Discriminant Feature Manifold for Facial Aging Estimation

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Abstract—Computerised facial aging estimation, which has the potential for many applications in human-computer interactions, has been investigated by many computer vision researchers in recent years. In this paper, a feature-based discriminant subspace is proposed to extract more discriminating and robust representations for aging estimation. After aligning all the faces by a piece-wise affine transform, orthogonal locality preserving projection (OLPP) is employed to project local binary patterns (LBP) from the faces into an age-discriminant subspace. The feature extracted from this manifold is more distinctive for age estimation compared with the features using in the state-of-the-art methods. Based on the public database FG-NET, the performance of the proposed feature is evaluated by using two different regression techniques, quadratic function and neural-network regression. The proposed feature subspace achieves the best performance based on both types of regression.

Keywords—face aging estimation; face modelling; LBP; OLPP;

I. INTRODUCTION

The human face, as a unique identity feature, conveys a lot of representative information such as gender, age and expressions. How computers analyze faces under a variety of variations, typically under different poses, illuminations, ages and expressions, is an interesting and challenging problem. Among these variations, facial aging is special because it is non-invertible when human grows up.

Human face aging analysis is important for several reasons. Firstly, automatic human-computer interaction techniques may require an estimation of the age to trigger more interesting communications or decide how the computer should respond to people with different ages, e.g., adjusting the game levels or denying inappropriate behaviour of young children. Secondly, face recognition techniques which are invariant to age variation are vital for robust security systems when there are difficulties in updating the database. Thirdly, aging simulation is interesting for forensic computing when it is necessary to process a wide age span.

Much work on facial aging analysis has been undertaken in recent years. Aging simulation finds a function to map to simulate the other group of faces shown in Fig. 1. Aging invariant based facial recognition verifies the identity across subjects with different ages [5], [6], [7]. Aging estimation regresses facial ages based on the facial appearance [8], [9], [10], [11].

In this paper, an age-discriminant feature subspace is proposed to improve the age estimation. The main advantages are the discriminant texture feature is more robust under illumination variation and intensity noise and the feature is distinctive to age variation.

II. RELEVANT WORK

One of the popular age estimation techniques is presented in [11]. An appearance model [12] is used to encode all the face instances followed by fitting a quadratic function to estimate the age. Some drawbacks are that the facial coding space, which represents all the variations, does not discriminate the age and some useful texture information related to the age pattern is not used efficiently. Therefore, better feature representations are required for improving the estimation.

More attention is paid to texture features to estimate and simulate age effects. In [13], an LBP histogram is extracted and a boosting algorithm is used to classify the face into different age groups. Tiddeman et al. [14] design a wavelet-based texture feature to enhance the age-related effects. In this paper, a discriminant projection subspace is designed to enhance the discrimination ability of texture features for age estimation.

In recent years, there has been a trend to use discriminant subspaces to encode the face for regression. In [8], the Orthogonal Locality Preserving Projections (OLPP) technique is used to encode the face into an aging discriminant subspace with support vector regression used to estimate the age. If the discriminant analysis is used directly on the grey-level intensity images, it will overfit on the intensity noise or the illumination variation. Therefore, in our proposed algorithm a local binary pattern (LBP) texture feature is extracted to solve the problem.

III. PROPOSED ALGORITHM

One of the most important features humans use to decide if a face is young or old is the face texture. In [1], the average residue between young and old faces is added to one age group to simulate the other group of faces shown in Fig. 1.
Hubball et al. [2] use PCA to capture the main patterns in the residue images which are shown in Fig. 2. Both approaches provide supporting evidence to suggest that texture change is the main indicator that people use to estimate the facial age.

This useful texture residue related to the age on the face could be treated as noise when only the main patterns are captured in an appearance model. Therefore, in this paper a texture feature is extracted and the patterns most closely related to age are retained for aging estimation.

In this work, we focus on texture feature although some kind of age feature is presented by the facial geometry, e.g., a baby face describes one typical kind of face shape. Some work using the facial geometry can be found in [2] and [11]. To remove the shape variations, the faces are normalized to an average shape before processing.

A. Alignment of faces

In order to find the corresponding texture feature across the face dataset, piecewise affine transformation is used to align all the faces into a normalized shape [12]. When the facial correspondences are given or registered automatically, a delauney triangulation algorithm is used to build the triangular mesh on the mean face. Then all the faces can be aligned based on the interpolation from each triangle by an affine transformation. Some aligned examples are shown in Fig 1.

B. Local Binary Pattern

A Local Binary Pattern [15] is an illumination invariant texture feature. By thresholding the pixels in the neighbourhood against the pixel value in the centre point, a series of binary numbers can be assigned and the binary numbers can be integrated and converted into a decimal value from 0 to 255. The code patterns can represent edges, corners and many other kinds of texture patterns. The feature description used in [13] is the histogram of the LBP which loses the spatial information of facial texture. In the proposed algorithm, the 2D LBP is directly used for projecting into the discriminant subspace. Compared with the original pixel intensity, the descriptor which considers the neighbourhood reflects the facial texture information.

Before we train the discriminant subspace, PCA is used to remove some noise in the LBP feature space and keeping 98 percent variance.

C. Orthogonal Locality Preserving Projection

Orthogonal Locality Preserving Projection (OLPP) [16] is one member in the family of locality preserving subspace projections. OLPP seeks a orthogonal linear subspace which penalizes large distances between the neighbours. When a similarity matrix $S$ is defined, the projection direction is given by the following:

$$\arg\min_w \sum_{i=1}^{n} \sum_{j=1}^{n} (w^T x_i - w^T x_j)^2 S_{ij}$$

$$= \arg\min_w (w^T XDX^T w)$$

with

$$w^T XDX^T w = 1 \tag{1}$$

where $w$ is the subspace basis, $X = [x_1, x_2, ... x_n]$, $S_{ij}$ represents the similarity between vector $x_i$ and vector $x_j$, $D$ is a diagonal matrix with $D_{ii} = \sum_j S_{ij}$ which is a scale parameter for the subspace and $L = D - S$ is the graph Laplacian.

The orthogonal basis vectors can be computed with Algorithm 1:

**Algorithm 1** Subspace Training

**INPUT:** 98% variance-kept PCA feature of LBP extracted from shape normalized gray-level images.

**OUTPUT:** Subspace basis $W_n$.

Obtain $w_1$ as the smallest eigenvector of $(XDX^T)^{-1}XLT^T$;

repeat

Update $W_{n-1} = [w_1, w_2, ..., w_{n-1}]$;

Update $P_{n-1} = [W_{n-1}]^T (XDX^T)^{-1} W_{n-1}$;

Obtain $w_n$ as the smallest eigenvector of $(I - (XDX^T)^{-1} W_{n-1} P_{n-1} - 1 W_{n-1}^T) (XDX^T)^{-1} XLT^T$;

until $n = N$ (Defined Dimension Number)

When a face is projected into this manifold, any regression techniques can be used to estimate the age more easily and robustly.
D. Regression Techniques

Because our main concern is improvement of the discriminant feature extraction, two traditional regression techniques presented in [10], 3 layers neural network (NN) and a genetic algorithm based quadratic function, are used to estimate the age. The NN includes one hidden layer with 25 neurons and Levenberg-Marquardt optimization is used to update its weights. In avoiding the overfitting problem of the NN, the training data is divided into a training set and a validation set. The quadratic function adopts the same configuration as in [11]. The genetic algorithm is designed to find the best parameters for the quadratic function and the fitness function is the simple mean absolute error between the actual ages and the estimated ages.

IV. EXPERIMENTAL RESULTS

In the experiments, the FG-NET database [11] is used to evaluate the performance of the proposed feature subspace. The database includes 1002 images (82 subjects) ranging from 0 to 69 years. Due to the small number of images in the 30 to 69 age group, the experiments are based on 855 images with ages from 0 to 30 years. In order to get an objective evaluation based on this small set of data, the ‘leave-one-out’ method is adopted to simulate the estimation of unfamiliar faces. This means in each iteration one image is left out for testing and the other images are used to build the manifold.

The results are measured by three parameters. The mean absolute error (MAE) which is defined as the mean of the absolute error between the actual ages and the estimated ages, standard deviation of the error which represents the robustness of the estimation and cumulative accuracy which calculates the accuracy rate based on different level of errors.

The proposed feature is compared with two features, combined shape and appearance model (APM) used in [11] and OLPP feature in [8]. APM is combined PCA models which can represent both the geometric feature and intensity feature. Face images are represented by the model parameters encoded by this model. OLPP feature is the parameters by projecting the image intensity values to the OLPP discriminant subspace.

As shown in Table I, the quadratic function performs better than the neural network regression because genetic algorithm based optimization avoids being trapped in a local minimum and finds the best parameters to fit the data. For both forms of regression we see our method achieves lower MAE and SD than the other two approaches.

In Fig.3, the cumulative accuracy shows that the proposed feature based on neural network regression achieves a 92% accuracy rate if the tolerant error is 10 years which is better than the two other features, which for APM is 86.4%, and for OLPP is 89.8%. In Fig.4, the proposed feature achieves approximately 95% accuracy rate on the 10-year tolerant error by using quadratic function regression which is also the best performance compared with the other features.

V. CONCLUSION AND FUTURE WORK

In this paper, a texture feature based discriminant subspace is proposed to extract features for age estimation. It uses not only robust texture information on the face but also the discriminant power to regress the facial age. The experiments show that the performance of age estimation is improved based on the parameters extracted from this manifold compared to some recent work.

In our future research, a more advanced regression technique such as boosting regression will be designed to further improve the results. Furthermore, we will test the performance based on some other databases such as MORPH database [17] and UIUC-IFP-Y age database to compare with those state-of-the-art techniques. Also, the age discriminant subspace can be used to make constraints for aging simulation enforcing the simulation function to generate a face as close as possible to its simulated age.

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