

Comparative Analysis of Back Propagation Neural Network and Self Organizing Feature Map in Estimating Age Groups using Facial Features

ABSTRACT

Aim: This paper presents a statistical analysis of the performance of two age estimation algorithms namely Back Propagation Neural Network (BPNN) and Self Organizing Feature Map (SOFM) on human face images.

Methodology: 630 human face images with age ranges 0 - 69 from the FG-NET database were considered, feature extraction was done using Principal Component Analysis (PCA) and classification was done using BPNN and SOFM. Two way ANOVA was used to analyse if there is significant difference between the two algorithms (BPNN and SOFM) by feeding in all the parameters such as training time, number of correctly classified, number of near-correctly classified, number of incorrectly classified and percentage accuracy.

Results: The results of the analysis shows that there is significant difference between BPNN and SOFM in the age estimation using facial features.

Conclusion: The results from the statistical analysis (Analysis of Variance (ANOVA)) reveals that SOFM is better than BPNN because $F\text{-critical} > F$ for the column and the decision rule states that we accept H_0 i.e. there is significant difference between BPNN and SOFM if $F\text{-critical} > F$ when the results (training time, testing time, number of correctly classified, number of incorrectly classified and accuracy) were compared and tested.

Keywords: Age estimation, Back Propagation Neural Network, Self Organizing Feature Map, Principal Component Analysis, Facial Features.

1. Introduction

Age is one of the most important features of a human being, and its estimation is essential in many applications, such as security control and surveillance monitoring. The problem of age estimation from a human face image has long been a focus of the computer vision and artificial and intelligence communities. Previous efforts on age estimation can be summarized into two types [1]:

a. Age group classification, such as in [2, 3], where a face is classified or labeled according to the age range. In age group classification, ages were grouped into corresponding clusters or groups, then the extracted facial features were used to classify the input face image into the corresponding age group [3].

b. Exact age estimation, such as in [4] - [7], which attempts to guess the age of a human subject.

Age estimation is concerned with the use of a training set to train a model that can estimate the age of human from face images [8]. It can be applied in the following areas, preventing people to access on computer programs, internet websites and electronic devices that are harmful for specific ages, indexing of face images based on the individual's ages for age - based retrieval of face images from videos, summarizing videos focused on specific ages and improving the accuracy and speed of face recognition systems [1].

One of the first facial age estimation algorithms was reported by Kwon and Lobo. They proposed an age classification method that focuses on both the shape and the wrinkles of human face to classify

input images into only one of the three age groups: babies, young adults and senior adult [2]. Kwon and Lobo use 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. Based on these features, Kwon and Lobo classify faces into babies, adults and seniors based on a computational theory for visual age classification from facial images.

Lanitis, Draganova, and Christodoulou proposed methods to imitate aging effects on face images in 2004. 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. The face images are represented by the AAM method and the best results were obtained when classifiers based on quadratic function and neural network based classifiers are used. They only considered database having face images of individuals less than 30 years of age [5].

In 2015, Oladele and Omidiora proposed an age group estimation method using facial features to classify input face images into eight age groups: babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young old and old [3]. SOFM was used for classification and an accuracy of 92.2% was recorded.

In year 2016, 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 [4]. The experiment produced an accuracy of 82.2% and Mean Absolute Error of 3.88 when experimented with 180 testing samples.

This paper aims at analysing Back Propagation Neural Network (BPNN) and Self Organizing Feature Map (SOFM) algorithms in age estimation using facial features from face images.

2. Materials and Methods

The paper focuses on implementing BPNN and SOFM algorithms on an age database and evaluates the recognition performance of the algorithms and also comparing their results on the face database. Some images from the FG-NET [9] aging database were used as inputs.

The age estimation process comprises of the image acquisition stage, image preprocessing stage, feature extraction stage and the classification stage [4]. The input face images were acquired from FG-NET database. The preprocessing stage comprises of grayscale conversion, image cropping, image resize and image normalization. Image preprocessing 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) [4]. Feature extraction stage extracts the features that will be used as input to the classifier. The classification stage classifies the face image into the various age groups.

The BPNN (Algorithm 1) and SOFM (Algorithm 2) algorithms were used to train the images. In the feature extraction stage, PCA was used to extract the facial image features and the extracted features were stored. The extracted facial features were passed to the classifier for classification of a given face image query. Images from FG-NET was used. Fig. 1 shows the block diagram of the age estimation stages.

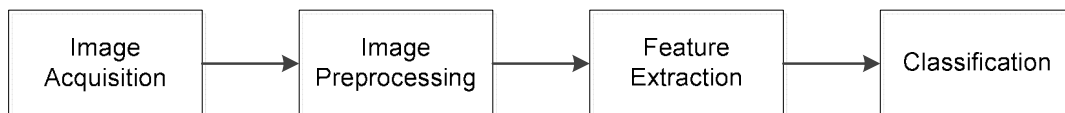


Fig. 1. Block diagram of the age estimation stages

2.1. Image Acquisition

A total number of 630 face images of different ages of individuals ranging from 0 – 69 years from FG-NET aging database was used for the system. The images were divided into training and testing sets.

450 image samples were used for the training set while 180 image samples were used for the testing set. Fig. 2 shows some of the sample face images from the FG-NET database that was used.

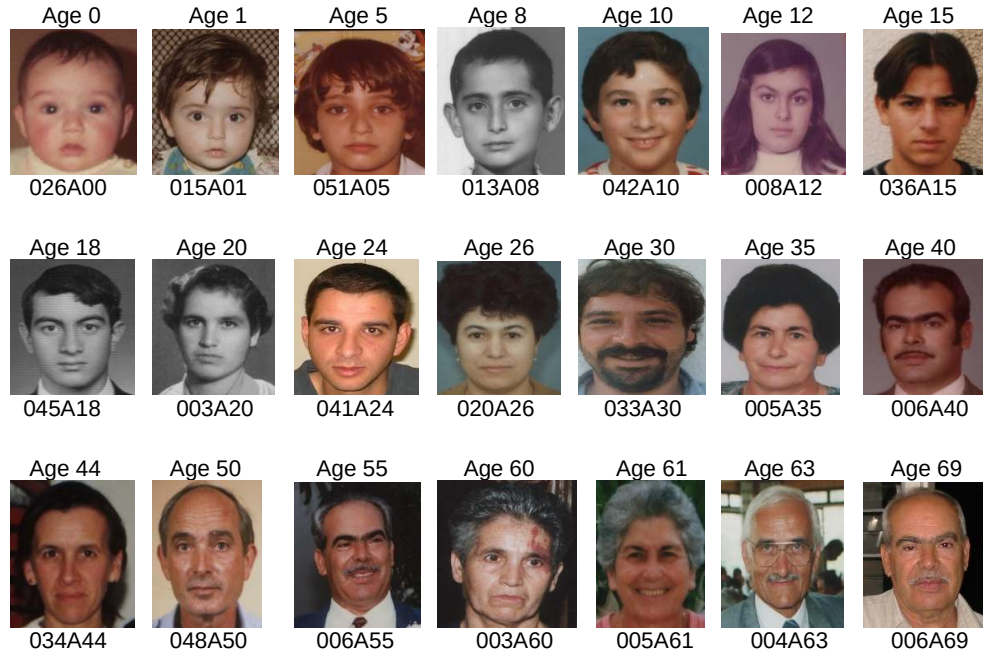


Fig. 2. Sample face images from FG-NET aging database [9]

450 images from these images will be trained on the two recognition algorithms (BPNN and SOFM) and their training parameters will be saved for classification.

2.2. Image Preprocessing

Image preprocessing is done before extracting the facial features from the images using PCA. As mentioned earlier, this is done so as 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). In this paper, image preprocessing was basically grayscale conversion, image cropping and image resize. Grayscale conversion was used to reduce the number of bits per pixel. 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. Fig. 3 shows the image preprocessing block diagram.



Fig. 3. Image Preprocessing block diagram

2.2.1. Grayscale Conversion

Grayscale conversion was used to reduce the number of bits per pixel. 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. Grayscale conversion helps to remove the colour information which hides certain low level information about the image.

With grayscale images, it is possible to access the low level features (pixels) of the image in lower dimension and it becomes easier to perform pixel - level transforms and mathematical operations on the image. Grayscale images are represented as two – dimensional matrices.

2.2.2. Image Cropping

After the image has been converted to grayscale, the grayscale image was detected and cropped accordingly such that only the facial region which contains the necessary features needed for age estimation are left. 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 facial features. Viola – Jones algorithm [13] was used to detect the facial part of the images that will be needed for age estimation. The algorithm helps to reduce the rigour of manual cropping and also the limitation of just using frontal images which helps in optimizing our results.

2.2.3. Image Resize

It is important to choose an appropriate size to which images will be scaled to avoid image distortion. Images must be scaled in a way that preserves the image quality and at the same time the chosen scale should be uniform for ease of processing. 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. After cropping and resizing, background information and other non-facial parts in the image have been reduced as much as possible and the image is now ready for feature extraction.

2.3. Feature Extraction

In this stage, relevant image features are extracted for analysis using Principal Component Analysis (PCA). An effective way to suppress redundant information and provide only one or two composite data from most of the information from the initial data is called Principal Component Analysis [10]. In this work, age-related information that will be used for training and classification were extracted using 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 and the projected images from PCA were used for BPNN and SOFM training and testing.

2.3.1. Principal Component Analysis (PCA)

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 [11]. 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 [12]. PCA does not attempt to categorize faces using familiar geometrical differences, such as nose length or eyebrow width. Instead, a set of human faces is analysed using PCA to determine which variables account for the variance of faces.

2.4. Classification

This is the last stage of the age estimation process. This stage comprises of the training stage and the testing stage. The training set comprises of 450 images and testing set 180 images for different ages. The features extracted from the training and testing images were fed into the BPNN and SOFM classifier and the images were trained and 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.

The SOFM classifier 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. The SOFM classifier used in this paper has 40 inputs and a map size of 40 by 40. Figs. 4a and 4b shows the BPNN and SOFM training and testing stages respectively.

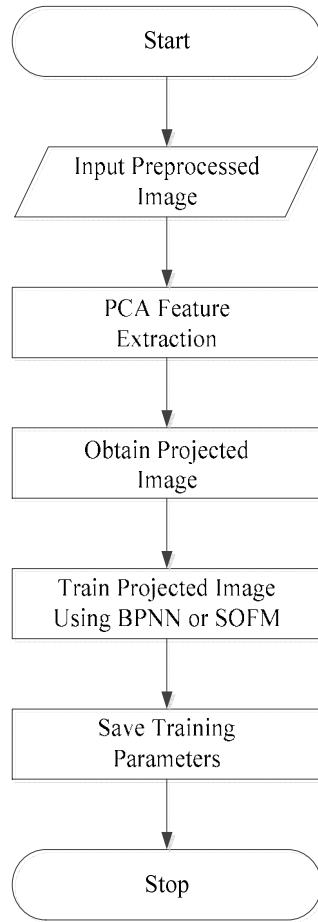


Fig. 4a. Training stage for age estimation

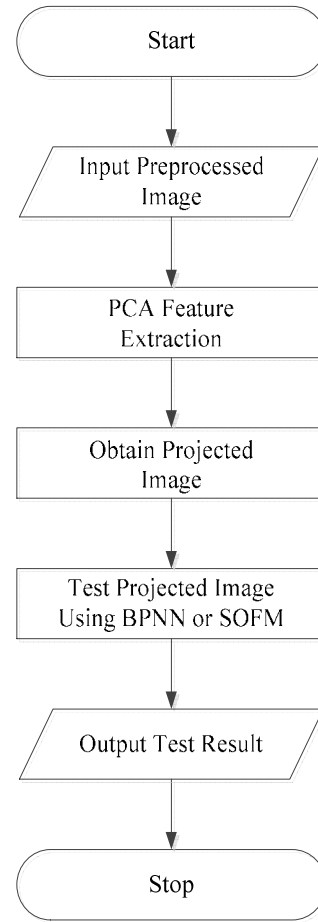


Fig. 4a. Testing stage for age estimation

3. Results and Discussion

BPNN and SOFM were analysed using the ANOVA two – way to determine if there is a significant difference between the two algorithms by using the following metrics: training time (seconds), correctly classified, near – correctly classified, incorrectly classified, and accuracy of the two algorithms as shown in Table 1. Number of near – correct classification is the number of face images that has an age difference of ± 2 years for upper and lower boundary of the age group. MAE was not used because it is not available in SOFM.

$$\text{Accuracy} = \frac{\text{Number of correctly classified images}}{\text{Total number of test images}}$$

Table 1. Performance summary of BPNN and SOFM

Evaluation Metrics	Algorithm	
	BPNN	SOFM
Training Time (Seconds)	110.914	116.333
Correctly Classified	138	156
Near Correctly Classified	10	10
Incorrectly Classified	32	14
Mean Absolute Error (MAE)	3.88	N/A
Accuracy	82.2%	92.2%

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185 From Table 1, it was observed that the SOFM has an accuracy of 92.2% while BPNN has an
186 accuracy of 82.2%, but in terms of training time, BPNN is better with a training time of 110.914
187 seconds compared with that of SOFM with 116.333 seconds. In order to evaluate the performance of
188 the two, i.e. to test if there is a significant difference, the two – way ANOVA was used to evaluate it by
189 feeding in all the parameters such as training time, correctly classified, near-correctly classified,
190 incorrectly classified and accuracy. The summary of the analysis is shown in Table 2 and Table 3.

191 From Table 2, the sum, average and variance was calculated for each rows and columns. Row 1 is
192 the training time, Row 2 is the correctly classified, Row 3 is the near-correctly classified, Row 4 is the
193 incorrectly classified and Row 5 is the accuracy. For column, Column 1 is the BPNN while Column 2
194 is the SOFM.

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Table 2. ANOVA: Two-Factor without Replication

SUMMARY	Count	Sum	Average	Variance
Row 1	2	227.247	113.6235	14.68278
Row 2	2	294	147	162
Row 3	2	20	10	0
Row 4	2	46	23	162
Row 5	2	174.4	87.2	50
Column 1	5	373.114	74.6228	2845.986
Column 2	5	388.533	77.7066	4118.657

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197 Table 3 now uses the results: sum, average and variance from Table 2 to calculate the Sum of
198 Squares (SS), Mean of Squares (MS), degree of freedom (df), Fisher's transformation (F), P-value
199 and F-critical for rows and columns. Also, the corresponding errors and total was calculated.

200

Table 3. Summary of ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Rows	27493.66	4	6873.416	75.34405	0.00051	6.388233
Columns	23.77456	1	23.77456	0.260609	0.636584	7.708647
Error	364.9082	4	91.22706			

201

202 To evaluate the performance, we draw two hypothesis H_0 and H_1 and a decision rule for both rows
 203 and columns as shown below:

204 H_0 : There is significant difference between BPNN and SOFM

205 H_1 : There is no significant difference between BPNN and SOFM

206 Decision rule: Reject H_0 if $F\text{-critical} < F$, otherwise, do not reject.

207 Therefore, from Table 3, considering the row, $F\text{-critical} < F$, therefore we reject H_0 and accept H_1 .
 208 Considering the column, $F\text{-critical} > F$, therefore we do not reject H_0 . In conclusion, since $F\text{-critical} > F$
 209 for column, we therefore conclude that there is significant difference between BPNN and SOFM.

210 4. Summary

211 From the above evaluation, the percentage accuracy of Back Propagation Neural Network (BPNN)
 212 and Self Organizing Feature Map (SOFM) are 82.2% and 92.2% respectively. The training time of
 213 BPNN and SOFM in the training of the 450 images are 110.914 seconds and 116.333 seconds
 214 respectively. Number of correctly classified images for BPNN and SOFM are 138 and 156
 215 respectively, number of near – correct classification for BPNN and SOFM is 10 each and the number
 216 of incorrectly classified images are 32 and 14 respectively. It can be concluded from the results of the
 217 ANOVA two – way factor that significance difference exists in each of the algorithms in facial age
 218 estimation.

219 5. Conclusion

220 From the above statistical analysis, SOFM is adjudged a better algorithm when compared with BPNN
 221 in the estimation of age from face images using facial features because $F\text{-critical} > F$ for the column
 222 and the decision rule states that we accept H_0 (there is significant difference between the two
 223 algorithms BPNN and SOFM) if $F\text{-critical} > F$ when the results (training time, testing time, number of
 224 correctly classified, number of incorrectly classified and accuracy) were compared and tested.

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