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Human Age Estimation using Hierarchical Approach

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***Abstract*—Age estimation has vast potential applications not only in scientific research but also in age-specific systems such as parental security control, prenatal control, etc. But human age estimation from face is challenging yet interesting task. Since the age progression is different in different age group, using single regression model is not effective. Hence in this paper the age estimation problem using hierarchical approach is proposed in which different regression models for different age groups are learned. In this approach the given face images are firstly classified into various age groups by extracting various facial features and then regression model for that age group is learned. Using different classifiers and fusing them together using majority rule make age estimation more effective and more accurate.**

Keywords—hierarchical approach; regression model;age estimation

I. INTRODUCTION

The behaviour and preference of people are different at different ages. [1] People always interact with technology, whether it be considerations regarding linguistics, aesthetics, or consumption habits, varies widely according to their age. This means there are immense potential applications of automatic age estimation.

Human age estimation (HAE) has many applications in Computer Vision, [3, 11], business intelligence, security, human-cantered image understanding, age-specific service systems, protecting minors from adult web sites and venues etc.

To estimate age the most important part human body is face. Hence automatic age estimation problem can be solved effectively by doing facial age estimation. Facial geometry extracted from 2 dimensional landmarks can indicates age. Age progression can be observed from these facial landmarks [2]. But, we can observe that age progression varies in different group. We can see that there are major changes in facial geometry taken place in young ages, but not that in old ages. Hence, if we learn different regression model for different age group, we can get more accurate age than before [26]. This could be simpler than exploitation single regression model for all age teams.

Hence to attain this, we have a tendency to propose a hierarchical approach during which totally different regression models are learned for various age teams. When test image is given, first we will classify it into one of age groups on the basis of facial features extracted from the images. Then according to the age group we use separate regression model on the test image.

In this way we have three steps as shown in flow graph 1.1 we have three steps. First, feature extraction from face images, then classifying the image into one of the four age groups and at last applying regression model for that age group.

Fig1.1: Hierarchical approach for age estimation

As proposed in [2] the geometric features are used as our feature vector [2] and as regression technique we use Relevance Vector Machine (RVM).

To achieve classification of the check image within the correct group, many various classifiers such as μ-SVC, Partial statistical method [8] will be used, Nearest Neighbour, and Naive mathematician and fuse them exploitation the bulk rule.

For classifying the test image in the proper age group, we use many different classifiers such as μ-SVC, Partial least squares (PLS)[8]. Fisher Linear Discriminant, Nearest Neighbour, and Naive Bayes and fuse them using the majority rule.

Organizing of the paper in this as section II describes the literature review, Section IV describes Issues in existing system Section V Provides the proposed work.

II. LITERATURE REVIEW

Hayashi, J. Yasumoto, researched about an age and gender estimation based on wrinkle texture and colour of facial images. An image processing algorithm for wrinkle modelling was proposed by 'Hayashi'. In addition, a method for making relationships between facial images and their keywords was proposed by using the latent semantic indexing by 'J. Yasumoto'.

In 2004, the author Andreas Lanities, Chrisina Draganova and Chris Christodoulou had generated statistical model of facial appearance, in which they used age estimation classifier for each age group and/or classifier for different cluster of subjects within their training sets.

XinGeng ,Zhi-Hua Zhou and Kate Smith-Miles[15] planned the correct aging pattern for antecedently unseen face image is decided by the projection within the topological space which will reconstruct the face pictures with minimum reconstruction error, whereas the position of the face pictures in this aging pattern, can then indicates its age . though these works failed to try age estimation, they did reveal a number of the necessary facts within the relationship between age and face..

Later they additionally planned the techniques within which the aging faces are organized during a third order tensor per each 'identity' and 'age'. Every aging pattern could be a sequence of a specific individual face pictures sorted within the time order.

Guodong Guo and Xiaolong Wang shows that age estimation is influenced by expression changes, based on a quantitative evaluation on two databases newly introduced to computer vision. They proposed a new framework for age estimation access expression changes. The concept of learning expression correlation is completely new to age estimation.

In 2012, author Pavleen Thukral, Kaushik Mitra and Rama Chellappa, they planned a very important hierarchical approach [26], where they initial divide the face pictures into number of age teams so learn a separate regression model for every group. Initially classify the image into one amongst the age teams so use the regression model for that exact group.

In 2012, author Ranjan Jana, Harekrishna Pal and Amrita Roy Chowdhury proposed a method which was based on face triangle which has three coordinates point between left eye ball, right eye ball and mouth point. The face angle between left eyeball, right eyeball and mouth point estimates the age of human.

In 2013, author XinGeng, Chao Yin, and Zhi-Hua Zhou, they distributed each face images as an instance associated with a label age distribution. This age distribution covers a certain number of class ages, representing the degree that each age describes the instance. Through this way, one face image can contribute to not only the learning of its chronological age, but also the learning of its adjacent ages.

III. ISSUES IN EXISTING SYSTEM

Some earlier works to estimate age with the help of face expression as an example, a technique for face verification across age on the basis of a theorem classifier [11] is projected by Ramanathan and Chellappa. Shi et al. [12] studied how effective are landmarks and their geometry-based approach for face recognition across ages.

Many previous systems require manual separation of males and females prior to age estimation. Such technique also require large database consisting thousands of face images of males and females differently. Collection of such a database is extremely laborious.

Another technique is based on human age estimation under facial expression changes [14]. This technique involves two major issues:

a) Is age estimation affected by facial expressions?

b) How significant is the influence?

c) No significant relationship between age and facial expression changes is known yet.

Another technique relies on the automated age estimation [16]. This includes recognition of most facial variations like identity, expression, gender etc. Compared with these facial changes in accordance with aging, show following characteristics:

The aging is uncontrollable. And this process is slow and irreversible.

Different people age in different ways. Aging pattern of each person is determined by his/her genes, health, lifestyle etc.

The aging pattern is temporal. It must obey the order of time.

Each of these characteristics contributes to difficulties of automatic age estimation.

The age estimation using multi linear subspace analysis is another technique [15]. In this method, aging face images are organized in a tensor according to identity and age. Due to difficulty in data collection, the aging pattern for each person is incomplete. Thus the tensor large amount of missing values.

The previous existing systems are based on single regression model for all the ages [2, 4, 5, 6]. However changes in facial features vary greatly in different age groups. For example, 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.

The previous existing systems are supported single regression model for all the ages [2,4,5,6]. But face expressions vary greatly in several age groups. As an example, facial geometry among young person changes quicker than at old persons. Hence, it's not effective to resolve the age estimation employing a single regression model.

IV. PROPOSED SYSTEM

Here a hierarchical model is proposed where the images of face are divided into various age groups and a regression model is made for each age group. The three major steps are involved: feature extraction learning regression model for each of the age groups and classifying the input image into the various age groups. The steps are explained in detail below.

A. Feature Extraction

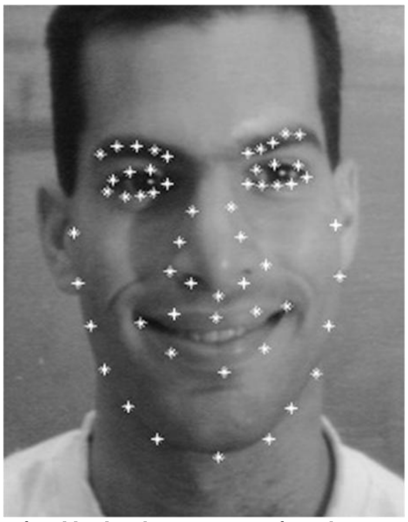

Fig 1.2: 2D facial landmarks on an image from the FG-Net dataset.

Geometric features are extracted from each face image. We locate the landmark 2D points on the test image which are based on such features on which we can reliably depend on such features are generally found in almost every face image such as extremities of nose, eyes etc. Several automatic methods are available which can locate the facial landmarks. Those methods work nicely on passport photos [11]. Even a small change in view can cause changes in these landmark points. Treating this extracted landmark point as Grassmanian manifold can solve this problem.

So at first we will calculate manifold mean of all such points and then at the mean of target plane we will project it. Average face can be transferred to the given face in unit time by velocity vector that parameterizes any given face (on tangent plane). Regression uses this velocity vector as the features. We can learn more about this in [2].

B. Learning of a Separate RVM Regression for Each Age Group

Learning the relation between 2 sets of variable is the main aim of regression , the independent variable x and the dependent variable y, using many example pairs (xi, yi), where i = 1, 2,3, 4, N. It is assumed that in RVM regression [6] the y and x are related as follows:

$$y = \sum_{i=1}^{N} w_i k(x, x_i) + w_0 + e \quad (1)$$

Where e is a Gaussian noise variable and k(x, xi) is a kernel function. By using the training set we estimate the weight vector w = [w0, w1,….wN]T.

$$p(w|\propto) = \prod_{i=0}^{N} N(w_i|0, \propto_i^{-1}) \quad (2)$$

Where each component w_i is a Gaussian random variable with mean 0 and variance α −1 i, where the αi variables, known as the hyper-parameters. These parameters are uniformly distributed. Once we integrate over the hyper-parameters the true nature of this hierarchical prior becomes apparent:

$$p(w_i) = 1/|w_i| \quad (3)$$

which is a sparse prior. To solve weight vector w maximum a posteriori (MAP) criterion is used where a training set of observations (x_i, y_i) is provided. As soon as we obtain W, the value of Y for any new X using RVM model (1) can be predicted. In this step a separate RVM regression model for each age group is learned. Based on the perceived homogeneity in the age-group and the number of data available for training the number and the age-range of the different age groups are decided. We allow some of the training samples to overlap between the age groups during the RVM training phase so that that the models are robust to classification errors that might occur while assigning the test image to the correct age group. We chose the Gaussian kernel which is of the form as a choice for the kernel function k(xi, xj) in the RVM model (1):

$$k(x_i, x_j) = exp\,(-\frac{||x_i - x_j||^2}{r^2}) \quad (4)$$

Choosing unknown parameter r is hard in order to obtain good regression performance. So during training phase optimizing this parameter for the different age groups can be a better way.

C. Classification of image into One of the Age Groups

Automatic classification is the last part of our approach for classifying test image into 1 of the age groups. We use multiple classifiers for this purpose. We will use five classifiers i.e. μ-SVC [10], Partial Least Squares (PLS) [8], Nearest Neighbour, Naive Bayes and Fisher Linear Discriminant [9]. At the end the majority rule is used to obtain the final classification of our test subject into the particular age group.

V. CONCLUSION

In proposed hierarchical approach for age estimation, we first extract features of the face images. On the basis of features extracted the age group of a person in which he/she falls is determined and then regression model of that particular age group is learned. Hence if the test images are classified into correct age group, then the task of age estimation can be performed effectively and accurately.

Hence the problem of age estimation can be solved by doing less number of comparisons of features extracted to the data available in the system and also more accurately than before as separate regression model is being learned. In this way hierarchical approach can improve result of age estimation.

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