bar{x}$ is the mean shape, V_s contains the eigenvectors of largest eigenvalues (λ_s) and b_s represents weights or shape model parameters. By writing Eq. 1, it is possible to calculate shape model parameters corresponding to a given example. The shape can be changed by varying the elements of b_s using eigenvalues (λ_s).

2.5. Euclidean Distance

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 class 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. Figure 1 shows the flow of the proposed age prediction steps.

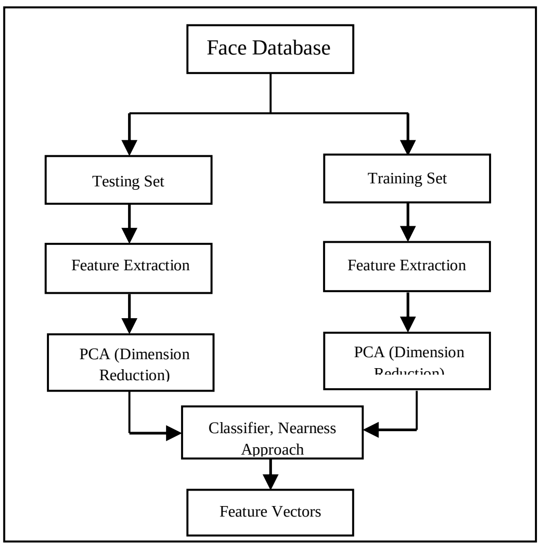


Figure 1. Flowchart of the human face age prediction system

3. Experimental Results

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. Figure 2 shows the experimental data for age prediction. Table 1 shows the training and testing data taken for experimentation and the reasonable age prediction result was described in Table 2.

Table 1. Training and testing data

Training data		Testing data	
Age Group	Number	Age Group	Number
≤ 10	100	≤ 10	80
11~20	150	11~20	100
21~30	110	21~30	100
31~40	100	31~40	90
41~50	100	41~50	80
51~60	80	51~60	60
≥ 60	80	≥ 60	70
Total	720	Total	580

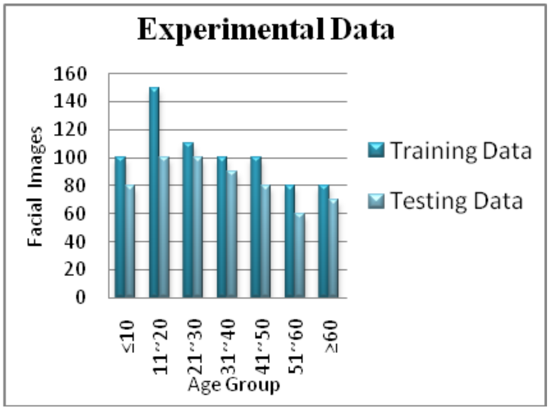
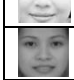


Figure 2. The experimental data for age prediction

Table 2. Reasonable age prediction result

Subjects	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	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		

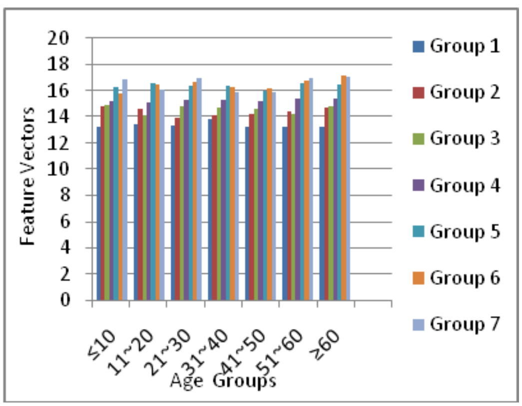


Figure 3. Performances of subjective age prediction

4. 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. 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 3, the tendency of incorrect prediction caused by individual difference of appearance was also seen.

Table 3. 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.

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