An Image-Based Method of Distinguishing Children from Adults

Alireza Keshavarz Choobeh

***Abstract*—Distinguishing children from adults via facial image analysis has lots of potential real-world applications such as security access control and human computer interaction. However, it is still a challenging problem for the computer vision systems to automatically and effectively distinguish children from adults. In this paper, we introduce a novel children recognition method, which improves both the accuracy and reliability of the latest work on this subject simultaneously. Results on the FG-NET aging database show that using the minimum distance classifier on the one dimensional feature space created by using Active Appearance Model (AAM) followed by Linear Discriminant Analysis (LDA), we can recognize the children and adults with accuracies up to 89% and 90%, respectively.**

***Index Terms*—Age estimation, active appearance model, LDA, minimum distance classifier.**

I. Introduction

Although distinguishing children from adults has a lot of applications, it shares many difficulties encountered in other similar topics related to face image interpretation.According to the literature, [1] is the first and the latest true children recognition algorithm, which is based on the face/iris size ratio. The first drawback of this algorithm is that it does not work in the case of closed eyes. The second drawback is that the face/iris size ratio cannot always distinguish children from adults as mentioned in their work. A very simple way of solving these problems is to use all information of face, i.e., facial appearance. Obviously, aging is a process related to both the shape and the texture of face. Thus, the Active Appearance Model (AAM) [2] can be used as a feature extractor, whose main advantage is that the extracted features combine both the shape and the intensity of the face images.

In this paper, a novel children recognition method is presented. The proposed method consists of three main steps. First, the AAM was applied to the face image to obtain the facial appearance model parameters. Second, the Linear Discriminant Analysis (LDA) [3] was applied to the facial appearance model parameters to extract more discriminative features. Finally, minimum distance classifier [4] was applied to classify face images into children or adults. The block diagram of this approach is shown in Fig. 1.

This paper is organized as follows: Section II introduces briefly the AAM. Section III reviews LDA algorithm. Section IV discusses the minimum distance classifier. Section V reports the experimental results of the proposed method on the FG-NET aging database. Conclusions are drawn in Section VI.

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A. K. Choobeh is with the Department of Electrical engineering, Buinzahra Branch, Islamic Azad University, Buinzahra, Iran (e-mail: keshavarz_c@yahoo.com).

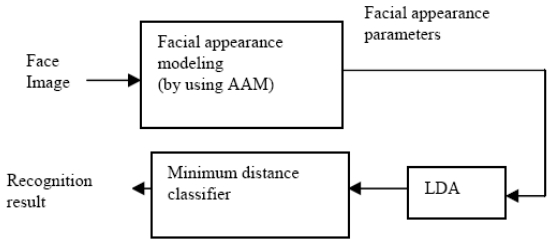

Fig. 1. Block diagram of the proposed children recognition algorithm.

II. Active Appearance Models

The active appearance model [2] is a statistical face model, which models the shape and intensity variation of face images. Given a set of training face images, a statistical intensity model and a shape model are learned seperately, based on the Principal Component Analysis (PCA):

$$b = P^{-1}(X - X_m) \tag{1}$$

where b is a vector of model parameters, P is the matrix of eigenvectors, X is a vector describing the shape or intensity pattern of a training face image, and X_m is the mean shape or intensity pattern of training face images. Then the two models are combined to build AAM.

III. Linear Discriminant Analysis

As noted by [3], LDA aims to reduce into a low-dimensional space in order to combine data of the same class, while dataof different classes are separated easily from each otherby using class information. Consider g groups of individuals, each group comprised of N_l individuals for which d factors were measured. The data can then be represented in the form of g matrices of the type:

$$X_l = \begin{bmatrix} x_{1,1} & \cdots & x_{1,N_l} \\ \vdots & \ddots & \vdots \\ x_{d,1} & \cdots & x_{d,N_l} \end{bmatrix} = \left[X_{l,1} \dots X_{l,N_l}\right] \tag{2}$$

In the space R^dwe obtain$g$ scatters containing respectively $N_1, \dots, N_g$ points. We assume that $N = \sum_{l=1}^{g} N_l$. The goal of the LDA is to find the best separation for these $g$scatters of points. To achieve this, we must first introduce the following definitions:

The mean, or barycenter, of a group:

$$m_l = {N_l}^{-1} \sum_{j=1}^{N_l} X_{l,j} \tag{3}$$

The overall mean of the g groups:

$$m = N^{-1} \sum_{l=1}^{g} \sum_{j=1}^{N_l} X_{l,j} = \frac{\sum_{l=1}^{g} N_l m_l}{\sum_{l=1}^{g} N_l} \quad (4)$$

The intraclass covariance (internal to the considered class)

$$R_I = N^{-1} \sum_{l=1}^{g} \sum_{j=1}^{N_l} X_{l,j} X_{l,j}{}^T - N^{-1} \sum_{l=1}^{g} N_l m_l m_l{}^T \quad (5)$$

The extra class covariance which can be interpreted as the dispersion of the barycenters of each class with respect to the overall mean:

$$R_E = N^{-1} \sum_{l=1}^{g} N_l (m_l - m)(m_l - m)^T \quad (6)$$

The total covariance:

$$R = N^{-1} \sum_{l=1}^{g} \sum_{j=1}^{N_l} X_{l,j} X_{l,j}{}^T - mm^T \quad (7)$$

These covariance matrices are $d \times d$ matrices. It can easily be proved that:

$$R = R_I + R_E \quad (9)$$

We are now going to find the direction, parallel to the vector v, such that the interclass dispersion is minimal and the extraclass dispersion is maximal. To achieve this objective, one possible criterion is to minimize the evaluation function defined by:

$$J(V) = \frac{V^T R_I V}{V^T R V} \quad (9)$$

These amounts to searching V such that:

$$\min_V V^T R_I V \quad with \ V^T R V - 1 = 0 \quad (10)$$

Using the Lagrange multiplier method, we end up with the following equivalent problem:

$$\begin{cases} \min_V (V^T R_I V - \lambda (V^T R V - 1) \\ with \ V^T R V - 1 = 0 \end{cases} \quad (11)$$

By setting the gradient with respect to v to zero, we find that v is such that:

$$R^{-1} R_I V = \lambda V \quad (12)$$

Notice that $R^{-1} R_I$ is a positive matrix. If we now express the constraint $V^T R V - 1 = 0$, we infer that $J(V) = \lambda \geq 0$. Hence we have to choose the eigenvector associated with the smallest eigenvalue. It can be proved that V is also an eigenvector of $R^{-1} R_E$ associated with the highest eigenvalue. Let $V_1, \dots, V_k$ be the k eigenvectors associated with the k highest eigenvalues of $R^{-1} R_E$. By compiling these k vectors, we get the $d \times k$ matrix:

$$V = [V_1, \dots, V_k] \quad (13)$$

This means that for each of the g families, the vectors are:

$$y_{l,j} = V^T X_{l,j} \quad (14)$$

This gives the representative points of each image. Theoretically, each of the g scatter has a minimal dispersion, and all of the scatters are as far away from each other as possible.

IV. Minimum Distance Classifier

The minimum distance classifier [4] is the simplest classification technique but in some cases also the best. Suppose that each pattern class, ω_i, is characterized by a mean vector m_i:

$$m_i = \frac{1}{N_i} \sum_{x \in \omega_i} x \qquad i = 1,2, \dots, W \quad (15)$$

where N_i denotes the number of training pattern vectors from class ω_i and W is the number of pattern classes. To determine the class membership of an unknown pattern vector x, we simply compute the euclidean distance of the feature vector x to each mean vector m_i:

$$D_i(x) = \|x - m_i\| \qquad i = 1,2, \dots, W \quad (16)$$

We then assign the feature vector x to class ω_i if $D_i(x)$ has the smallest distance. It should be noted that in this paper, W is equal to 2.

V. Experimental Results

In the experiments, subjects between newborns and 12 are marked as children and those over 12 are marked as adults. It is discovered in the experiments that if the age threshold is set to 12, the recognition result will be better than applying other thresholds. The proposed children recognition algorithm is evaluated on the FG-NET aging database [5] which contains 1002 face images from 82 subjects with the age range between newborns up to 69 years. This database contains 411 children and 591 adults. Typical face images from this database are shown in Fig. 2.

The children recognition algorithm is tested on the FG-NET database through the Leave-One-Person-Out (LOPO) mode [6], i.e., in each fold, the images of one person are used as the test set and those of the others are used as the training set. After 82 folds, each subject has been used as the test set once and the final results are calculated based on all of the recognitions. Sixty-eight landmark points are used to train the shape model. For training the intensity model, the number of pixels from internal region of the shape-normalized faces is approximately, 18000 pixels. In total, 130 features are extracted as the facial appearance model parameters. After that, LDA is applied to the 130 facial appearance model parameters to extract only one feature. Finally the minimum distance classifier is utilized to classify the extracted feature into one of the two age groups (children and adults). Practical experiments show that the children recognition accuracy is deteriorated when the number of features is more than one feature. Other classifiers including Support Vector Machine (SVM), back propagation neural networks , and KNN are

also tested, but the performance is not improved. The confusion matrix of the proposed children recognition algorithm are tabulated in Table I.

TABLE I: THE CONFUSION MATRIX OF THE PROPOSED CHILDREN RECOGNITION ALGORITHM

Ground Truth\Recognized	Child	Adult
Child	%89	%11
Adult	%10	%90

Fig. 2.Typical face images in the FG-NET aging database.

Based on the results, the proposed algorithm is able to attain better recognition performance (accuracy is approximately 7% higher) compared to [1].

VI. CONCLUSION

Children recognition has numerous commercial and law enforcement applications. This paper presents an automatic system based on LDA and minimum distance classifier for children recognition. After modeling of face images by using Active Appearance Model (AAM), LDA and minimum distance classifier are applied to distinguish children from adults. Experimental results on the FG-NET aging database show that the proposed method achieves better performance than the existing one.

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Alireza Keshavarz Choobeh was born in Karaj, Iran, on August 3, 1982. He received the B.S. degree in electronics engineering from Mazandaran University, Babol, Iran, in 2005. He received the M.S. degree in biomedical engineering from TarbiatModares University, Tehran, Iran, in 2009.He is currently a researcher with the Young Researchers Club, Azad University, Iran. His research interests include computer vision and imageprocessing.