Using Artificial Neural Network for Human Age Estimation Based on Facial Images

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Abstract— **Facial image analysis has received a great deal of attention from many researcher because it leads to very important knowledge that help in improving the human-machine interaction. Recently human age estimation by face images arise as a challenging research topic. In this paper, the application of neural networks to estimate human ages was explored. The uniqueness about our research project is that we consider fine tuned age ranges than most of the previous research work do and apply our experiment to real human face image. After collecting real face images, facial features was extracted and used as inputs to learn Multi-layer perceptron neural networks (MLP). The results show that MLP network has minimum estimation error and can be considered as a good method to model accurate age estimator that could be used in many useful applications like age-based access control and age adaptive human machine interaction.**

Keywords—**Neural Networks; Age Estimation; Facial Fetures.**

I. INTRODUCTION

Face images convey a significant amount of knowledge including information about the identity, emotional state, ethnic origin, gender, age, and head orientation of a person shown in a face image. This type of information plays a significant role during face-to-face communication between humans [1]. Current trends in information technology dictate the improvement of the interaction between humans and machines, in an attempt to upgrade the accessibility of computer systems. As part of this effort, many researchers have recently directed their research effort toward age estimation problem. Age estimation is the determination of a person's age based on biometric features [18]. Although age estimation can be accomplished using different biometric traits, this research focus on facial age estimation that relies on biometric features extracted from a person's face. The process of age determination could figure in a variety of applications ranging from age-based access control, age adaptive human machine interaction., age invariant person identification and data mining and organization [18].

In additional to problems encountered in other typical face image interpretation tasks such as face detection, face recognition, expression and gender recognition, age estimation displays additional unique challenges due to the complex variations, including cosmetics usage, personal specialties, living conditions, gender and ethnic differences [5].

In this research, we try to prove that computer can estimate/classify human age according to features extracted from human facial image using Artificial Neural Network (ANN). Artificial neural networks (ANN) are parallel computational models, comprising closely interconnected adaptive processing units. The important characteristic of neural networks is their adaptive nature, where 'learning by example replaces programming'. This feature makes the ANN techniques very appealing in application domains for solving highly nonlinear phenomena. ANN have been applied successfully to many application. Most of these applications are based on statistical estimation, optimization and control theory such as speech recognition, image analysis and adaptive control. A Multi-layer neural network can approximate any smooth, measurable function between input and output vectors by selecting a suitable set of connecting weight and transfer functions.

In our research, we devote our study to produce a system which is capable for estimating the age of a person as reliably as humans. To achieve this goal we follow a research methodology that consists of the following steps: First we capture a real human face image from people around (friends and family). Second we use our special tool to locate and extract the face features. Third we preprocess and prepare the data for ANN training. Finally we apply our experiments and analyze the results.

The rest of this paper is organized as follows: Section 2 presents some related works. Section 3 summarize data collection process. Section 4 describes the data preprocessing and preparation step. Section 5 present and discuss our experimentation. Finally conclusions are presented in the last section.

II. RELATED WORK

General topic of face image processing received considerable interest [4][12][13]. Recently, modeling and/or simulating aging effects on face images has received a great deal of attention from researcher.

Existing methods for facial age estimation typically consist of two main steps: image representation and age prediction. For the image representation, the most common models are Active Appearance Model (AAM) [11], Anthropometric model [9], aging pattern subspace [14] and aging manifold analysis method [3]. The final step for age estimation is either the multiclass classification problem or the regression problem.

The AAM was developed by Cootes, Edwards and Taylor [11]. It is an algorithm for matching a statistical model of object shape and appearance to a new image. Active appearance model is related to the active shape model. Adopting the AAM approach, Khoa Luu et al. [6] used AAM features, which combine both shape and texture information in their age estimation studies. Ricanek et al. [7] developed a multiethnic age-estimation system that can deal with the races problem using AAM features extracted from image with 161 landmarks.

Recently, based on the arguments that age information is often encoded by local information, such as wrinkles around the eye corners, anthropometric model method applies the cranio-facial development theory and facial skin wrinkle analysis to create the aging model, whereby the changes of shape and texture patterns of facial images are measured to categorize a face into several age groups. Hence, this method is suitable for coarse age estimation rather than refined cases [16].

The problem of having an appropriate approach for age estimation for getting more specific categories of age ranges is still a challenging problem. A fine tuning age-estimation scheme proposed by Duong et al. [2]. They combine holistic (global) features extracted by AAM and local features extracted by Local Binary Pattern (LBP). Age estimation is performed in a two-step method: fine-tuning method which requires an initial age guess followed by a refining step (fine prediction). Another work for classify age into very specific ranges using artificial neural networks created by hewahi et al. [8]. It is worth mentioning that in all the used approaches, the age range classifications are not as we are planning to consider in our classifications. We aim at tuning the age ranges to produce the most accurate estimation.

One of the main difficulties in facial age estimation is the lack of sufficient training data for many ages. In order to handle this problem, the aging pattern subspace (AGES) method [6] models a sequence of individual aging face images by learning a subspace representation. The age of a test face is determined by the projection in the subspace that can best reconstruct the face image.

Another facial age estimation research challenge (facial image analysis in general) is the high dimensionality of features [15]. Age manifold analysis has two advantages to overcome this problem. First, the manifold analysis is a way to represent the original age data in low dimensionality which is necessary to overcome lack-of-fit of the regression model. Second, the manifold learning captures the underlying face aging structure which is important for accurate modeling and age prediction [3].

Most existing facial age estimation methods, however, usually unitize only the appearance features (texture information) of facial images for age estimation. Previous work in face modeling has demonstrated that the shape information of facial images also plays an important role in human age estimation [9], especially for the youth persons. Motivated by this reason, we try to extract and use the shape information from facial images to characterize human ages. Then we use this information as input for the neural network to learn.

III. DATA COLLECTION

To achieve this study, we use a set of 300 images. The images were collected from real peoples around us (friends and family). Some images where taken by our camera and the others provided by its owner. The age of the individuals shown in the face images of the set range between newborns up to 89 years. The images include people from different countries with different facial expressions. The quality and size of images also varies from one image to another. However we do not apply any image processing method to the collected images.

IV. FEATURE EXTRACTION AND DATA PREPERATION

After images have been collected we try to model each face shape. The shape of an face in each training image can be illustrated by according to the order n-point. n this work, 94 points are chosen as illustrated in Figure 1.

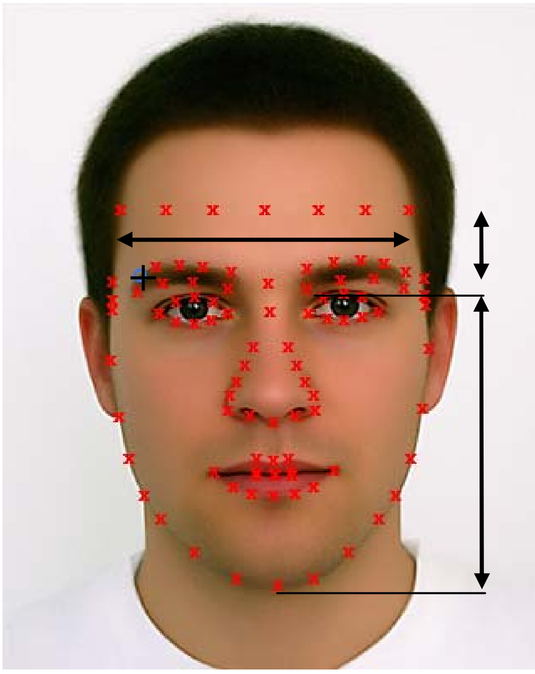

Figure 1: Landmarked face.

We have manually locate the points (landmarks) for each training image using a special tool we made. The tool help us in locating the points to its appropriate places manually and extract the features in text files. Each point is an (X,Y) pair coordinate where the origin point located at the end of the right eyebrow.

Table 1 illustrates the distribution of the landmark points at the different facial features and its importance in modeling the face shape.

Because the data produced are represented by (X,Y) pairs, we two dimensional transformation must applied. Two dimensional transformation is useful to correlate each (X,Y) pairs in one meaningful unit. There are many transformation methods used on imaging analysis fields. In our work we use Singular Value Decomposition (SVD) method.

Singular Value Decomposition is simply a factorization of a matrices into a series of linear approximations that expose the underlying structure of the matrix [17]. It have been used widely for dimensionality reduction where it can effectively reduce large dataset into smaller one which still contains a large fraction of the variability present in the original data [10]. Singular Value Decomposition applied successfully in many applications such as data analysis, signal processing, pattern recognition, image compression, weather prediction, and Latent Semantic Analysis.

Table 1: Facial landmarks

Facial Feature	Number of Points	Shape Modeling Features
Face Contour	30	Distance from Jaw to eyes, from eyes to forehead, length of the forehead
Eyebrow	9 for each	Thickness, Length
Eye	8 for each	Area, Angle
Nose	14	Width
Mouth	16	Length, Thickness, Corner

After applying SVD method we obtain 94 attributes each represent a point (X,Y) pair. In some experiments we reduce the number of attributes by sorting them in ascending order according to correlation of each attribute with the label attribute and then we chose the top ***k*** attributes with highest correlation. This speed up the learning process and make it easier.

V. EXPERIMENTS AND RESULTS

This section presents our experimentation and discusses our results. We divide this section into two sub-sections according to label value type. In the first section we apply our experiments in order to estimate the age of a person as humans do (in number). In the second section we try to classify the person into one of several groups (classes) each with different range.

A. Age Estimation with Regression

We run many experiments with different MLP structures and different parameters. The best results and optimal structures for developed Multi-layer perceptron neural network (MLP) for obtaining minimum estimation error and highest correlation coefficient between actual and estimates age are shown in Table 2 and Table 3.

Table 2 illustrate best experimentation setting and results without applying dimensionality reduction. We use all the facial features (24 feature) as input to neural network in addition to gender attribute. The network structure include three hidden layers each with 50 neurons. We trained the MLP for 2000 epochs. We test the network using 10-cross validation with shuffled sampling. Results show highest correlation coefficient = 0.88 and maximum error = 38 between estimated and real age. The chart in Figure 2 show the two curves of real and estimated age values for testing examples. Note that the two curves are very close to each other.

Table 2: Best MLP structure and obtained results

#Imput layers	95 (94 facial feature + gender attribute)
#Hidden layers	3
#Neuron in each hidden layer	50
#Epochs	2000
Activation function in hidden and output layer	Sigmoid
Learning rate	0.3
Momentum	0.2
Training error	0.00003954
Correlation coefficient	0.88
Maximum error	38

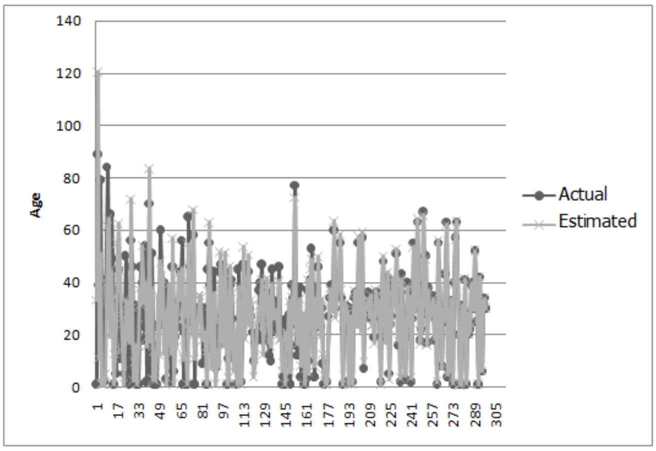

Figure 2: Comparison between actual and estimated age

Table 3 illustrate best experimentation setting and results after applying dimensionality reduction. Number of attributes reduced to 50. Same testing options used as previous experiment. This experiment provide less maximum error between estimated and real age. Correlation coefficient decreased but not significantly.

Table 3: Best MLP structure and obtained results after dimintionality reduction

#Imput layers	50 attribute (with highest correlation with label attribute)
#Hidden layers	2
#Neuron in each hidden layer	25
#Epochs	4000
Activation function in hidden and output layer	Sigmoid
Learning rate	0.3
Momentum	0.3
Training error	0.00013523
Correlation coefficient	0.8564
Maximum error	30

B. *Age Classification*

In age classification we concentrate in nominal label. We discretize the label attribute into nominal attribute. This discretization is performed by binning. The main range of ages [1day - 89 years] is partitioned into categories. Each category represents a bin, and examples are assigned to the bin representing the segment covering its numerical value. Most of the researchers categorize the ages into four classes, childhood, young, youth and old. In our experiments we try to classify ages into this common classes. In addition to that we try to classify ages into eight fine tuned classes with more specific ranges. Figure 3 present the two way of discretization and illustrate the age range for each bin and the number of examples belong to this bin.

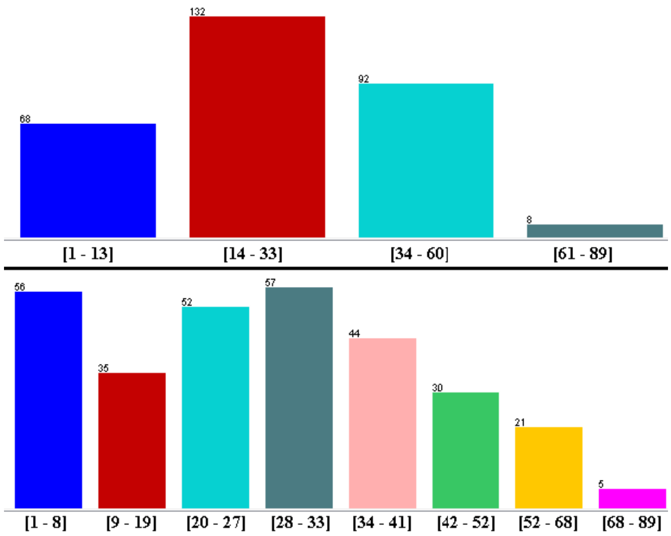

Figure 3: Age range for each class and the number of examples belong to this class

Table 4. Experiments for age classification (best MLP structure and obtained results)

# bins	**Inputs**	**#hidden layer**	**#Neurons in hidden layer**	**Accuracy**
4 bins	95 attribute including gender attribute	1	75	88.29 %
4 bins	50 attributes (with highest correlation with label attribute)	1	56	86.83 %
8 bins	95 attribute including gender attribute	1	61	79.67 %
8 bins	50 attributes (with highest correlation with label attribute)	1	21	63.55 %

We train our MLP using adaptive learning rate and momentum algorithm. We test the network using 10-cross validation with stratified sampling. The best obtained results and MLP details are recorded in Table 2. The results show best accuracy when number of bins are smaller. When ranges get more specific the accuracy decreases.

When we track the misclassified examples we notice that most of them incorrectly classified with small difference from the true classification. This is confirmed by regression experiments, where the correlation between the real and estimated age is high.

VI. CONCLUSION AND FUTURE WORK

This paper demonstrated how Artificial Neural Networks (ANN) could be used to build accurate age estimator. In order to train the neural network we extract shape features from real human face images that we captured at earlier time. We use Multi-layer perceptron network (MLP) as classification and regression tool. It's estimation reliabilities were evaluated by computing correlation coefficient between the exact and estimated age values (for regression experiments) and classification accuracy (for classification experiment). The results shows that MLP network has a good performance and reasonable estimation accuracy it could be an important tool for age estimation.

Our Future work involve developing an automatic landmark detection algorithm, try to include more meaningful features for age estimation process, increase our training set examples and try to build a universal age estimator that can be a plug in for search engines, social networks and adaptive e-learning systems.

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