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An Unsupervised Neural Network Method for Age Group Estimation using Facial Features

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ABSTRACT

Age estimation from facial features is an important research subject in the field of face recognition. It is an active research area that can be used in wide range of applications such as surveillance and security, telecommunication and digital libraries, human-computer intelligent interaction, and smart environment. This paper developed an unsupervised neural network by using a Self – Organizing Feature Map (SOFM) to estimate age group from facial features.

The face images were divided into eight different age groups ranging from babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young old and old and SOFM was used to estimate the age group from the input face image. Principal Component Analysis (PCA) was used to extract the facial features and the extracted features were presented to the SOFM for training and testing. 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 116.333 seconds and an accuracy of 92.2%.

***Keywords**:* Age estimation, Facial Features, Unsupervised Neural Network, Principal Component analysis, Self-Organizing Feature Map.

1 Introduction

The face is one of the most important biometric features of the human being which is normally used for identification. Each person has their own innate face and mostly a different face. As a human, to recognize the different faces without any difficulty is easier but it is difficult for systems to recognize human faces [6]. Face recognition system can be used in various research applications such as age estimation, gender determination, emotion detection, head orientation etc [7].

Human age classification is one of the most challenging problems in computer vision and pattern recognition. Estimating human age from his or her face is a hard problem not only for the existing computer vision systems but also for humans in some circumstances [1]. Age classification is concerned with the use of a training set to train a model that can estimate the age of human from face images.

The developed system was able to group the ages into corresponding clusters or groups, then use the extracted facial features to classify the input face image into the corresponding age group using the

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SOFM. Principal Component Analysis (PCA) was used to extract the facial features. It 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 (Oladele, Omidiora and Afolabi, 2015). Principal Component Analysis is a suitable strategy for feature extraction because it identifies variability between human faces, which may not be immediately obvious [8].

2 Existing Age Group Methods

Various age estimation methods has been developed so far in the field of face recognition. In human computer interaction, aging effects in human faces has been studied from two main reasons: automatic age estimation for face image classification and automatic age progression for face recognition [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 [5].

In 2001, Horng, Lee and Chen proposed an approach for classification of age groups based on facial features [4]. 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.

Yang and Ai used Real AdaBoost algorithm to train a classifier by composing a sequence of Local Binary Pattern (LBP) features as a representation of face texture. Age is classified into only three periods: child, adult and oldness [10]. In 2009, Guo, Fu, Dyer and Huang presented a locally adjusted regressor which uses age manifold learning to map pixel intensity of the original face images into a low dimensional subspace for the learning and the prediction of the aging patterns [3].

In 2015, Oladele, Omidiora and Afolabi used principal component analysis to extract facial features and back propagation neural network to classify age into age groups: babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young old and old [7]. The experiment produced an accuracy of 82.2% and Mean Absolute Error of 3.88 when experimented with 180 testing samples.

3 Design Approach

The block diagram for the age group estimation system is described in Figure 1. The first stage is the image pre-processing stage which comprises of the grayscale conversion, image cropping and resize. The second stage is the facial feature extraction stage where the facial features were extracted using PCA and finally the age estimation stage which uses SOFM to estimate the age group.

Figure 1: Block diagram of the Age group Estimation System

3.1 Image Database

Images from the FG-NET database was used for the system. From the FG-NET database, 630 face images of different ages of individuals were used. The images were divided into training and testing sets. 450 samples were used for the training set while 180 samples were used for the testing set. The images ranges from ages 0 – 69 years. Figure 2 shows some of the sample face image from the FG-NET database.

Figure 2: Sample images from the FG-NET database [2]

3.2 Image Pre-processing

Image pre-processing stage comprises of the grayscale conversion, image cropping and image resizing. This 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). 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. Figure 3 shows the flowchart of the image pre-processing stage.

3.2.1 Grayscale Conversion

FG-NET database consists of both coloured image and gray image. The coloured image were converted into grayscale using the MATLAB function rgb2gray so as 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.

3.2.2 Image Cropping

The detected face image was cropped such that the image was left only with the facial region which contains the necessary features needed for the age group estimation. 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.

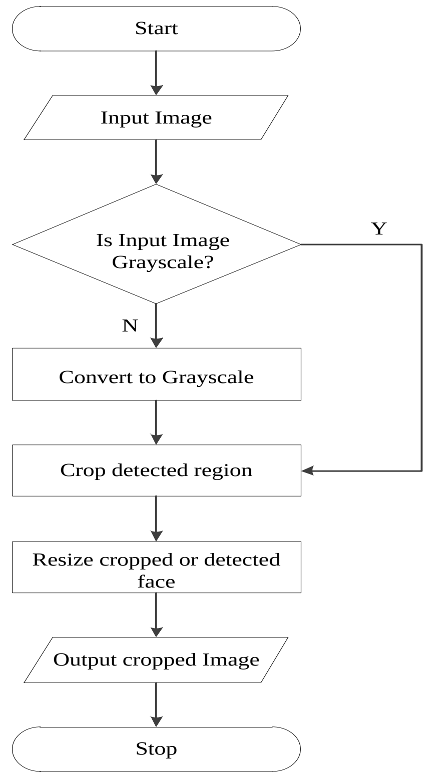

Figure 3: Flowchart of the image pre-processing stage

3.2.3 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.

3.3 Facial Feature Extraction

Principal Component Analysis (PCA) was used to extract the facial features from the images. PCA is a suitable strategy for feature extraction because it identifies variability between human faces, which may not be immediately obvious. In facial feature, these variables are called eigenfaces because when plotted they display a ghostly resemblance to human faces.

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 20 eigenvectors were used in this work. Facial features including Eyes, Nose, Lips and Chin were extracted using the PCA.

3.4 Age Group Estimation

The final stage is the age group estimation using the unsupervised neural network. This stage consists of two phases: training and testing phases. In the training phase, the extracted PCA features were presented to the SOFM for training. SOFM is a clustering algorithm. During training, it classifies a set of input vectors of face parameters in a number of clusters corresponding to different age groups. For the testing stage, when given a new vector of face parameters, i.e. the input face image, the trained networks will determine the age group of the person corresponding to the face image and output the age group. Figure 4(a) and Figure 4(b) shows the training and testing stages.

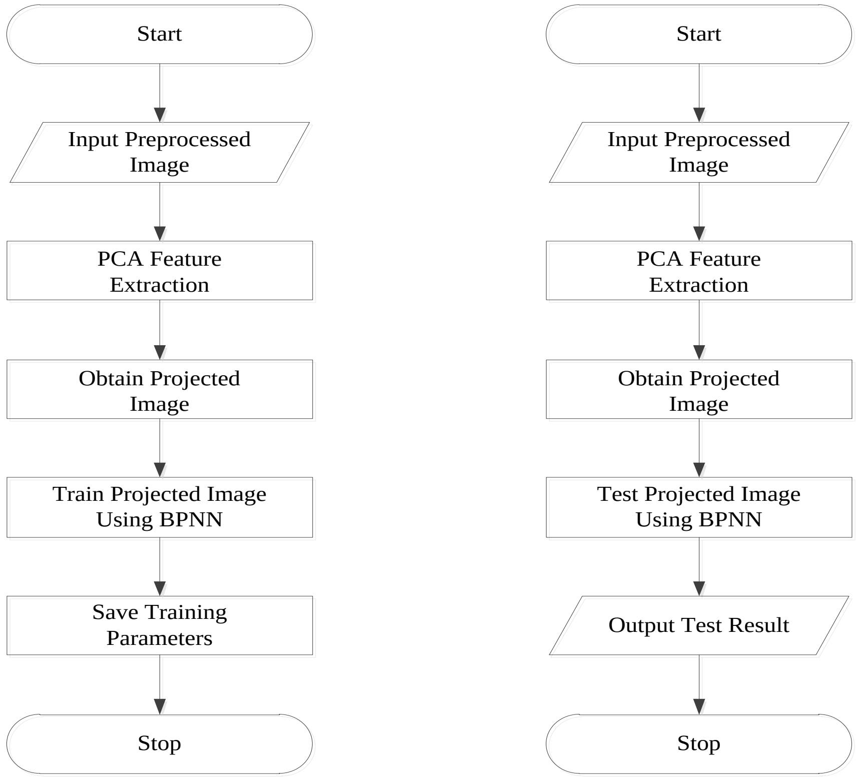

Figure 4(a): Training stage for Age Group Estimation

The results of the developed system were evaluated using total training time (total time to train the face images), and percentage accuracy. The metric that was used for the evaluation of the percentage accuracy is:

$$Percentage\ Accuracy = \frac{Number\ of\ correctly\ classified\ samples}{Total\ number\ of\ samples} * 100$$

4 Results and Discussion

The results obtained from the developed system with a training sample of 450 images and testing sample of 180 images (40% of the training images) shows a training time of 116.333 seconds. A total of 156 images were classified correctly, 10 images were near correct classification and 14 images was wrongly classified which shows an accuracy of 92.2%. Near-correct classification is the estimated age that fall above or below the next age group with an estimated error of ±2 years. Table 1 shows the results of SOFM on the different age groups.

Table 1: Results of Self Organizing Feature Map on the Age groups

Age Group	Number of Samples	Number of Correctly Classified	Number of Incorrectly Classified	Number of Near Correct Classification	Average Testing Time (Seconds)	Accuracy
(Baby) 0 – 5	25	25	0	0	17.512	100%
Young Teenager (6 – 10)	30	28	0	2	23.649	93.3%
Mid Teenager (11 – 15)	30	26	0	4	25.152	100%
Teenager (16 – 20)	25	17	4	4	18.744	84%
Young Adult (21 – 30)	25	22	3	0	19.263	88%
Mid Adult (31 – 50)	30	25	5	0	24.399	83.3%
Young Old (51 – 60)	10	9	1	0	17.860	90%
Old (Above 60)	5	4	1	0	12.876	80%

From Table 1 it was observed that the age group above 60 has the least accuracy of 80% while age ranges 0 – 5 and 11 – 15 have the highest accuracy of 100%. Also, a total of 10 samples fall to the near-correct classification category. This category lies between young teenagers and teenagers i.e. age group 6 – 20 because this age range reveals the similarities and distinguishing characteristics that constitutes facial textures during the formative years noticeable within the age group.

The developed system was further tested with some black faces and the results in Table 2 was gotten. From the table, it was observed that the performance was not as accurate as desired when compared with the test results from white faces that was used for training. This could be attributed to different skin textures peculiar to both black and white skins.

It was also observed that illumination affects the results when tested with the black faces, which can as well affect the performance. Therefore, accurate result can be gotten when the system is trained with black faces.

Table 2: Results of developed system when tested with black faces

S/N	Index Number	Real Age	Real Age Group	Estimated Age Group	Classification Result
1	090A04	4	Baby	Baby	CC
2	090A50	50	Mid Adult	Mid Adult	CC
3	090A30	30	Young Adult	Young Adult	CC
4	090A07	7	Young Teenager	Mid Teenager	NC
5	090A12	12	Mid Teenager	Baby	IC
6	090A14	14	Mid Teenager	Baby	IC
7	090A52	52	Young Old	Teenager	IC
8	090A15	15	Mid Teenager	Young Adult	IC
9	090A48	48	Mid Adult	Mid Adult	CC
10	090A00	0	Baby	Baby	CC

Figure 5 shows the output of the developed age group estimation system

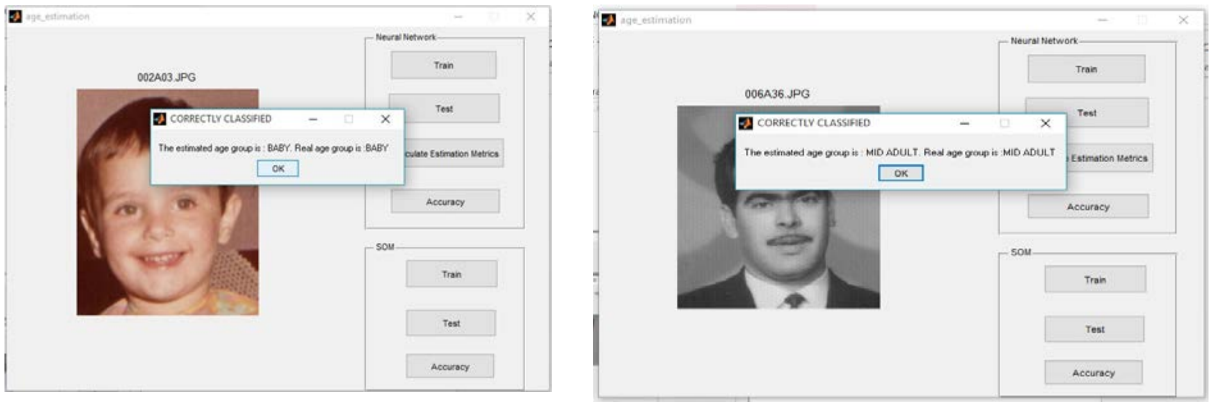

Figure 5: Output of the developed Age group Estimation System

5 Conclusion

An unsupervised neural network system for age group estimation with an improved accuracy was developed to extract facial features and determine age group from face images using the extracted facial features. The face images were classified into eight groups: babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young old and old. An accuracy of 92.2% was achieved and thus provided an improved method for age group estimation in terms of accuracy.

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