Facial Age Estimation Based on KNN-SVR Regression and AAM Parameters

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Abstract   Age estimation is the determination of a person's age based on biometric features. It is an important technique to estimate age from facial pictures automatically in Computer Vision. The application using age estimation for interface, robot, and human interaction is expected. In recent years, many approaches for age estimation were proposed while the results were not ideal. To solve this problem, we propose an age estimation method by KNN-SVR using AAM parameters to evaluate the age. The experimental result shows that the averaged age estimation errors of subjects were mainly improved.

Keyword   Age estimation, Active Appearance Models, Regression analysis, KNN-SVR Regression

1. INRODUCTION

Simulation and recognition of faces as one ages has recently been gaining popularity as a topic in biometrics literature. Compared with the finger-print and iris recognition, the precision of face recognition is not accurate enough. However, the human face is easily accessible and can be captured without notice of user, so the face recognition is popularly developed. For example, the identity recognition by facial image analysis is applied for entrance security and the facial expression recognition can be applied for human machine interface. Various practical applications could benefit from an automated aging system, for instance, finding missing children. A special case of the above application would be to predict the current facial appearance of children missing for several years.

Among a lot of lifestyle factors, aging is an inevitable process and it causes problems in face recognition. Estimating human ages is a challenging task due to multi-class nature where an aging label can be considered as an individual class. First of all, as a result of the diversity of personal aging process, the growth process is significantly different so it is difficult to find the relationship between the coded representation of the face and the age of subjects. Secondly, age estimation is difficult in fitting due to the humongous size of database.

Besides the two main challenges of age estimation, there are also some difficulties in the age estimation. First, the aging process is so complicated that it cannot be captured by a single classifier and regression [1]. For example, the facial geometry at young ages changes much faster than at old ages. Hence, it is not effective to solve the age estimation problem using a single regression model.

Furthermore，with the amount of aging database，the number of image label is so different that it causes mistakes in machine learning. While collecting training data, it is important to distinguish the actual age from the perceived age of an individual. Effects such as heavy make-up and plastic surgery can make people look a lot younger than they actually are. This effect comes into play when collecting facial images whose actual age does not match the perceived age.

In this paper, considering the factors above a new age estimation method is proposed to establish the age estimation.

- Active Appearance Model (AAM)[2] has been popularly used to represent the appearance and shape variations of human faces. We can obtain the feature regions effective for age estimation based on the feature points obtained by AAM.
- An age-specific local regression algorithm named KNN-SVR[3] is used to capture the complicated aging process.

The paper is organized as follows: in section 2, we propose our hierarchical approach for age estimation. In section 3, the experiment is divided into 2 parts. Training the data using Hollywood database [4] and results on the FG-Net dataset. In section 4, the results of age estimation by

different regression methods are compared and section 5 concludes the paper.

2. METHOD

We use a set of training images from Hollywood database to learn a global relationship between the coded representation of the face and the actual age of subjects. The age of an unseen facial image can be estimated by means of the established relationship. The relationship can also be used to estimate ages of the synthesized images.

Age Estimation contains three parts as below.

Age Progression

Age Progression synthesizes new images of a person at a future age based on a current appearance. In other words, an older facial picture can be obtained by the computer generated age.

Age Regression

Age Regression is to presume what he/she looks at an earlier age. It is the reversal process of age progression.

Age Prototype

An age prototype is a visual facial model of a particular age or small age group. It is an image that captures the main characteristics of that age group.

There are three major steps in our approach: feature extraction, learning regression model for each of the age groups and classifying the test image into the various age groups. We discuss these steps in the following sub-sections.

First, we use Adaboost to find both eye locations and normalize the face according to the center positions of both eyes. In the second step, we use AAM to search the facial feature points, then extract and quantify the local age features.

There are four main age feature regions extracted - the corner and bag regions of both eyes, the left and right grain regions and the hair region is removed. We quantify the age feature regions by the relationship between the model and

Fig.1　Flowchart of age estimation

age.

Finally, we make use of KNN-SVM to classify the test face image into supposed age. The flowchart of our system is shown in Figure 1.

2.1. Active Appearance Model (AAM)

AAM is a statistical model including two aspects: model building and fitting algorithm. AAM learns characteristics of objects by building a compact statistical model. The statistical model, which represents shape and texture variations of objects is obtained from applying principal component analysis PCA to a set of labeled data.

In AAM, an object is described by a set of landmarks which indicate important positions at the boundary of the object. Landmarks are labeled manually on each object in the training data. A shape s is defined as coordinates of v vertices:

$$s = (x1, y1, \ldots, xi, yi, \ldots, xv, yv)^{\mathrm{T}} \tag{1}$$

Where (x_i, y_i) is the coordinate of the i-th landmark in the object and v is the number of the landmarks in an image. Given a set of labeled shapes, firstly align these shapes into unified framework by procrustes analysis method. Then, PCA is applied to extract shape eigenvectors and a statistical shape model is constructed as

$$s = \bar{s} + P_s b_s \tag{2}$$

where $\bar{s}$ donates the mean shape of all aligned shape and is calculated using $\bar{s} = \frac{1}{N}\sum_{i=1}^{N} s_i$, $P_s = (p_{s1}, p_{s2}, \ldots, p_{st})$ is the matrix of the first t eigenvectors and b_s is a set of shape parameters. p_{st} is the eigenvector of the shape covariance matrix. We calculate the covariance matrix Σ as

$$\Sigma = \frac{1}{N}\sum_{i=1}^{N}(s_i - \bar{s})(s_i - \bar{s})^T \tag{3}$$

The texture of AAM is defined by the gray level information at pixels $x=(x, y)^T$ which lie inside the mean shape $\bar{s}$, after aligning the control points and the mean shape of every training face image by using Affine warping. Then we sample the gray level information g_{im} first and a scale α, and offset β are applied as

$$g=(g_{im}-\beta I)/\alpha \tag{4}$$

where I is a vector of ones. Let $\bar{g}$ define the mean of the normalized texture data, scaled and offset so that the sum is zero and the variance is unity. α and β are selected to normalize
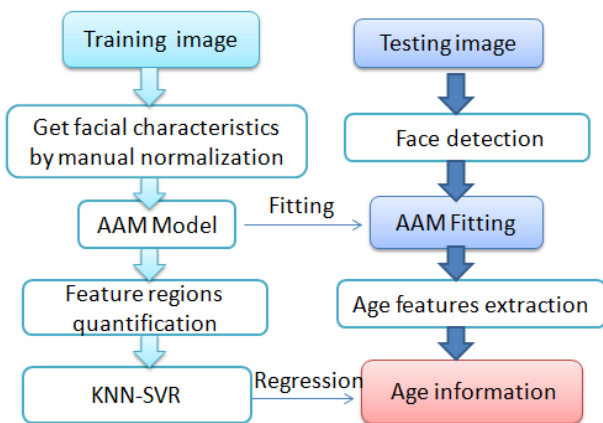
$$g_{im} \text{ as } \beta = (g_{im} \cdot I)/n \tag{5}$$

where n is the number of pixels in the mean shape. We iteratively use Equations (4) and (5) to estimate $\bar{g}$ until the estimation stabilized. Then, PCA is applied to the normalized texture data so that texture example can be expressed as：

$$g = \bar{g} + P_g b_g \tag{6}$$

where P_g denotes the eigenvectors and b_g is the texture parameters.

$$b = \begin{pmatrix} Ws \, bs \\ bg \end{pmatrix} \tag{7}$$

where W_s represents a diagonal matrix of weights for each shape parameter. A further PCA is applied for removing the possible correlations between the shape and texture variations.

$$b_c = Q_c c \tag{8}$$

where Q_c is the eigenvectors and c is the appearance parameter.

Given an appearance parameter c, we can synthesize a face image by generating gray level g the interior of mean shape and warping the texture from the mean shape $\bar{s}$ to model shape s, using Equation (9)

$$s = \bar{s} + P_s W_s^{-1} Q_s c$$

$$g = \bar{g} + P_g Q_g c \tag{9}$$

where $Q_c = \begin{pmatrix} Qs \\ Qg \end{pmatrix}$

The ultimate goal of applying AAM is that given an input facial image, we may find the model parameters. We have the initial estimate of appearance parameters which may be applied to the AAM model to synthesize an image similar to the input image. Given a new image, we have the initial estimate of appearance parameter c, position, orientation and scaling placed in the image. We minimize the difference E as

$$E = g_{image} - g_{model} \tag{10}$$

where based on the pre-estimated c ,we may have $g_{model} = \bar{g} + P_g Q_g c$ and $s_{model} = \bar{s} + P_s W_s^{-1} Q_s c$.
It needs an algorithm to adjust parameters to make the input image and that image generated by model as closely as possible. There are many optimization algorithms proposed for parameters searching. In this thesis, we apply the so-called AAM-API[2] method.

2.2. KNN-SVR Regression

The algorithm catches all the training samples, and it predicts the response for a new sample by analyzing a certain number (k) of the nearest neighbors of the sample. Originally, support vector machines (SVM) was a technique for building an optimal (in some sense) binary (2-class) classifier. Then the technique has been extended to regression and clustering problems. A Support Vector Machine is a learning technique that learns the decision surface through a process of discrimination and has good generalization properties. SVMs have been successfully applied to a number of applications ranging from particle identification, face identification, text categorization, engine knock detection, bioinformatics and database marketing.

The KNN and SVR algorithms are combined to yield a localized ε-SVR, which we will name KNN-SVR. If the number of KNN neighbors is represented by k,

Face recognition involves classification to categorize an unseen image into one of several predefined groups. However, age is a real-valued number. Therefore, our aim is to learn the relationship between the coded representation of the image and a real number representing the age.

As a result, we use Support Vector Regression (SVR) Machines. Eq(11) summarizes our objective.

$$A_p = F(I) \tag{11}$$

where I is the coded representation of the facial image and F is the regression function we want to train. A_p is the real number representing the predicted age of the subject in image I. SVR uses the ε-insensitive loss function. If the deviation between the actual and predicted value is less then ε, then the regression function is not considered to be in error.

3. AGE SIMULATION EXPERIMENTS

Age estimation based on AAM begins with building the shape model and texture model. We used 89 landmark points as shown in Fig.2 to mark the characteristics on the face, such as the eyebrows, eyes, nose and mouth, lip, chin and pupil. The collection of sufficient training data for age estimation is extremely laborious. In the literature, the standard aging database is FG-NET which covers a wide range of age, but nobody can age at will. Since it is not a good choice for data-training, we newly build a database

Fig.2 2D facial landmarks on an image from the Hollywood database

Original   Image(20 years old)   30-39 Prototype

40-49 Prototype   50-59 Prototype

Fig.3 An age prototype for women

called Hollywood database[4]including 350 images from 30 movie stars who have a career starting from teenage years to senior years.

Now given a new image, the extracted AAM features are processed. Finally, the age is estimated by the proposed KNN-SVR.

Two different prototypes are used for men and women as shown in Figure 3. The data in table1, in particular, proves that our proposed method gained the best accuracy. In Figure 3, we demonstrate age progression on a female subject.

The prototypes capture significant wrinkle information (seen in Figure 3), which is reflected in the age simulations of the subject.

It is difficult to predict the accuracy of the age progression or regression and the standard is too ambiguous by different people. We cannot compare our simulations to true images but we can compare the ages. One real images of Tom Hanks were collected at ages 46 years.

We also do an experiment whose age regressed from 46 down to 30 years, the age progression from 46 to 55 years and also compare the simulation to the actual image. The age regression is quite close to the actual image. While the synthesized image in the age progression has more facial wrinkles than the actual image. This can be explained by the error in age.

The larger the database is, the results get better. However we cannot get an ideal result due to different individual's lifestyle.

4. METHODS COMPARISON

The performance of the age estimation was evaluated by MAE (Mean Absolute Error) defined in Eq (12)

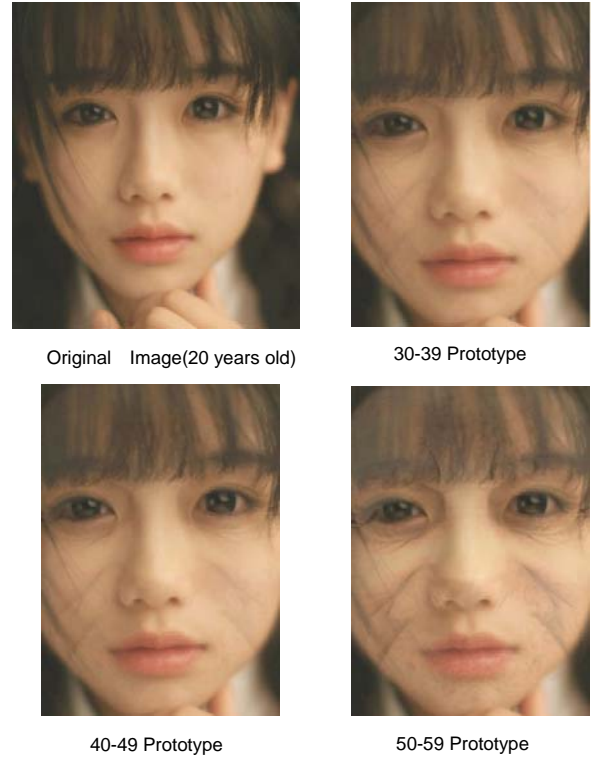$$MAE = \sum_{k=1}^{M} |\overline{age}_k - age_k| / M \tag{12}$$

where $\overline{age}_k$ the estimated age of person k and age_k is his/her true age.

We evaluate our proposed approach on the FG-Net dataset [5], which contains 1002 images of 82 subjects at various ages to compare the results. The results shown in Table.1 indicate that our proposed method achieves the best MAE.

Table 1 Prediction errors (in MAE) of different age estimation algorithms on the FG-NET database

Mean Absolute Error of Age Estimation		
Method	Description	MAE(years)
Ages[7]	Aging Pattern Subspace	6.82
RVM[8]	Relevance Vector Machine	6.71
SVM[6]	Support Vector Machine	6.65
RB-RVM[13]	Basis Pursuit RVM	6.52
HA[12]	HIERARCHICAL APPROACH	6.2
GPR [4]	Gaussian Processes for Regression	5.35
LARR[9]	Locally Adjusted Robust Regression	5.07
RPK[10]	Regression from Patch-Kernel	4.95
MTWGP [11]	Multi-Task Warped Gaussian Process	4.83
Proposed	k-Nearest Neighbors SVR	4.47

5. CONCLUSION

The simulation results performed on the widely-used FG-NET aging database show that the proposed algorithms and framework achieve the lowest MAE against the state-of-art algorithms.

We proposed a hierarchical approach for age estimation, where the face images were divides into different age groups and separate regressions were trained for each of the age group. The experiments show that if the test image can be classified into the correct age group, then the task of age estimation can be performed very accurately by the proposed KNN-SVR framework. In future, to improve the accuracy of the proposed approach, we would like to optimize the number and range of age groups.

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