British Journal of Mathematics & Computer Science
13(5): 1-9, 2016, Article no.BJMCS.22869
ISSN: 2231-0851

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A Face-based Age Estimation System Using Back Propagation Neural Network Technique

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Authors' contributions

This work was carried out in collaboration between all authors. Authors EOO and AOA designed the study, wrote the protocol and supervised the work. Authors MOO and EOO carried out all laboratories work and performed the statistical analysis. Author MOO managed the analyses of the study. Author MOO wrote the first draft of the manuscript. Authors EOO and AOA managed the literature searches and edited the manuscript. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/BJMCS/2016/22869
Editor(s):
(1) Kai-Long Hsiao, Taiwan Shoufu University, Taiwan.
Reviewers:
(1) Rajkumar V. Raikar, KLE Dr. M. S. Sheshgiri College of Engineering and Technology, India.
(2) Esam A. AlQaralleh, Princess Sumaya University, Jordan.
(3) Shiahn-Wern Shyue, National Sun Yat-sen University, Kaohsiung, Taiwan.
Complete Peer review History: http://sciencedomain.org/review-history/12831

Original Research Article

Received: 2nd November 2015
Accepted: 18th December 2015
Published: 29th December 2015

Abstract

Age estimation is the determination of a person's age based on biometric features such as face, finger print etc. it is a hard problem for both humans and the computer system. In this paper, back propagation neural network was used to classify face images into eight different age groups ranging from babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young old and old. The process is divided into three stages: Image preprocessing, Feature Extraction and age classification. The images were cropped, resized and converted into grayscale in the preprocessing stage. Principal Component Analysis was used to extract the facial features that will be fed into the neural network classifier. Finally, back propagation neural network was used to classify the face images into any of the eight groups. The developed system was experimented with 630 face images with different ages from the FG-NET database. 450 samples were used for training while 180 were used for testing. The results showed a training time of 110.914 seconds, Mean Absolute Error (MAE) of 3.88 years and an overall accuracy of 82.2%.

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Keywords: Age estimation; biometric; preprocessing; feature extraction; back propagation neural network.

1 Introduction

Face recognition is one of the biometrics methods to identify individuals by the features of the face. Research in this area has been conducted for more than 30 years and as a result, the current status of the face recognition technology is well advanced. Algorithms for face recognition typically extract facial features and compare them to a database to find the best match [1,2]. Face recognition system can be used in various research such as age estimation, gender determination etc.

Age estimation is the determination of a person's age based on biometric features. The determination of the age of a person from a digital photography is an intriguing problem which involves the understanding of the human aging process [3]. Of the various available soft biometric features, age is one of the most difficult to determine [4,5]. The following characteristics make it difficult to determine age from face images.

a. Aging is an uncontrollable process: Aging cannot be delayed or advanced at will. It is slow and irreversible process.
b. Personal Age Patterns: The aging factor of a person is defined by his genetic structure as well as external factors like health, lifestyle, weather conditions, ethnicity, etc.
c. Aging Pattern is a temporal data: Age and face patterns vary with time. Age pattern at an instance affects all future patterns [6].

Aging is not a general progress, different individuals' age in different ways. Aging pattern of each person is determined by many internal and external factors such as genetics, health, lifestyle, and even weather conditions [6,7]. In order to achieve successful results in applications like age estimation or age classification, the data set that will be used to train the algorithm must contain all these factors.

This work developed a system that will classify face images into babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young old or old. Principal Component Analysis (PCA) was used to obtain the facial features and back propagation neural network was used to classify the images.

Principal Component Analysis (PCA) is an analytical tool used in identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences. It is a powerful tool for analysing data [8]. PCA can do prediction, redundancy removal, feature extraction, data compression, etc. Principal Component Analysis is a suitable strategy for feature extraction because it identifies variability between human faces, which may not be immediately obvious [1].

2 Literature Review

There are several research works on age estimation based on face images. One of the first attempts to develop facial age estimation algorithms was reported by Kwon and Lobo [9]. Kwon and Lobo uses two main types of features: Geometrical ratios calculated based on the distance and the size of certain facial characteristics and an estimation of the amount of wrinkles detected by deformable contours (snakes) in facial areas where wrinkles are usually encountered.

Horng, Lee and Chen proposed an approach for classification of age groups based on facial features [10]. The process of the system was mainly composed of three phases: Location, feature extraction and age classification. Two back propagation neural networks were constructed. The first one employs the geometric features to distinguish whether a facial image is a baby or not. If it is not, then the second network uses the wrinkles features to classify the image into one of three adult groups.

In 2004, Lanitis, Draganova, and Christodoulou proposed methods to imitate aging effects on face images. They developed an aging function (quadratic function) based on a parametric model of face images and performed tasks such as automatic age estimation, face recognition across age progression [11]. The face images are represented by the Active Appearance Model (AAM) method and the best results were obtained when classifiers based on quadratic function and neural network based classifiers are used.

In year 2013, Chao, Liu and Ding proposed an age estimation approach with three novel contributions. Firstly, they explored the relationship between facial features and age labels using distance metric learning and dimensionality reduction, secondly, they exploited the intrinsic ordinal relationship among ages using a label - sensitive concept and finally, they proposed an age - oriented local regression to capture the complex nature of human ageing [12]. Their experiments with their proposed approach using several combinations of learning algorithms and found the combination of K-Nearest Neighbour (KNN) and SVR to produce the best results with MAE of 4.38.

3 Methodology

The complete framework for the age estimation system is described in Fig. 1. The first step is acquisition of face images for different ages from the FG-NET database [13]. The second step is the preprocessing stage where the image is converted to gray image, cropped, resized and normalized. Feature extraction stage extracts the features that will be used as input to the classifier. The classification stage will classify the face image into the various age groups.

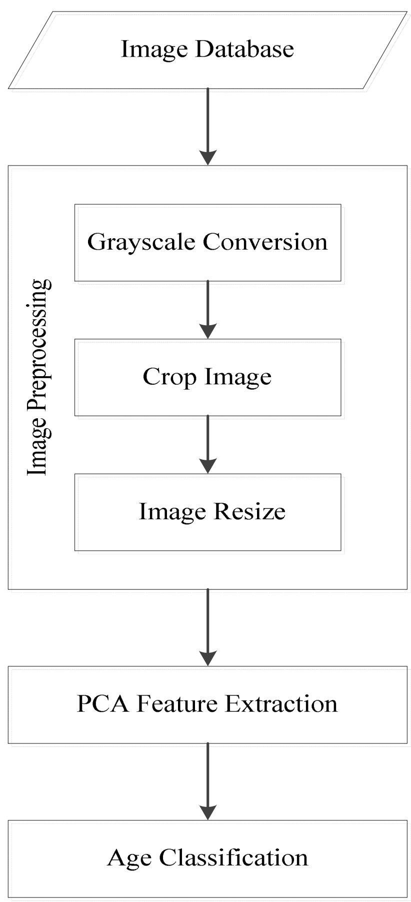

Fig. 1. Framework of the age estimation system

3.1 Image preprocessing stage

Image preprocessing stage helps to get rid of unwanted information that would have been extracted as features and reduces the work to be done during dimensionality reduction (feature extraction). Preprocessing stage involves three stages namely: grayscale conversion, image cropping and image resize. Grayscale conversion was used to reduce the number of pixels. Cropping was done using the Viola-Jones algorithm so as to remove the irrelevant features of the face image. The image was then resized to 40 by 40.

3.1.1 Grayscale conversion

Coloured images could hide certain cogent low-level image information from the image while filling the obtained features with colour information which is not needed for this work. Grayscale images, being 2-dimensional matrices, are more compact to process than coloured images, which are 3-dimensional.

The MATLAB function rgb2gray was used for grayscale conversion. Grayscale image is preferred to coloured image to reduce processing time being a two-dimensional matrix. After the image was converted to grayscale, the facial part of the image was detected so as to remove unwanted information such as the image background. Converting the image to grayscale helps remove the colour information which hides certain low level information about the image.

3.1.2 Image cropping

The face image was detected and cropped accordingly such that the image was left only with the facial region which contains the necessary features needed for face image processing. Cropping helps to remove unnecessary features such as the background from the image, leaving just the portion that is needed to provide the required age – relevant face features. The facial part of the images was detected using the Viola-Jones algorithm. The body parts detected by the Viola-Jones algorithm were frontal face, a single or pair of eyes, Nose and Mouth.

3.1.3 Image resize

Having obtained the required portion of a given facial image it is important to ensure that the cropped portion of the facial image is neither too small nor too big for further processing. Therefore, it is important to choose an appropriate size to which images will be scaled to avoid image distortion. The images used in this research were resized to 40 by 40 pixels which contains only the facial part of the original image. The MATLAB function imresize was used to resize the image.

3.2 Feature extraction stage

The next stage after the image preprocessing stage is the feature extraction stage. In this work, age-related information that will be used for training and classification were extracted using Principal Component Analysis (PCA). In PCA, Eigenface finds the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. These eigenvectors is a set of features that together characterize the variations between face images. The highest 40 eigenvectors were used in this work. The projected images from the PCA were then fed into the classifier for training and testing.

3.3 Classification stage

Classification stage is the last stage of the age estimation system. This stage comprises of the training stage and the testing stage. The dataset from FG-NET database were used for training and testing. The training set and testing set composed of a number of faces for different ages. The features extracted from the training and testing images were fed into the Back Propagation Neural Network (BPNN) classifier and the images were classified to the corresponding age group. The BPNN classifier has three (3) layers (Input, Hidden and

Output). The input layer has 40 inputs, the hidden layer has 50 neurons and the 1 output in the hidden layer. The 40 inputs are the highest 40 eigenvectors i.e. the features extracted from the face images using PCA.

Figs. 2a and 2b shows the training and testing stages respectively. For the training stage, the extracted images were fed into the neural network and the training parameters were saved. For the testing stage, the input image from the testing set was preprocessed and compared with the saved training parameters, then output the result.

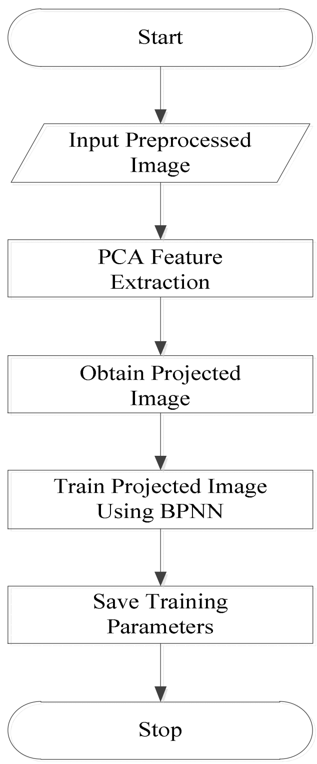

Fig. 2a. Training stage for age estimation

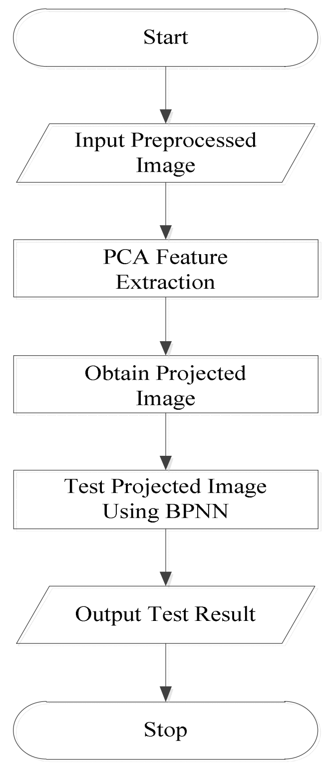

Fig. 2b. Testing stage for age estimation

The results of the developed system were evaluated using total training time (total time to train the face images), Mean Absolute Error (MAE) and accuracy. The metrics that were used for the evaluation of MAE and accuracy are as stated below:

$$MAE = \frac{\sum_{i=0}^{n} |EA_i - RA_i|}{n}, \qquad Accuracy = \frac{Number\ of\ correctly\ classified\ samples}{Total\ number\ of\ samples}$$

Where EA_i is the estimated age for the *ith* of *n* tested samples

RA_i is the real age for the *ith* of *n* tested samples

n is the number of samples

4 Algorithm for the Face-based Age Estimation

The algorithm for the face-based age estimation is given below. The algorithm was experimented on the preprocessed face images.

Step 1: Start
Step 2: Input face images.
If the input image is RGB, convert to grayscale and crop the image
Else,
Crop the image
Step 3: Resize cropped image
Step 4: Extract the features of the cropped image using PCA and obtain a projected image
Step 5: Train the projected images and save the training parameters
Step 6: Input a face image to test
If the input image is RGB, convert to grayscale and crop the image
Else,
Crop the image
Step 7: Resize cropped image
Step 8: Extract the features of the cropped image using PCA and obtain a projected test image
Step 9: Test the projected image
Step 10: Output age and age group
Step 11: Repeat steps 6 to 10 to test for another face image
Step 12: Stop

5 Results and Discussion

The face-based age estimation system was simulated and tested on a 6GB RAM, Intel core i5 and 2.40GHZ CPU speed HP pavilion laptop computer and the results obtained from the developed system shows a total training time of 110.914 seconds with 450 face images. 180 face images (40% of the training samples) were used to test the system.

A total of 138 images were classified correctly. 10 images were near-correct classification and 32 images were wrongly classified which shows an accuracy of 82.2%. Near-correct classification is the estimated age that fall above or below the next age group with an estimated error of ±2 years. MAE of 3.88 years was also obtained from the 180 samples. Table 1 shows the results on the different age groups.

It was observed from Table 1 that the age group 31 – 50 has the least accuracy of 66.7%. This is because there are no distinctive textual changes from faces within this age range and also because of the larger classes (20). Age ranges 6 – 10, 11 – 15 and 51 – 60 has the highest accuracy of 90%.

Table 2 shows the MAE for each age group. It was observed from Table 2 that age group 6 – 10 has the lowest MAE of 1.28 years because during this stage falls within the formative years i.e. there are distinctive changes in the face texture. Age group 31 – 50 has the highest MAE of 10.94 years because there are no distinctive textual changes from faces within this age group.

Table 1. Results of face-based age estimation on the age groups

Age group	Number of testing images	Number of correctly classified images	Number of incorrectly classified images	Number of near correct classification	Accuracy
0 – 5	25	22	3	0	88%
6 – 10	30	25	3	2	90%
11 – 15	30	24	3	3	90%
16 – 20	25	18	5	2	80%
21 – 30	25	17	6	2	76%
31 – 50	30	19	10	1	66.7%
51 – 60	10	9	1	0	90%
Above 60	5	4	1	0	80%

Table 2. MAE for each age group

Age group	Number of samples	Mean absolute error (MAE) in years
0 – 5	25	2.38
6 – 10	30	1.28
11 – 15	30	1.75
16 – 20	25	3.73
21 – 30	25	3.17
31 – 50	30	10.94
51 – 60	10	3.77
Above 60	5	5.38

Fig. 3 shows the output of the face-based age estimation system

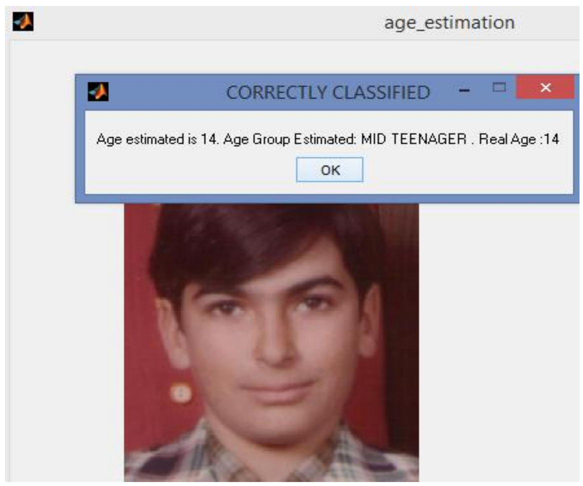

Fig. 3. Output of the face-based age estimation system

6 Comparison with Existing Works

The result of the system was evaluated with the results of existing works. It can be deduced from Table 3 that MAE for BPNN (3.88) is less than the results obtained by Quadratic Model (QM) (6.55), Aging Pattern Subspace (AGES) (6.77), Bio-inspired Features (BIF) (4.77), Weighted Appearance Specific (WAS) (8.06) and Locally Adjusted Robust Regressor (LARR) (5.07).

From Table 4, the classifier accuracy of BPNN (82.2%) of the system is higher than the results obtained by Neural Network (4 – Class age group classification) (80%), Gaussian (57.3% for Male and 54.7% for Female) and Aging Pattern Subspace (40.92%) used in the existing work.

Table 3. Comparison of BPNN MAE with the existing classifiers

Age estimation method	MAE
Quadratic model (QM) [11]	6.55
Aging pattern subspace (AGES) [6]	6.77
Bio-inspired features (BIF) [14]	4.77
Weighted appearance specific (WAS) [6]	8.06
Locally adjusted robust regressor (LARR) [15]	5.07
BPNN (developed model)	3.88

Table 4. Comparison of BPNN accuracy with the existing classifiers

Age estimation method	Accuracy
Neural network (4 – class age group classification) [16]	80%
Gaussian [17]	57.3% for male and 54.7% for female
Aging pattern subspace [18]	40.92% (Hit rate)
BPNN (developed model)	82.2%

7 Conclusion

A face-based age estimation system which reduced the Mean Absolute Error (MAE) with an improved accuracy was developed to extract facial features and determine age and age group from face images. The face images were classified into eight groups: babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young old and old. A MAE of 3.88 years and an accuracy of 82.2% was achieved and thus provided an improved method for face-based age estimation in terms of MAE and accuracy.

Consent

It is not applicable.

Competing Interests

Authors have declared that no competing interests exist.

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