International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 2, No. 2, 2015, pp. 285-292.
ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

Studying the Impact of Talent Management on Performance of Staffs

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Abstract

The age estimation is one of the common issues in the field of pattern recognition which aims to estimate individuals' age on face image using machine learning methods. Each model in age estimation consists of two main steps: feature extraction and classification. In the feature extraction stage, a diagram of the main features of the face which are effective in the problem of age estimation are extracted and with age tag have been used to train classification algorithm. This paper presents a new method to estimate the age that Pseudo-Zernike moment and classification algorithm of multi-layer perceptron neural network is used in feature extraction stage. In this paper, two databases, NET and MORPH, are used. Estimation system of the proposed age has achieved accuracy 15/96 in estimation phase on FG-NET images database and accuracy 26/92 on MORPH data collection. Also in terms of two dimensions, age estimation and feature extraction were compared with other proposed procedures in the field of age estimation and have provided the best results compared to other methods.

Keywords: Age Estimation, Pattern Recognition, Neural Network, Pseudo-Zernike Moment

Introduction:

Aging is a non-reversible process. Characteristics of human faces have changed over time so that significant changes appear in the appearance of humanoid. Human face is considered amongst biological characteristics that has numerous information and features in itself. Age analysis is divided into two categories in machine vision problems: age synthesis and age estimation. Age synthesis aims to simulate the effects of aging on individuals' face [1].

In recent years, the Bio-Inspired Features (BIF)are considered important factors in the success of many machine vision problems as group recognition[2] and identifying faces [3], but in the age estimation , they have recently been used [4]. We can point to security control and surveillance systems of age estimation applications which are also used in the field of health care and information retrieval. The age estimation normally is a challenging issue. Because it depends on many factors and it is documented in [5] that smoking, genetic predisposition, emotional stress, illness, weight changes etc. increase the aging process. Visual characteristics (e.g., characteristics of human faces) that are used to estimate age are changed by the gesture, lighting and shooting conditions. It is possible that males and females are viewed by different characteristics of separation in image due to reasons such as makeup, jewelry and cosmetic surgery. In many pictures of women, people appearance with makeup or cosmetic surgery is shown younger than their actual age. Problems of large and complete images database collection that includes images of people in different age groups (childhood, adolescence, youth, adulthood and old age), increases the practice of age estimation. Although images collection from the web can also contribute to the preparation of the above-mentioned database, but it usually is difficult and impractical to collect a huge database of large number of people images in all ages with a variety of topics. This paper presents a new method to estimate the age in which Pseudo-Zernike moment and multi- layer perceptron neural network classification algorithm are used that will be described in the following sections [6-11].

2. Literature

People can have different patterns at different ages and people faces are displayed differently over time and at different ages. But a set of differentiated and general features are available for each individual figure which can be used at any time [12]. In the estimation of human age, mathematical formulation is not used for two reasons: the mathematical models do not take into account the natural growth reason of head (especially for older adults [13] and it is difficult to calculate growth of head based on the two-dimensional images of face. Compared to methods based on body size [13] which is used only for the younger age groups, AAM models are utilizable to estimate all ages. Moreover, unlike the methods based on body size that use geometric characteristics, methods based on AAM models utilize face characteristics with textural features for estimating age based on the face image.

Geng et al. [14-15] offered the AGES system in which a sequence of people face images have been used at different ages at one time to model the aging process. AGES algorithm consists of two stages: learning and age estimation. In learning stage, age pattern subspace uses PCA algorithm to show (get) used subspace.

Suo et al [16] proposed a multi-resolution hierarchical model in which a visual features topology of face with their geometry position has been used. In this method for feature extraction, filters are applied in hierarchical model on various parameters at different levels. This system has obtained on the absolute error mean 97/5 year by MLP neural network on the FG-NET database and absolute error mean 68 year on another database.

Guo et al. [4] suggested using biological inspired features (BIF) to estimate age based on the face. This system has got average of absolute error 77/4 year on the FG-NET database as well as 47/3 year on the YGA database for men pictures and the mean of absolute error 91/3 year for women pictures.

Lowe [17] presented SIFT (Scale Invariant Feature Transform)method in this way that it works based on the structural features in the feature extraction stage (structural features were analyzed based on the components model which in fact pattern feature vector is formed based on the characteristics of small components and their placement next to each other).

This method converts an image into a set of local feature vectors that this change is independent of conversion, scalability and rotation and is partially independent of changes in ambient lighting. Previous methods, in order to generate local characteristics, were not independent of scalability and were sensitive to changes in their brightness.

3.Pseudo-Zernike Moment (PZM)

As previously mentioned, age estimation is used in age estimation system after feature extraction stage. Pseudo-Zernike moment is one of the feature extraction methods. Pseudo-Zernike moments are mapping of a two-dimensional function on functions of complex and orthogonal basis$\{V_{nm}(x,y)\}$ These functions are defined inside the unit circle$x^2+y^2\le 1$ and form a complete set. Polynomials$\{V_{nm}(x,y)\}$ are defined as follows[18] :

$$V_{nm}(x,y)=R_{nm}(x,y)\exp\left(jm\tan^{-1}\left(\frac{y}{x}\right)\right) \qquad (1)$$

In this equation, n and m are called the rank and frequency respectively that n is an integer and $n\ge 0$ and m is an integer$(|m|\le n)$ and$R_{nm}(x,y)$ is a radial polynomial and defined as follows:

$$R_{nm}(x,y)=\sum_{s=0}^{n-|m|}D_{n,|m|,s}(x^2+y^2)^{\frac{n-s}{2}} \qquad (2)$$

$$D_{n,|m|,s}=(-1)^s\frac{(2n+1-s)!}{s!(n-|m|-s)!(n-|m|-s+1)} \qquad (3)$$

According to above mentioned equations $R_{n,-m}(x,y)=R_{n,m}(x,y)$. Therefore$V_{nm}(x,y)=V_{nm}^{*}(x,y)$ Pseudo Zernike moments are of two-dimensional functions on these basis functions. Pseudo-Zernike moments of time n and frequency m for two-dimensional discrete function $f(x,y)$, which is zero outside the unit circle, are calculated as follows:

$$PZM_{nm}=\frac{n+1}{\pi}\sum_x\sum_y f(x,y)V_{nm}^{*}(x,y) \qquad (4)$$

The number of pseudo-Zernike moments to time n is equal to$(n+1)^2$. If positive m-ths are only considered, the number of pseudo-Zernike moments to n-th time will be equal to $\frac{(n+1)(n+2)}{2}$.

Pseudo-Zernike moments can be calculated in two ways: the first method is direct calculation of (4) equation on pattern and the second method uses central geometric moments and moments of radial geometry. Accordingly Pseudo-Zernike moments can be defined as follows:

$$PZM_{nm}=\frac{n+1}{\pi}\sum_{(n-m-s)even,s=0}^{n-|m|}D_{n,|m|,s}\sum_{a=0}^{k}\sum_{b=0}^{m}\binom{K}{a}\binom{m}{b}(-j)^b.CM_{2k+m-2a-b,2a+b}+\frac{n+1}{\pi}\sum_{(n-m-s)odd,s=0}^{n-|m|}D_{n,|m|,s}\sum_{a=0}^{d}\sum_{b=0}^{m}\binom{d}{a}\binom{m}{b}(-j)^b.RM_{2d+m-2a-b,2a+b} \qquad (5)$$

In which $d=k=(n-s-m)/2$, $CM_{i,j}$ the central geometric moment and $RM_{i,j}$ is geometric-radial moment. Also the pseudo-Zernike moments which are calculated in this part, have divided on the

PZM_{00} moment which is indicative of model area which results to scalable moments. Therefore, the PZM_{00} will be equal to unit for all models. On the other hand, as regard, $PZM_{nm} = PZM^{*}_{n,-m}$ therefore Pseudo-Zernike moments are calculated only for positive m-ths. It has been shown that if an image is rotated, only Pseudo-Zernike moments phase has changed and its absolute value remains constant [19]. Therefore, if absolute value or size of Pseudo-Zernike moments is taken into account as feature, these characteristics are independent of the rotation.

4. Proposed method

This paper presents a new method to estimate the age that Pseudo-Zernike moment in its feature extraction and classification algorithms of multi-layer perceptron neural network in classification stage is used to estimate age. Vector elements and pseudo-Zernike feature are shown in below equation:

$$FV_j = \{PZM_{km} | k = j, j+1, \cdots, N\} \quad (6)$$

In this equation, parameter j is selected from range $[1, N]$ and thus above vector includes all Pseudo-Zernike moments from j time up N. It should be noted that an amount equal to 10 is considered. In the proposed method after getting feature vector, extracted features are used to train the classification algorithm that multi-layer perceptron neural network is used in this article that it will be discussed.

4-1. Multilayer Perceptron Network

Multilayer Perceptron Neural Networks involve an input layer, some hidden layers and an output layer. Neurons in each layer only are connected to the next layer of neurons and each neuron is connected to all neurons of the next layer. Input layer neurons do not practice and all have equal and constant weight. These neurons do not have compression function. All neurons are collector apart from input layer and each neuron can have independent compression function. In addition, each neuron can have an independent bias and the number of hidden layer is not specified. There is no practical method to estimate the number of units (neurons) in each hidden layer. Thus trial and error methods should be used to achieve the average value of desired total error. For P-th input sample, the sum of squared errors is calculated for all nodes in the network's output layer as follows:

$$E_p = \frac{1}{2}(d^p - y^p)^2 = \frac{1}{2}\sum_{j=1}^{s}\left(d_j^p - y_j^p\right)^2 \quad (7)$$

Where d^p and y^p are the vector and the vector of real output, respectively, d_j^p and y_j^p aredesired outputs and real output for the j-th node of the output layer and s is the size of the output vector.

Therefore, the sum of squares of error is calculated for the P patterns sample as follows:

$$E = \sum_{p=1}^{p} E_p = \frac{1}{2}\sum_{p=1}^{p}\sum_{j=1}^{s}\left(d_j^p - y_j^p\right)^2 \quad (8)$$

Weights are updated to reduce E error rate according to the following equation:

$$w_{ij}(t+1) = w_{ij}(t) + \eta \times \Delta w_{ij}(t) + \alpha \times \Delta w_{ij}(t-1) \quad (9)$$

$$\Delta w_{ij}(t) = -\left(\frac{\partial E_p}{\partial s w_{ij}(t)}\right) \quad (10)$$

Where η is learning rate, α coefficient and $w_{ij}(t)$ the weight of the edge t and $w_{ij}(t+1)$ is weight edge from node i to j at next time. MLP learning process continues as much as the error rate is less than the threshold or the maximum number of repetitions [20].

5. Practical results

In the proposed method system, a pseudo-Zernike moment is used to extract features and multilayer perceptron neural network is used to estimate age and estimate the distribution of age labels. To evaluate the proposed method, age images database of FG-NET[21] has been used with 640 images of 80 individuals (male and female) and MORPH has been used [22] with 55,000 images of 13,000 individuals that there are 8 images for each person between the ages 0 to 100 years in the images database. To train and test the proposed method, the algorithm was trained and tested 10 times, in repetition for any

individual at any time, 4 images for training and 4 images for testing are utilized to test the proposed method. In this paper, the evaluation criteria used for estimating the age phase, MAD (Median Absolute Deviation) criterion is defined as follows:

$$MAD = \left(1 - \frac{\sum_{i=1}^{N} |x_i - \hat{x}_i|}{N}\right) \times 100 \qquad (11)$$

In the above measures, the difference between the actual age (x_i) and amount of estimated age $\hat{x}_i$ is calculated for i-th individual. In the above equation, N shows the test images. To put it simply, MAD criterion determines age estimation accuracy for the test images. In Table 2, three feature extraction methods were compared on the images database FG-NET [21-26] , in order to estimate age that these methods are Pseudo-Zernike moment, AAM method and SIFT . $n = 9,10$ is intended for Pseudo-Zernike in this test that pseudo-Zernike moment has extracted 21 features elements of each image. Also AAM method has extracted 18 features from the image and SIFTS method extracts a variable number of features for each image that, on average, 128 features are intended for all images that each feature of a vector is 128. According to Table 1, Pseudo-Zernike, AAM and SIFT methods have achieved the best age estimation accuracy, respectively. Also Pseudo-Zernike has achieved better results than the other two methods on both databases. This indicates that the statistical properties have significantly improved the accuracy of classification algorithm than geometric features. The reason for poor performance of AAM and SIFT approaches is that two methods extract features which are dependent on the geometry of the face and if it rotates, magnification (zoom out) and image change do not extract appropriate features. However, the Pseudo-Zernike method belongs to the characteristics of the statistical category and is independent of the face geometry and, in the event of occurrence of above changes, appropriate and optimal features extract from images. In this table, two parameters of feature vector elements and accuracy have mentioned for each method of feature extraction that Pseudo-Zernike moment has obtained most accurate age estimation with 21 elements of feature vector in comparison with other feature extraction methods.

Table1. Comparison of feature extraction methods on FG-NET database [21] and [22] to estimate age. FE means the number of feature vector elements.

Dataset	Feature extraction method					
	SIFT		AAM		PZM	
	FE	MAD (%)	FE	MAD (%)	FE	MAD (%)
FG-NET	128	85.46	18	90.70	**21**	**96.15**
MORPH	128	82.92	18	86.65	**21**	**92.26**

Visual examples of the age estimation results have displayed using pseudo-Zernike moment and neural network algorithm in Fig 1. According to this form, two values have been taken into account for each image that are high value for real age and lower value for estimated age.





Fig 1: The proposed method results in the age estimation phase on the pictures of FG-NET database.

As mentioned above, learning algorithm, which is proposed to estimate age in this paper, is multi-layer perceptron neural network. In addition, the combination of Pseudo-Zernike moment and multi-layer perceptron neural network model has been proposed as an age estimation system in this paper that input feature vector into multi-layer perceptron neural network are extracted by pseudo-Zernike moment. In table 2, results of multilayer perceptron neural network were compared with other models to estimate age on FG-NET and MORPH images database. In this table, multilayer perceptron neural network model was compared with AGES, nearest-neighbor classification algorithm (*K*-Nearest Neighbor (*k*-NN) and support vector machine (SVM) [27]. In this comparison, the best results are obtained by multilayer perceptron neural network.

Table 2- the comparison of multilayer perceptron neural network model with other methods of age estimation on NETFG and MORPH database.

Dataset	Method			
	k-NN	SVM	AGES	MLP
FG-NET	90.55	92.93	92.78	**96.15**
MORPH	88.07	91.44	90.52	**92.60**

According to the presented results in Table 2, the neural network has demonstrated that it has earned the best results of age estimation compared to other methods of age estimation on the FG-NET and MORPH images database. Based on the provided results in the age estimation phase, Pseudo-Zernike moment provides the best results due to the effective and original feature extraction from image and that is independent of the rotation, scalability and image transfer which are obtained in the shortest possible time. Based on the results presented in this section, pseudo-Zernike moment is compatible with multilayer perceptron neural network model.

6. Conclusion

As mentioned above, each model of age estimation includes two main steps: feature extraction and classification. In the feature extraction stage, one vector from the main features of the face, which is effective on age estimation problem, is extracted and with age label are used to train classification algorithm. Pseudo-Zernike moment shows high performance and efficiency in the extraction of facial features from the image to estimate age due to the reasons such as lack of attachment to rotate the figures, lack of dependency to face scalability and face physics in the image as well as computing speed and feature extraction. This paper provides a new method to estimate age that pseudo-Zernike moment has been utilized in order to extract feature in the process of feature extraction and multilayer perceptron neural network classification algorithm has been used to estimate age in classification stage. Proposed age estimation has been evaluated on FG-NET and MORPH images database and it was compared in two dimension of feature extraction and age estimation with other proposed methods in the field of age estimation and it has proposed the best results compared to other methods.

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