Chapter 46
Age Group Estimation on Single Face Image Using Blocking ULBP and SVM

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Abstract Since age implies essential individual information for human beings, age estimation has more and more applications in intelligent human–computer interactions and personalized recommendation in SNS, etc. However, precise age estimation based on single image is difficult due to diverse appearances among people, and irregular quality of sample acquisition. Based on general knowledge that wrinkles increase with age, Uniform Local Binary Patterns (ULBP) is always an effective texture descriptor, but it loses relative location information. In this paper, an age group estimation algorithm is proposed, where after efficient preprocessing, blocking ULBP is used to gain facial textures and a trained multi-class SVM is applied to fulfill age classification. The ages of subjects are divided into five groups: children (0–6), juveniles (7–18), youth (18–40), middle-aged (40–65), and old people (≥66). Experiments are implemented on FG-NET and Morph Aging Database and the estimation accuracy achieves 81.27 %.

Keywords Age group estimation · ULBP · PCA · SVM

46.1 Introduction

Age provides essential individual information for human being, for it can somewhat reflect the psychological and social states of certain age group. In a few decades, age group estimation based on face image has more and more applications in

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intelligent human–computer interaction, personalized recommendation in Social Network Service, Juvenile protection system, and so on.

The earliest work of age group estimation based on single face image was published in 1993 by Young Ho Kwon and Niels da Vitoria Lobo, where a method of age estimation based on craniofacial development theory and wrinkle analysis was proposed [4]. In this paper, face images can only be classified into three age-groups: babies, adults, and senior adults. Recently, a number of in-depth studies have appeared, and according to the research methods, there are three kinds of age estimation algorithms: anthropometry model, aging pattern subspace [3], and regression model [5–7].

Since wrinkles increases with age, the facial texture is one of the important facial information. We use ULBP which is an effective texture descriptor to estimate age. However, not all textures at multiple different locations are equally important to age estimation. The location information is lost in the ULBP descriptors. So image regions are divided into N × N partition and blocking ULBP is adopted. PCA is utilized here to prove blocking ULBP is a better feature descriptor.

In this paper, an age group estimation algorithm is proposed, where after efficient preprocessing, blocking ULBP is used to gain facial textures and a trained multi-class SVM is applied to fulfill age classification. The ages of subjects are divided into five groups: children, juveniles, youth, middle-aged, and old people.

In the remainder of the paper, Sect. 46.2 describes the algorithm of age estimation based on face images, including preprocessing, feature extraction, and feature classification. Section 46.3 presents experimental 1 results and analysis. Conclusions are given in Sect. 46.4.

46.2 Algorithms

In this framework, face detection algorithm is first applied to obtain face regions, followed by preprocessing. Then features are extracted using ULBP; meanwhile, PCA is a global complementary descriptor for comparison experiments. Finally, feature vectors are put into SVM to train classifier for further age group estimation.

46.2.1 Preprocessing

First face images are converted into grayscale; then histogram equalization is applied to reduce the effect of illumination and complexion. As face may be tilted, we should revolve the face image to make the two eyes at the same level. The process and effect of face gesture normalization is shown in Fig. 46.1.

Locating eyes accurately is a pivotal step in the face gesture normalization. The coordinates of left eye and right eye are denoted as (x_1, y_1) and (x_r, y_r), respectively. The rotation angle θ at which the face image should be rotated is defined as formula (1):

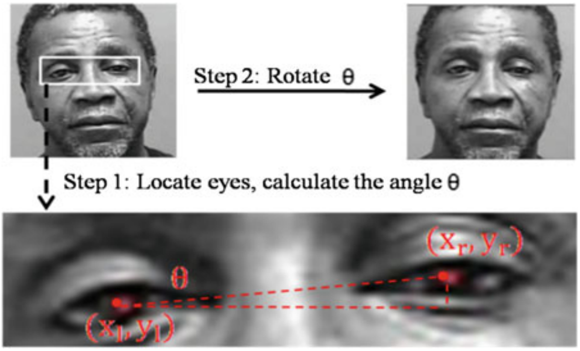

Fig. 46.1 Face gesture normalization

$$\theta = -\arctan\left(\frac{y_r - y_l}{x_r - x_l}\right) \tag{46.1}$$

P(x, y) is the final coordinate after P(x_0, y_0) has rotated along θ. So the rotation matrix is shown as formula (2):

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_0 \\ y_0 \\ 1 \end{bmatrix} \tag{46.2}$$

Through the matrix, the pose of face is standardized. Finally, the size of face image is normalized. The size of preprocessed face images is 200 × 200 pixels.

46.2.2 Feature Extraction Using Blocking ULBP

It is generally known that wrinkles increase with age, so the facial texture is one of the important information of age. ULBP [8] (Uniform Local Binary Patterns) is based on LBP [1] which is widely used in object recognition, image retrieval, and video analysis, is an effective operator in texture measure. First, the face image is extracted by ULBP, as shown in Fig. 46.2.

Then the ULBP image is divided into N × N partition. Then ULBP histograms of each block are obtained. Finally, the feature vector of face image is accumulated of ULBP histograms of each block. The process of 4 is shown in Fig. 46.3.

46.2.3 Feature Extraction Using PCA

PCA (Principal Component Analysis) is a holistic method of descriptors for face texture [9]. It is a multivariate statistical method for getting principal information

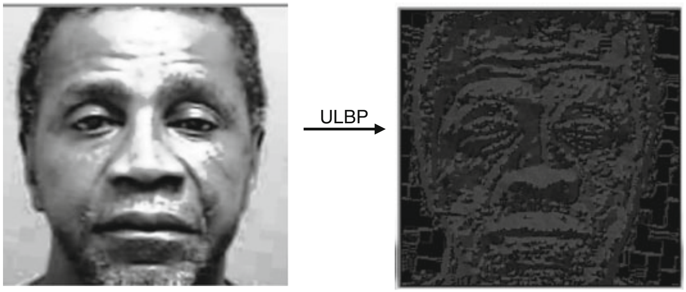

Fig. 46.2 The textual feature extracted by ULBP

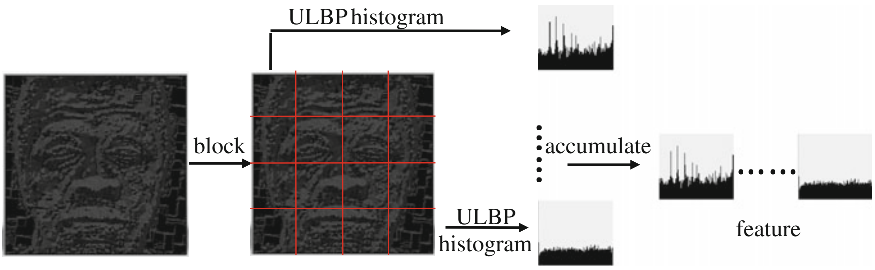

Fig. 46.3 The blocking ULBP

from observational data. So we use PCA to reduce the face image dimensions and extract the face image feature to estimate age.

46.2.4 *Feature Classification*

In this paper, age estimation is considered as age classification. SVM (Support Vector Machine) is a popular classifier in pattern recognition. Here a multi-class SVM is applied to fulfill the age group classification. At the same time, we take KNN (k-Nearest Neighbor) to the classification for comparing the effect of SVM.

46.3 Experimental Results and Analyses

Experiments are implemented on the platform of C++ and LIBSVM [2] from C. In the part of face detector and eyes detector, we use the free source code which is provided by mplab.ucsd.edu, which is an improved version and has been shown to perform rather well.

46.3.1 Databases

The aging datasets consist of 2,000 training images and 2,000 testing images selected randomly from the FG-NET Aging Data base and Morph Aging Database. The range in ages is from 0 to 69. Since the facial expressions are diverse and light intensity is various, the environments of datasets are close to the real world. Typical images from datasets are shown in Fig. 46. 4.

Depending on the psychological and social needs, age is divided into: children (0–6-years old), juveniles (7–18-years old), youth (18–40-years old), middle-aged (40–65-years old), and old people (older than 66-years old).

46.3.2 Effects of Different Preprocessing Phases

In the part of image preprocessing, histogram equalization and face gesture normalization are adopted. In order to verify the effects of these pretreatment methods, experiments are designed and the result is shown in Fig. 46.5.

As shown above, according to histogram equalization without face gesture normalization (deep blue bars) compared with face gesture histogram equalization and face gesture normalization (middle blue bars), the accuracies have very big promotion after face gesture normalization, especially blocking ULBP. This is because face may be tilted, without face gesture normalization, the texture in the same area of the face is divided into different blocks.

When histogram equalization and face gesture normalization (middle blue bars) is compared with face gesture normalization without histogram equalization (light blue bars), the accuracies of the former one have strange slight declines. This is because ULBP compare the relative values among near pixels of image, it is

Fig. 46.4 Typical images from datasets

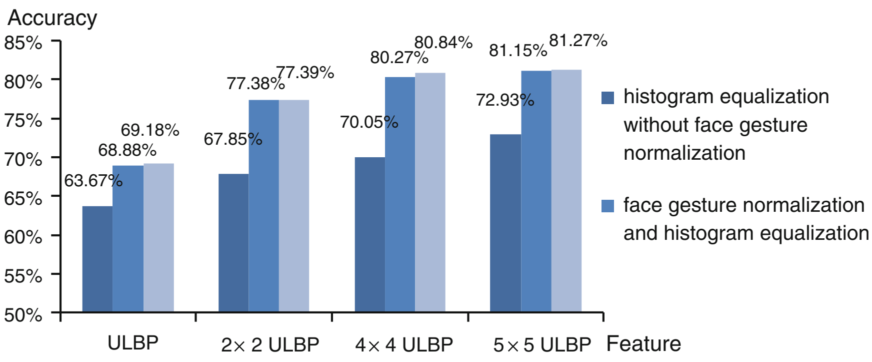

Fig. 46.5 Accuracies of different pretreatment method

insensitive to illumination conditions. Meanwhile, in the processing of histogram equalization, different grayscales are merged into the same grayscale, so some texture information is lost and accuracy declines.

In conclusion, histogram equalization is not necessary in preprocessing of face regions, as face gesture normalization does.

46.3.3 Comparison of PCA and Blocking ULBP

In this part, blocking ULBP is compared with global PCA. For ULBP, if features are extracted directly, only global texture property of face images is obtained, and the information of texture position is lost. Since not all textures at multiple different locations are equally important, image can be divided into N × N partition. The computation increases as the number of sub-blocks increases, such that complexity increases. Comparative experiments were made by using different numbers of blocks to selecting the appropriate one.

As Fig. 46.6 demonstrates, the accuracy of ULBP is higher than the accuracy of PCA, because ULBP is an effective operator in texture measure. Wrinkle is one of the important characteristics reflecting ages, so ULBP has a good effect for age estimation.

As the number of the blocks increase, the accuracy becomes higher, but accuracy will stay steady when the number of the block achieves some value. That is because when the number of the block reaches a certain value, it is enough to distinguish the different location of the texture.

The computation complexity increases as the number of blocks increases. That is because feature number increases, such that complexity increases.

According to the experiment results, age features extracted based on 4 × 4 ULBP are adopted, guaranteeing not only accuracy requirements, but also shorter time.

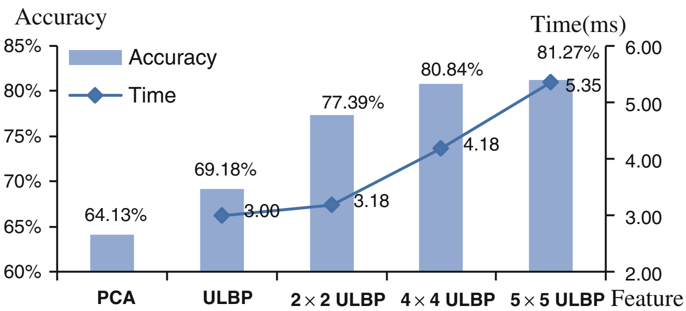

Fig. 46.6 Time/accuracies of PCA/different blocking ULBP

46.3.4 Comparison of Different Classifiers

In this part, as vector classifier, SVM is compared with traditional KNN classification.

As shown in Fig. 46.7, SVM performs better than KNNs. Because KNN is the clustering algorithm based on comparable measurement between data and face images are classified according to minimum-distance method. It is too simple to handle complex classification problems. SVM shows good performance in classification of high dimensionality. Some estimated results are listed in Fig. 46.8.

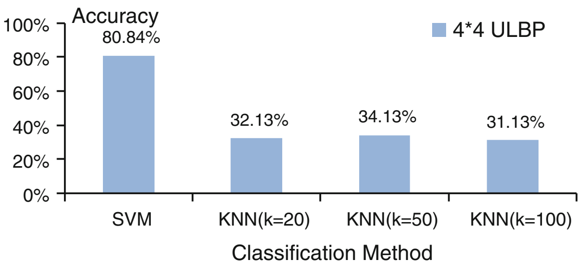

Fig. 46.7 Accuracies of different classifiers

Fig. 46.8 Some estimated results

46.4 Discussions

In detail, the accuracy reaches 80.27 % after face gesture normalization, compared to 70.05 % before, so it is very important for our algorithm. Meanwhile, ULBP is insensitive to illumination conditions, so histogram equalization is unnecessary. The age estimation rate reaches 80.84 % by 4 × 4 ULBP, with shorter feature extraction time. So it is adopted.

In this paper, ages of subjects are divided into five groups: children, juveniles, youth, middle-aged, and old people. An age group estimation algorithm is proposed, where after efficient preprocessing, blocking ULBP is used to gain facial textures and a trained multi-class SVM is applied to fulfill age classification. Besides, complementary experiments were conducted for the preprocessing effect, feature extraction, and classifier selection. The estimation rate of the algorithm achieved 81.27 %.

References

1. Ahonen T, Hadid A, Pietikäinen M (2004) Face recognition with local binary patterns. In: Computer vision-eccv, pp 469–481
2. Chang CC, Lin CJ (2011) LIBSVM: a library for support vector machines. ACM Trans Intell Syst Technol (TIST) 2(3):27
3. Geng X, Zhou ZH et al (2006) Learning from facial aging patterns for automatic age estimation. In: Proceedings of the 14th annual ACM international conference on multimedia: ACM, pp 307–316
4. Kwon YH, da Vitoria Lobo N (1993) Locating facial features for age classification. In: Optical tools for manufacturing and advanced automation: International Society for optics and photonics, pp 62–72
5. Lanitis A, Taylor CJ (2000) Robust face recognition using automatic age normalization. In: Electrotechnical conference, 2000 MELECON 10th Mediterranean: IEEE, pp 478–481
6. Lanitis A, Taylor CJ, Cootes TF (1999) Modeling the process of ageing in face images. In: The proceedings of the seventh IEEE international conference on computer vision, 1999, pp 131–136
7. Lanitis A, Taylor CJ, Cootes TF (2010) Toward automatic simulation of aging effects on face images. IEEE Trans Pattern Anal Mach Intell 24(4):442–455
8. Ojala T, Pietikainen M, Maenpaa T (2002) Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans Pattern Anal Mach Intell 24(7): 971–987
9. Turk M, Pentland A (1991) Eigenfaces for recognition. J Cogn Neurosci 3(1):71–86