

Study of Approaches for Human Facial Age Estimation

Vaishnavi Badame^{#1}, Mugdha Jamadagni^{*2}

[#]Department of Computer Engineering, RMD Sinhgad School of Engineering, India

^{*}Department of Computer Engineering, RMD Sinhgad School of Engineering, India

ABSTRACT: Recently the Human facial age estimation has allured more attention because of its wide range of applications in security, Human Computer Interaction(HCI), biometrics, entertainment, medical, forensics. Now a days various vital real time applications have eased their complexities due to the human age estimation techniques. The rudimentary goal is to develop a system for precise age group or age estimation of an individual derived from a facial image. Even with the advances in automatic age estimation, it still remains a challenging problem as ageing is a gradual process and varies according to the various aspects of the subject like genetics, lifestyle, environment, etc. In this review, we are going to consider various human facial age estimation techniques and learn the brief working, advantages and disadvantages of these techniques. Furthermore we are also going to study various datasets used for human age estimation technique.

KEYWORDS: age estimation, data mining, machine learning, Human Computer Interaction

I. INTRODUCTION

Human facial age estimation aims to estimate a label for the given facial image with exact age or age group automatically based on the visual features derived from a facial image and by using learning algorithms and facial datasets. It comprises of various interesting applications in security(surveillance control, culprit identification), HCI(artificial intelligence, robotics), cross face verification, recognition of facial expressions, aging- sensitive intelligent advertising and fashion recommendation(Coded Couture).

However precise age estimation is still considered to be a challenging problem. This is because aging is a gradual process and is affected by many extrinsic factors such as lifestyle, expressions, environment, gender. Because of these different aging rates people with similar age may have different facial appearances. Facial age estimation has various unique challenges apart from other facial analysis tasks[2]:

- a) *Group specific:* Aging process varies according to the genders and ethnic groups of the individuals.
- b) *Individually specific:* Personal living styles and health conditions also affect the age estimation process of an individuals.
- c) *Insufficient data:* There is much difficulty in collecting sufficient data to cover the whole range of ages.
- d) *Ordinal label:* Numerical ordinal information based age labels are used for the facial age estimation. For example, consider the ordinal age label of 13 years which would be more close to 14 year than that of 15 year.

Various approaches of the facial age estimation of human beings are developed today. Each of these approaches have their upsides and downsides. The approaches are majorly classifies as:

- A) *Multi class classification based approaches*
- B) *Regression based approaches*
- C) *Ordinal ranking based approaches*
- D) *Deep learning based approaches*
- E) *Low rank trace norm matrices based approaches*

These approaches are sensitive to the number of the training examples. The training examples are provided by the datasets. FG-NET, MORPH, WebFace are some of the examples of datasets used for human facial age recognition.

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These datasets consists of data images with labels which are used for the prediction of the age of input facial image using data mining and machine learning techniques. We will be briefly over-viewing the human facial age estimation techniques in this review.

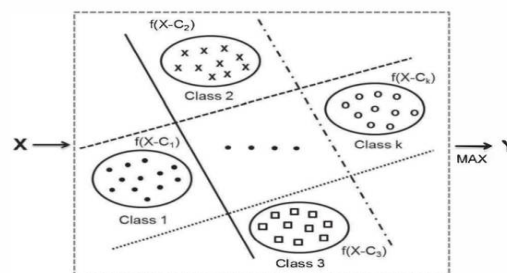
II. BACKGROUND

Age estimation plays a vital in real time applications. It decreases the complexities in the implementations of these applications. Recent years have witnessed a considerable interest in facial age estimation. The face descriptors like Local Binary Patterns (LBP) and Gabor features were well know earlier[3]. Fu et al. provided a survey of the comprehensive efforts taken for the age estimation[1]. Some of the prerequisites for the study of human age estimation are data mining, machine learning, facial feature extraction, kernel methods, data-sets, etc.

III. LITERATURE SURVEY

A. Multi Class Classification based approach:

In multi-class classification approach the label distribution is generated on the basis of the chronological age of the facial images[11]. Later various label distribution learning algorithms like IIS-LLD, modified CPNN and kNN-LD are applied to learn from previously generated label distributions. Different facial datasets can be used to test the learning algorithms. Multi-class SVM has learned to determine an optimal classification plane to discriminate one class from other classes that is to generate binary SVM class[4]. The multi-class classification approaches treat the age labels as a set of discrete labels and learn a classifier to estimate the subject's age[1]. The three kinds of denotations of label distributions are 'Gaussian', 'Triangle', and 'Single'. The age y to be predicted for a test image x' is determined by $y^* = \text{argmax } p(y|x')$ [7]. However, the inter-relationship among different age labels is ignored[1]. This reduces the sensitivity of the label with the training examples. Following is the diagram of Multi class classifier:



Multi Class classifier

B. Regression based approaches:

Regression based approaches can be implemented using three steps. In the training stage(first stage), the facial images with broad range of age classification are collected which are then detected and cropped into patches from the training images using automatic face detector[5]. In the next stage normalization of the training feature is done by performing standard alignments. Regression based approaches basically learn a function that best fits the mapping from facial visual features to age labels with appropriate regularization[1]. The third stage consists of a multiple linear regression procedure to estimate a statistical age model is used with a quadratic function. The testing stage, transforms the input image to a low dimensional aging feature in the same manner. Using the sub-space learning and manifold method of analysis the dimensional redundancy of the original image can be reduced significantly.[5]

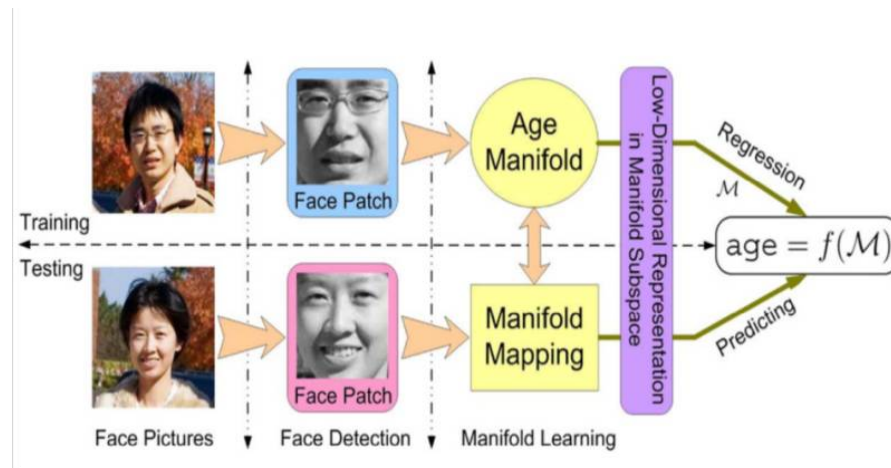
In the regression based approaches, the labels are treated as linearly increased values that cannot reflect the non-stationary of human aging process[1]. It can be used in supervised learning, semi-supervised learning and also in unsupervised learning tasks with help of pairwise information quantifying the degree of analogy and difference among samples[6].

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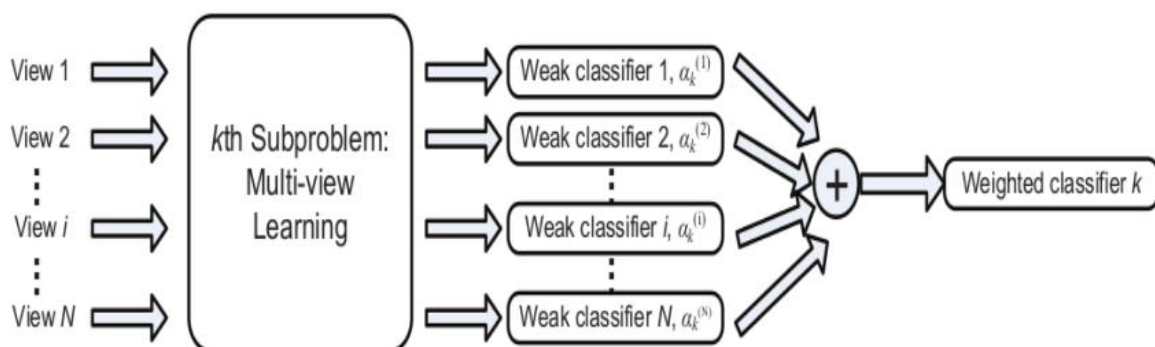


Regression based facial age estimation approach

C. Ordinal ranking based approach:

In the approach of ordinal ranking, the age estimation problem is converted into a series of $K - 1$ sub-problems of binary classifications. For each given facial image the discriminating features of the image are extracted and taken into consideration. The concept of age ranking, which utilizes relative age ranks instead of exact age labels[1]. It's beneficial to combine different features together by learning a set of weighted classifiers to form a stronger classifier for age estimation[2]. It transforms an age estimation task into multiple cost-sensitive binary classification sub-problems, and solves the problem with an ordinal hyper-plane ranking (OHRank) algorithm [1]. The ranking approach makes use of the binary decisions by a series of queries which makes the task of facial age estimation quite easier.[12]. Ranking based approach uses comparably more dependable information to train the age estimator instead of learning from non stationary kernel[12].

The use of this approach is responsive to the number of training examples which require sufficient training examples. As the number of training examples are limited in the existing data sets, the performances achieved by this approach are not satisfactory.



Ordinal ranking classifier [8]

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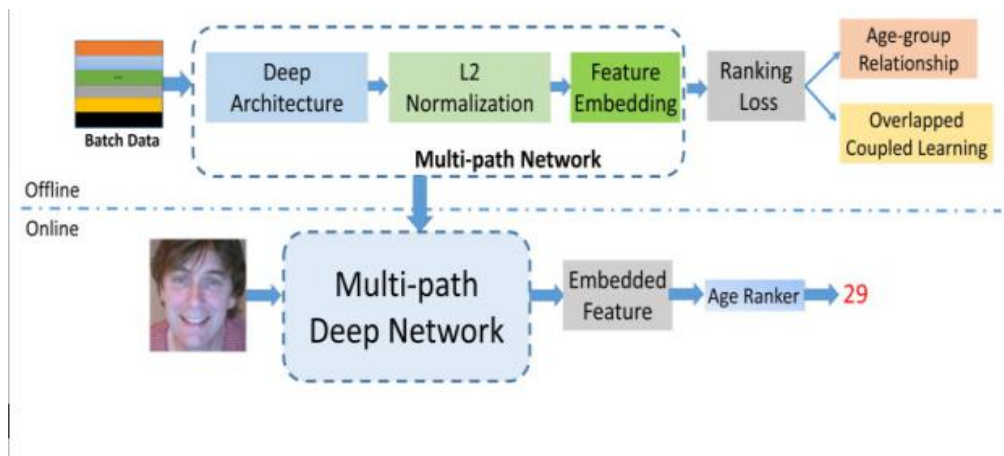
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D. Deep learning based approach:

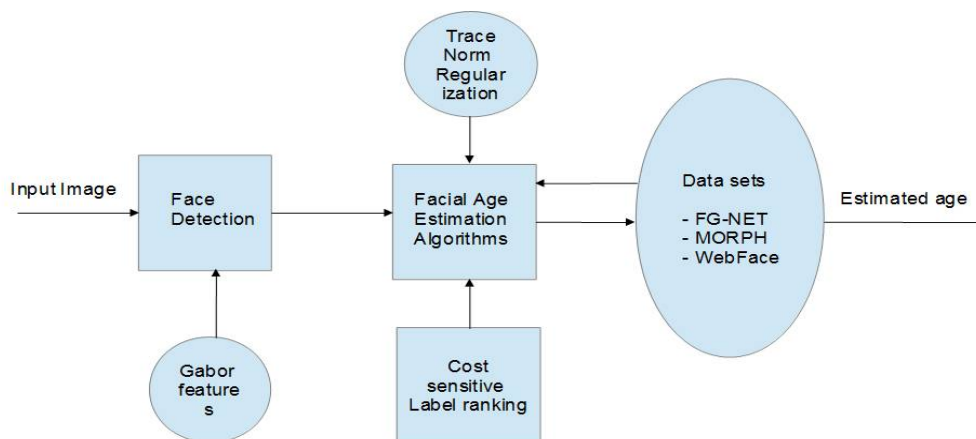
Recently, deep Convolutional Neural Networks (CNNs) have demonstrated a promising performance in feature learning, and is used for facial apparent age estimation[1]. This approach consists of a wavelet scattering network with three layers (L1,L2,L3), a dimensionality reduction component and 3 fully-connected layers (L4–6)[3]. The dimensionality reduction can be done by PCA(Principal Component Analysis). ScatNet is used for facial representation extraction; PCA is used for reducing high dimension of the concatenated scattering coefficients generated by the ScatNet. Further an outer layer is constructed with category and ranks for individual age estimation. The accuracy of the human age estimation is increased in deep learning approach than in regression based approach.



Deep learning approach for facial age estimation

E. Low rank trace norm regularization based approaches :

This approach adopts both the cost-sensitive label ranking methods and the low-rank matrix recovery theories for estimating the facial age of the subject[1].The age labels are ranked in descending order according to their estimated relevance to reduce the sensitivity of precision to the number of training examples in the datasets. Kernel methodologies are used for trace norm regularization from a finite dimensional space to an infinite dimensional space[1]. By taking into consideration the number of sign configurations of low rank matrices the generalization error bounds for the age prediction can be obtained.



Trace Norm regularization approach for facial age estimation

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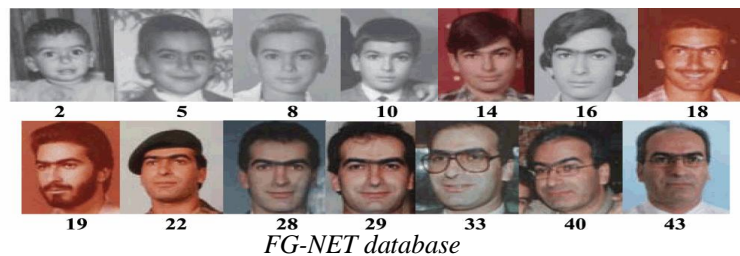
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Major datasets in human age estimation:

- A) FG-NET
- B) MORPH
- C) WebFace

A) *FG-NET*: The FG-NET dataset has 1,002 color or gray facial images composed of 82 different subjects. The age in the dataset ranges from 0 to 69 years old. Each individual has 6-18 images labeled with the chronological ages. The dataset has the ages upto 40 years in large population. It comprised of the feature of Active Appearance Models (AAM). FG-NET dataset is obtained free of charge for various research purposes. Following image shows the training example in FG-NET.



B) *MORPH*: The MORPH has 55,132 facial images from more than 13,000 subjects containing faces belonging to various races. The ages of the facial images in MORPH dataset range from 16 to 77 years old. As the data images are assembled from the real world conditions in MORPH, it is not a controlled collection. MORPH is divided into 2 sections/datasets[10]:

Section I : 515 digital images of subjects taken from October 26, 1962 to April 7, 1998. It is available in full.

Section II: Still under evolution. Images in this section are obtained in each quarters. Album II or the section II of the MORPH datasets consisting of 55,134 images of 13,000 subjects obtained is available for the academic research purposes.

Following figure shows the training example in MORPH.



MORPH dataset

C) *WebFace*:

It can be obtained from Flickr and Google Image using a set of age related text queries ranging from 1 to 80. It contains 62,216 facial images and is the largest data-set available for age prediction. It comprises of the feature of AAM[1].



WebFace dataset

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Performance Measure of all the given approaches:

Two criterias are used for performance evaluation in the human age detection system they are:

A) *Mean Absolute Error(MAE)*:the average absolute difference between the estimated age and the chronological age

B) *Cumulative Score(CS)*: the accuracy of age estimator at different error tolerance

$$MAE = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} |a_i - \hat{a}_i| \quad \text{---(1)}$$

$$CS(e) = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} g(|a_i - \hat{a}_i| - e) \quad \text{---(2)}$$

here N_{test} is the total number of testing samples, a_i is the chronological age and \hat{a}_i is the estimated age.

Following table shows the performance of the discussed approaches in terms of MAE[1]:

Sr No	Approach	Method	MAE
1	MCC	KNN	9.39
2	MCC	SVM	7.34
3	R	SVR	6.99
4	R	CA-SVR	5.88
5	OR	OHRank	5.69
6	DL	IIS-LDD	5.67
7	DL	CPNN	4.87
8	LRTNM	Trace-Norm	5.49

Where,

MCC:Multi class classification,

R: Regression,

OR:Ordinal Ranking,

LRTNM: Low Rank Trace-Norm Matrix.

IV. SUMMARY

We have studied various Human facial age estimation approaches with their performance evaluation. These approaches can be used in various age prediction applications according to convenience. Comparative analysis of different approaches help in understanding the implementation in a better way. Moreover we have also seen the widely used data sets for age estimation along with their characteristics.

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REFERENCES

1. Songhe Feng, Congyan Lang, Jiashi Feng, Tao Wang and Jiebo Luo Fellow, "Human Facial Age Estimation by Cost-Sensitive Label Ranking and Trace Norm Regularization", IEEE Transactions on Multimedia, 2016
2. Weng Renling, "Multi-View Ordinal Ranking for Facial Age Estimation", ROSE-nanyang technological university
3. Hwei-Fang Yang, Bo-Yao Lin, Kuang-Yu Chan, Chu-Song Chen, "Automatic Age Estimation from Face Images via Deep Ranking", Institute of Information Science Academia Sinica, 2015
4. Kyekyung Kim, Sangseung Kang, Sooyoung Chi and Jaehong Kim, "Human Age Estimation Using Multi-Class SVM", Ubiquitous Robots and Ambient Intelligence (URAI), 2015 12th International Conference, 28-30 Oct. 2015.
5. Yun Fu, Thomas S. Huang, "Human Age Estimation With Regression on Discriminative Aging Manifold", IEEE Transactions on Multimedia, Vol. 10, NO. 4, June 2008
6. Na Fan, "Learning Nonlinear Distance Functions using Neural Network for Regression with Application to Robust Human Age Estimation", IEEE International Conference on Computer Vision, 2011.
7. Xin Geng, Chao Yin, and Zhi-Hua Zhou, "Facial Age Estimation by Learning from Label Distributions", IEEE Transactions on Pattern Analysis and Label Distributions,
8. Wei Zhao and Han Wang, "Facial age estimation based on advanced ordinal ranking", IEEE Electronics Letters (Volume: 51, Issue: 2015)
9. Nathan Srebro and Adi Shraibman, "Rank, Trace-Norm and Max-Norm",
10. <http://www.faceaginggroup.com/morph/>
11. V. G. Khetade, S. C. Sagare, S. S. Darbastwar, "Image based Human Age Estimation by Label Distribution Learning", International Journal of Advanced Research in Computer Science and Software Engineering, Volume 6, Issue 7, July 2016
12. Kuang-Yu Chang, Chu-Song Cheng, Yi-Ping Hung, "A Ranking Approach For Human Age Estimation Based On Face Images", IEEE International Conference on Pattern Recognition, 2010.