Research on Static Face Age Estimation Method Based on Deep Learning

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Abstract: In view of the limitations of simply treating age estimation as a classification or regression problem, a fusion model of classification and regression was proposed, and the methods of classification and regression were used at the same time. In view of the influence of other face attributes (gender, race, etc.) on the aging process, attributes such as gender and race are included into the age estimation system, and the correlation information between attributes such as gender and age is fully utilized. In addition, it is planned to use a single multi-task CNN model to complete tasks such as age estimation and gender identification at the same time, so as to reduce the number of models and calculation consumption.
Keywords: Age Estimation; Convolutional Neural Network; Multi-Tasking Learning; Identification of Gender

Introduction

Face age estimation is through the age characteristics of the face to judge its age, face with the growth of age will change slowly, such as: In daily life, people can quickly judge the real age of a person by these features, but the human eye observation ability has certain limitations. Meanwhile, under the influence of people's dress and dress, the estimation of a person's age by the naked eye is also affected by subjective impression. So there's a lot of error in estimating someone's age.

In this paper, the convolutional neural network-based method is used to extract facial age features with more representational significance to avoid the limitations of traditional feature extraction methods. To improve the traditional classification or regression age estimation algorithm, age estimation is regarded as a mixed problem of classification and regression, and the influence of other face attributes such as gender on the aging process is considered, so as to further improve the accuracy of face age estimation and broaden the application field of face age estimation.

Face image-based age estimation usually adopts a typical machine learning method. Figure 1 shows the basic flow of face image-based age estimation algorithm.

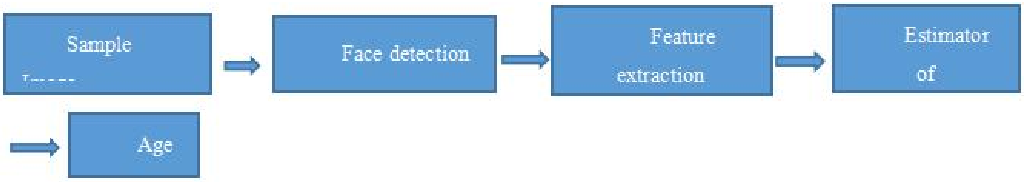

Figure 1: Basic process of age estimation based on face image

1. Facial age feature extraction

The main models of facial image feature representation based on hand-designed features include: (1) anthropometric Model, (2) Active Appearance Model (AAM) and AGing pattErn Subspace (AGES) model. Anthropometric models predict age by measuring the proportion of distance between facial feature points as age changes. In literature [1], the active appearance model was used to extract facial geometric features and texture features, which can describe face images of any age, but this method requires accurate positioning of facial feature points in images. Literature [2] establishes an age growth model for each person and puts forward the age growth model subspace. This algorithm requires everyone to have a face image at all ages, which is often difficult to achieve in real life.

No single feature can fully reflect a person's age, so a simple solution is to combine multiple features. In literature [3], Local Direction Pattern (LDP) and Gabor wavelet transform were used to extract global and local features of faces respectively. After feature fusion, Principal Compocent Analysis was used. PCA), and finally the Support Vector Regression (SVR) model was used for age estimation. However, this method only extracted the local feature of facial wrinkles, which could not fully reflect the change of age. Literature [4] introduces Histogram of Oriented Gradients (HOG) features, fuses them with Local Binary Pattern (LBP) features, and extracts a soft two-layer estimation model. The first layer is divided into "minors" and "adults" two categories, the second layer in the boundary of the two categories set overlapping areas, the first layer of error to remedy, but the method in the feature extraction stage of each local area of the face are given the same weight, but the face of each part of the degree of change with age is different. Literature [5] proposed a new age estimation method combining the global features extracted by AAM and the local features extracted by LPQ. This method consisted of multi-class support vector machine (SVM), divided the subjects into an age group, and then used support vector regression (SVR) to estimate a specific age.

The above traditional methods use artificially designed feature descriptors to extract facial features and then treat the age estimation problem as a classification or regression problem. However, the design of artificial features requires prior knowledge of specific fields, and these features are difficult to fully reflect the changing process of human face [6].

2. Face age estimation algorithm

The above work is mainly aimed at the improvement of the feature extraction part of the age estimation process. However, the age estimation task based on the face image has its particularity. If each age is regarded as an independent category label, the age estimation problem can be naturally treated as an ordinary classification task; If the increase of age is regarded as a process of continuous change, then the age estimation can be treated as a regressive problem.

2.1 Model of classification

In literature [7], multiple classifiers are used for layer by layer classification, and a better result is obtained than that of a single classifier. This method compares the performance of face age estimation using a single classifier, including quadratic function based classifier, shortest distance classifier, multi-layer perceptron MLP, SOM classifier.

In literature [8], age markers were regarded as the ranking order, and the relative order information between age markers was used for age estimation, and the OHRank (Ordinal Hyperplanes Ranker) algorithm was proposed. The MAE of OHRank algorithm is 4.48 years in FG-NET data set and 6.07 years in MORPH data set.

2.2 Regression model

Literature [9] uses linear age growth function to estimate age, and calculates the correlation coefficient between facial appearance similarity and the similarity of age growth function, and the correlation coefficient between facial appearance and life style similarity and the similarity of age growth function through experiments. weighted appearance specific (WAS) age growth function and weighted person specific (WPS) age growth function are presented.

In literature [10], Kernel Partial Least Squares (KPLS) regression was used for face age estimation. KPLS can simultaneously carry out feature reduction and learning age estimation function. Its regression output is a vector, which can contain multiple marks. This method can learn face aging process and solve multi-task problems while reducing the feature dimension.

2.3 Use a mix of classification and regression models

Literature [11] points out that LARR cannot automatically determine the search range of the classifier when adjusting the local age, so it needs to heuristically try different ranges and manually select the optimal solution among them. The Probabilistic Fusion Approach (PFA) was proposed, which constructed a probabilistic framework based on conditional Bayesian rules, converted the output of SVR and SVM into probabilities, and fused regression and classification methods for age estimation.

3. Face image feature extraction and age prediction based on deep learning

The rise of deep learning has triggered a revolution in machine learning and feature learning. In recent years, deep learning technology represented by Comvolutional Neural Network (CNN) has been widely used in object recognition, face recognition and other fields. Therefore, in order to obtain features that can better express age information, the classification and regression models used in this paper are all based on CNN. The main advantage of CNN is that it can directly input images into the model without preprocessing, and it can automatically learn image features and has strong robustness. Age estimation is essentially a task, that is, the expected predicted age value can be infinitely close to the real age value, and the simultaneous use of classification and regression can be regarded as a task using different methods under the same goal, and age classification and regression are highly correlated tasks, in line with the basic premise of multi-task learning.

Conclusion

Face age estimation has also become a cutting-edge technology with great development potential, attracting the in-depth study of scholars, but it is still faced with great difficulties and challenges. On the one hand, many of the existing age estimation methods only use age-related facial features, but do not take into account the impact of other face attributes on the aging process. However, the age change pattern is not the same for different gender, different race and skin color. On the other hand, age has a certain time sequence, and the facial features of similar faces are very similar. The traditional classification or regression algorithm cannot make full use of the correlation and uncertainty between the sample markers.

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