# Survey of Age Recognition Methods Based on face Images

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## Abstract

**As one of the most widely used biometrics, human face contains age information with high application value, which is widely used in the fields of auxiliary authentication, electronic customer management and juvenile protection. However, due to the influence of genetic factors, living background, photo environment and other factors, the research of age recognition is still challenging. This paper reviews the main research work and progress of age recognition from the perspectives of problem definition, data collection, feature extraction and evaluation index.**

## Keywords

**Deep Learning; Age Recognition; Data Collection; Feature Extraction; Evaluation Index.**

## 1. Introduction

Face attribute analysis is a hot topic in the field of computer vision and biometric recognition, including face recognition, expression recognition and other technologies. Face age recognition is also an important sub topic of face attribute analysis, which has been widely concerned in recent years. Age recognition can provide a good living environment for minors, realize personalized marketing of different age groups, and provide auxiliary evidence for identity verification in criminal investigation. Therefore, age recognition research has wide application value in the fields of human-computer interaction, commodity recommendation and market analysis.

Age estimation based on face image is to use computer algorithm to estimate the age information of face according to the face appearance of the input image. Age information can be divided into two types: general age range and specific numerical label[21]. Age tags can be divided into real age and apparent age according to different labeling methods. The age tag of the former is the real physiological age of the face image, while the latter is the age evaluation value given by volunteers according to the appearance of the face image. The apparent age is variable compared with the real age. Different taggers may give different estimates of the apparent age, but the mean value of the apparent age given by different taggers is usually highly stable.

Although researchers have made some progress in age estimation, age estimation is still a challenging topic. Even artificial age estimation is difficult to accurately estimate a person's specific age. First of all, face has the characteristics of complex structure and rich changes. Besides age attribute, it also contains a large number of attributes such as gender, race, expression, posture, etc., which cause some interference to age estimation; Secondly, the age of human face is not only related to the global changes of human face, such as skull shape and skin color, but also related to local changes of face, such as forehead wrinkles, eye corner wrinkles, etc; Finally, the acquisition of face age image is also affected by illumination, occlusion and other factors, which will bring great difficulties to the current age estimation research.

There are three commonly used evaluation indexes in age estimation research: mean absolute error (MAE), cumulative index (CS) and $\varepsilon$ - error [22]. The mean absolute error is the absolute error between the estimated age and the labeled age. Its calculation is shown in formula (1), where SK is the labeled age and s'k is the estimated age [22]. The smaller the MAE, the smaller the age error and the higher the accuracy of the algorithm. The cumulative index is a measure of the accuracy of age estimation within the acceptable error range, and its calculation formula is as follows (2), where $ne \leq J$ is the number of test images whose absolute error between estimated age and label age does not exceed J;

n is the total number of test images [23]. ε - error is mainly used to evaluate the estimation of the observed age. It is an evaluation method to measure the comprehensive relationship between the estimated results and the mean and variance. Its calculation is shown in formula (3), where μ is the mean value of the age label given by several evaluators, σ is the standard deviation, and X is the predicted age label.

$$MAE = \frac{\sum_{k=1}^{N} | s_k - s'_k |}{N} \tag{1}$$

$$CS = \frac{N_{e \le j}}{N} \times 100\% \tag{2}$$

$$\varepsilon = 1 - e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{3}$$

The research of age estimation based on face can be divided into image preprocessing, feature extraction, age estimation model design and so on[10]. The main steps of image preprocessing are face detection and correction, normalization and other operations; feature extraction and age estimation model mainly extract age-related features from face images, and use effective estimation model for age tag recognition [24].In addition, age estimation data set is another important factor that affects and restricts the progress of age estimation research. In this paper, we summarize the existing research work and progress in three important parts of age estimation based on face image, which are the common data sets, age feature extraction and age model estimation.

## 2. Common data set

A high quality, large-scale face age image data set is the foundation of efficient age estimation algorithm. However, for age estimation, it is difficult to collect a large number of data due to the privacy of age. The commonly used data sets for age estimation are as follows:

### 2.1 MORPH2(2006)

Morph2 is a cross time data set that contains images of the same person at different ages. The data set is divided into commercial and academic versions. The academic version includes 55134 images of 13000 people. The photos were collected from 2003 to 2007. The age of the characters ranged from 16 to 77 years old, with an average age of 33 years. In addition to age, the morph2 dataset also records other information about the characters, such as gender, race, whether wearing glasses, etc. It is one of the most popular data sets for age estimation.

### 2.2 Adience(2014)

The Adience[3,12] dataset contains 26580 images of 2284 people. It is characterized by the fact that the photos are taken in real scenes, and the photos are greatly affected by noise, posture and illumination. It aims to solve the problem of age and gender detection in the real world. The original data and corrected face are provided on the website at the same time. The data set is divided into eight intervals: (0-2, 4-6, 8-13, 15-20, 25-32, 38-43, 48-53, 60 -).

### 2.3 CACD(2014)

CACD[12,15] collected 163446 images of 2000 celebrities, ranging in age from 16 to 62. By the time of publication, it was the largest cross age data set at that time. The time span of collecting photos was 2004-2013. At the same time, the data set also provides the annotation information of 16 face key points.

### 2.4 IMDB-WIKI(2015)

Imdb-wiki data sets [11,28] are one of the largest age data sets at present. The data set sources include 20 000 people from IMDB (a star website) and Wikipedia, and the number of images is 460723 and 62328, respectively. The labeling method is to find the photo of a famous person, and then get his age tag by subtracting the year of his / her birth from the year of photo shooting.

### 2.5 AFAD (2016)

The data set[15] size is 164432 faces, including 63680 female and 100752 male. The age group was 15-40 years old. The characteristic of this data set is that almost all the data are Chinese. The source of the data is renren.com. Firstly, it crawls the image data of renren.com and gets the age of the photo album owner, and then uses manpower to filter the wrong pictures. The annotation of the data set is accurate, and some images are not good.

### 2.6 AGE-DB(2017)

AGE-DB contains 16488 images of various celebrities, such as actors, writers, scientists and politicians, each with identity, age and gender attributes. There are 568 different subjects. The average number of images per subject is 29. The minimum and maximum ages were 1 and 101, respectively. The average age range for each subject is 50.3 years.

### 2.7 UTKFace (2017)

UTKFace dataset is a large face dataset with a long age span (range from 0 to 116 years). The dataset contains more than 20000 facial images, including annotations for age, gender and race. Images cover big changes in posture, facial expression, lighting, occlusion, resolution, etc. The data set can be used for various tasks, such as facial detection, age estimation, age progression /regression, landmark positioning, etc[25].

### 2.8 CAF(2018)

CAF is collected by Tencent and has not been disclosed at present. It includes about 313986 facial images from 4668 identities. Each identity has 80 facial images. All of these images are carefully and manually annotated. Considering the lack of accurate age information, they used the public pre training age estimation model DEX to predict the rough age tag of each face image.

### 2.9 CAFR(2019)

CAFR has a total of 1446500 facial images from 25000, the theme of cafr dataset. Each person had an average of 57.86 images. It should be the largest cross age database at present.

### 2.10 AGFW-v2(2019)

The dataset contains 36299 images with ages ranging from 10 to 64 years. Then it is decomposed into 11 age groups with a 5-year-old age span.

## 3. Age feature extraction method

Efficient age feature extraction is an important basis for the design of age estimation model in the next step, and it is also a key factor affecting the performance of age estimation[26]. The main changes of human face in the process of aging are usually manifested in the face shape, skin brightness, facial wrinkles and so on. Therefore, the existing artificial age feature extraction methods mainly use shape and texture features to represent the face age in the appropriate image space, which can be classified into model-based features, age pattern subspace based features, manifold space-based features, and so on Based on the apparent characteristics. With the great success of deep learning method in the field of image recognition, deep learning feature extraction method is applied to the research of age estimation to extract multi-level face age features. In this paper, the existing characteristics and methods of age estimation are summarized.

### 3.1 Model based features

Anthropometric model and active appearance model (AAM) are two representative face image representation methods in early age estimation research.

AAM is a kind of face model for statistical modeling of the shape and texture of human face. In reference [2], active appearance model is used for age estimation of human face for the first time, and 50 parameters of AAM model are used as age features of face images. Compared with the anthropometric model which only contains the geometric information of the face, AAM establishes the shape information and global texture information model of the face at the same time, so it can recognize any age in general. The disadvantage of AAM is that it depends on the accurate location of facial feature points, and can not extract the texture information of local face area.

### 3.2 Features based on age pattern subspace

Age pattern subspace (ag-es) [1] is a personalized age feature representation method based on AAM. Different from the method of AAM modeling for a single face image, ages method models a group of image sequences of the same object in different age periods. The image sequence is called the age pattern of the object. If all age face images exist in the pattern, the pattern is called complete age pattern, otherwise it is called incomplete age pattern. In the training stage, AAM model is used to represent each face image in ages model, and then principal component analysis (PCA) method is used to learn the subspace model of each age pattern. For incomplete age patterns, ages uses the minimum reconstruction error iterative algorithm to learn the feature vector of the missing image. In the test phase, the age value of the unknown image is determined by all the positions of all age patterns and their age positions with the minimum reconstruction error.

The advantage of ages method is that it can model the aging process of different individuals, which is in line with the age evolution law of different individuals. The disadvantage of ages method is that the face images of each object in the data set at different ages are required to be as complete as possible, otherwise the accuracy of age estimation will be affected. However, it is difficult to meet this requirement because of the difficulty in collecting age images.

### 3.3 Features based on appearance

Based on the appearance features, the age features of face are extracted by studying the appearance differences of different age faces. The key to effectively represent the age of human face is to extract the information of face appearance change closely related to age change, including multi-scale texture and shape information. Appearance features in the process of aging can realize the age estimation of face images of all ages. However, due to the complexity of face attributes, appearance features not only contain age information, but also contain other redundant information, which will have a certain negative impact on age estimation.

### 3.4 Features based on deep learning

In recent years, with the rapid development of deep learning theory, convolutional neural network (CNN) as the representative of depth features has been widely concerned. CNN is a deep-seated neural network model, which has the characteristics of local receptive field and hierarchical features, and has achieved great success in the field of image recognition. In reference [3], a method of using CNN to learn age features is proposed. In order to reduce the risk of over fitting, the CNN feature only has three convolution layers and two full connection layers.

Using deep learning network can extract more levels of age information, but it usually requires a large number of samples to learn robust models, and over fitting is easy to occur in small data sets. In order to overcome this shortcoming, the existing deep learning methods usually pre train a general deep network on a large image classification or face recognition data set, and then fine tune the network on a large age data set.

## 4. Age estimation algorithm

Different from the disorder of tags in other face attribute recognition tasks, such as identity, gender, expression, and so on, age estimation is a special pattern recognition task. The existing age estimation models mainly include classification method, regression method, sorting method and mixed method. In this paper, the representative methods of these models are reviewed and compared.

### 4.1 Classification based approach

The age estimation method based on classification regards different ages as different categories, and uses classification model to model age. In the paper [3], hassner et al. Divided the age into eight segments, trained and tested with deep convolution neural network, and carried out experiments on adience data set. The recognition accuracy rate was 50.7%. Z. Hu et al. [4] proposed a method to estimate the age of human face with the help of age difference information. S. Wang et al. [5] used relative attribute learning algorithm to construct the most appropriate privilege data for age estimation. M. M. sawant et al. [8] proposed a novel hierarchical Gaussian process framework for automatic age estimation. It is composed of multi class Gaussian process classifiers to classify the input image into different age groups, and then the distorted Gaussian process regression is used to model the aging mode of a specific group. Y. Chen et al. [7] proposed facial age estimation based on discrete wavelet transform depth convolution neural network (dwt-dcnn). Wavelet transform acts as preprocessing part, and DCNN provides powerful classification function. From the experimental results of these literatures, it can be found that the classification method can solve the problem of age estimation to a certain extent, but its disadvantage is that it does not consider the temporal characteristics of age tags, and there will be boundary problems in classification. Geng Kaiyue [12] designed a more accurate face age classification model from two aspects of network depth and network branch. The residual module is improved and the bottleneck structure is introduced to deepen the network structure and improve the accuracy of the model. The bottleneck residual network of single channel is divided into parallel networks with the same structure of multiple branches, which can effectively improve the network performance.

### 4.2 Regression based approach

In the regression based age estimation method, the age tag is regarded as a continuous value, and the regression model is used to model the age. H. Liu et al. [6] proposed an ordinal deep feature learning (odfl) method to learn feature descriptors for facial representation directly from original pixels. Age tags are associated in chronological order, and age estimation is a sequential learning problem. Meng Wenqian et al. [20] used convolutional neural network (CNN) trained on IMdb-wiki age database to extract features, and principal component analysis was used to reduce the dimension of features. Finally, support vector machine regression method was used for age estimation [28]. The age estimation method based on regression is more consistent with the time series characteristics of age tags, so its performance is usually better than that based on classification. However, the age regression model may lead to over fitting problem when there are occlusion, illumination and other noises in the face. Zhang Xiaoning [15] proposed a coupled evolutionary network based on deep expectation based on convolutional neural network and vgg-16 network, which has excellent performance at present, to estimate age from tag distribution and regression expectation respectively.

### 4.3 Ranking based approach

In the ranking based method, the problem of age estimation is regarded as a series of binary classification problems, that is, whether the age is greater than or less than a certain age. S. Chen et al. [9] proposed a novel framework based on convolutional neural network (CNN), namely ranked CNN, for age estimation. Rank CNN contains a series of basic CNN, each of which uses sequential age tags for training. Age tag is an ordered label. The ranking method obtains the age estimation of face through a series of binary classification results. Compared with regression and classification methods, it can learn the dynamics of aging process better, but it also needs more model learning time. Zhao Yiding [16] adopted an age coding method based on sorting mode, which used comparative information of age rather than specific value to reduce the impact of inaccurate age labels. The sequential age label estimation problem is transformed into a series of age size comparison problems, and the output of CNN is modified to a series of binary sub classifiers, which realizes the simultaneous training and output of sub classifiers.

### 4.4 Methods based on multi task learning

Multi task learning method improves the learning performance of each task through the joint learning of related tasks. Due to the individuation of face aging process, a better age estimation model can be obtained by multi task learning framework. Liu Lingbo [17] introduced multi task learning into age estimation in order to distinguish the differences among individuals. Firstly, the face was divided into several age groups by linear classification method, and then a multi-level age regression model was constructed by using multi task learning in these age groups.Chen Jinan et al. [30] proposed a deep convolution neural network model (CNN cnin) for complex and changeable application scenarios. The first layer uses cascaded 3 × 3 convolution kernel to extract richer spatial structure information, which is conducive to extracting richer texture features of human face and improving recognition accuracy. The cross convolution layer considers both high-level features and low-level features. Cheng Jianfeng [31] designed and improved the structure of convolutional neural network from the perspective of multi task learning to improve the accuracy of face attribute recognition. Compare the performance differences of different network structures in age estimation (mainly related variants of resnet80 and resnet18). Considering the correlation between attributes in attribute recognition, based on the convolutional neural network of multi task learning, the loss functions of different attributes are embedded into the network of multi task learning, end-to-end training is adopted, and the model is tested and analyzed.

## 5. Performance comparison and summary

In the research of age estimation based on face image, we first need to use face detection and location method to determine the face position, and then we use two key technologies to solve the problem of age estimation: age feature extraction and age model learning. In this paper, we compare the representative age estimation methods from the data set, feature representation, evaluation index and accuracy. (Table 1)

Table 1: Comparison of the performance of age estimation algorithms

| essay | feature | dataset | accuray/% | MAE | CS(W5)/% | £-error |
|---|---|---|---|---|---|---|
| essay[3] | CNN | Adience | 50.7 | | | |
| essay[4] | CNN | MORPH | | 5. 37 | | |
| essay[6] | AAM | FG-NET | | 6. 59 | | |
| essay[1] | AGES | FG-NET | | 4.96 | 89 | |
| essay[2] | AAM | MORPH | | 6. 32 | 53. 2 | |
| essay[8] | CNN | LAP2016 | | 3.84 | | 0. 32 |
| essay[9] | CNN | MORPH | | 2.89 | 83.1 | |
| essay[10] | CNN | CACD | | 5.68 | | |
| essay[18] | CNN | MORPH | | 2.99 | | |
| essay[11] | CNN | IMDB-WIKI | | 4. 73 | | |
| essay[14] | CNN | LAP2015 | | | | 0. 27 |
| essay[15] | CNN | AFAD | | 3. 23 | | |
| essay[27] | CNN | FG-NET | | 4. 11 | | |
| essay[12] | CNN | Adience | 78.9 | | | |
| essay[21] | CNN | MORPH | | 3.21 | | |
| essay[15] | CNN | CACD | 81.1 | | | |
| essay[28] | CNN | IMDB-WIKI | | 3.6 | 84.4 | |

It can be seen from table 1 that the end-to-end deep learning method has a greater performance improvement than the artificial feature-based age estimation model. The reason is that deep learning method can automatically learn the rich multi-level features of human face, and in the end-to-end model training process, the feature extraction process uses age tags, which can extract features more related to the age of the face, while unsupervised artificial feature methods mainly rely on experience for age features.

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