

## Estimating the Position, Number and Length of Forehead Wrinkles Using Neural Network

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**Abstract:** A novel approach towards 2D Facial Aging (FA) techniques using Neural Network (NN) is proposed in this study. This approach is proposed to automatically predicate the position, number and length of wrinkles on the forehead area. The method is divided into three main stages; the first stage is the preprocessing stage, where the forehead area is manually cropped then filtered to gain sharpness. After that, the wrinkles segmentation process is carried out using row-by-row threshold, morphological erosion and connected component labeling to accurately extract the wrinkles form the image. Finally, the NN is used to convert the detected wrinkle lengths from 2D to 3D curvature shape. The proposed method is objectively compared with other techniques and can accurately predict the position, number and length of the forehead wrinkles in different ages.

**Keywords:** Facial aging, forehead wrinkles, neural network, row by row threshold

### INTRODUCTION

FA is a branch of Facial Recognition (FR) and the main reason for facial recognition is delivered from the forensic needs to identify victims or suspects (Clement and Marks 2005; Lee *et al.*, 1999). FR is a remarkable process; the human brain has the ability and capacity to distinguish between many known and unknown faces with a high speed. The biggest advantage of using the face (over other parts of the human body) in many applications is that the face is always with the person. Moreover, the face carries a significant number of features that identify individuals such as gender, emotional state, ethnic origin, age etc. In the study of (Geng *et al.*, 2006) it is mentioned the impossibility of finding two identical people, in fact even twins have some differences (Kalamani and Balasubramanie, 2006). FA is used in security, helps identifying missing children and many other applications that are stated in the study of Albert *et al.* (2004) and Mehdi *et al.* (2009a), such as a web browser can decide by itself whether the user satisfies the age restrictions to view certain web pages; a vending machine will not sell cigarettes or alcohol to underage people. Finally, it is very important to study the FA phenomenon, as it is part of our human development and implement various systems and methods to achieve better estimations that are performed by machines. The reliability of the machines depends on how accurate the input systems are.

In order to estimate facial aging, the behavior of the wrinkles development over time has to be understood (Suo *et al.*, 2007). Indeed it is a challenging problem, as aging varies in individuals depending on many factors like the surrounding environment, life style, ethnic origin, etc., for example (Albert *et al.*, 2004; Lanitis *et al.*, 2004; Geng *et al.*, 2007).

In this study, an intelligent method was developed to study the behavior of the forehead wrinkles for certain individuals using NN. In this method, the preprocessing stage that includes sharp filter and segmentation process for the forehead wrinkle were implemented as a first stage. Then the neural network is implemented to estimate the length of the wrinkle in 3D forehead region. As a result, the proposed algorithm can automatically estimate the number, position and length for each wrinkle in the forehead region in different types of forehead images.

### LITERATURE REVIEW

In the task of automatic age estimation (Lanitis *et al.*, 2004), a quantitative analysis of the performance of different classifiers is discussed. The idea was to generate an estimation of the age of a person shown in a face image by designing classifiers that recognize the model-based representation of the unseen face images. But on the other hand, the study of Lanitis *et al.* (2002) described (using learned age transformations) the effect of facial aging on the face appearance and how it can be

clarified. They presented some results indicating that acceptable age estimations can be generated for unseen images. The study was based on a statistical face model (Edwards *et al.*, 1998) that allows reversible coding of face images. The author of Lanitis *et al.* (2004) and Geng *et al.*, (2007) were relying on a 2D database that is available online called the FG-NET database.

This database is an image database that contains face images of different individuals at different ages. The downside of this database is that there is no consistency in the available images, i.e., some images are presented in black and white and some of them are colored; some images have busy backgrounds, others are blurred and some subjects in the images are wearing glasses etc. The images of people were categorized according to age in the following groups: 21-30, 31-40, 41-50, 51-60 and 61-70, this will help categorizing the number of wrinkles that are visible in each age group, therefore estimating the number of wrinkles, as a ratio, for the missing images for certain age groups. Obtaining very accurate results in such a huge variation of data might not be possible. Another method for automatic age estimation, called the AGES (AGing pattErn Subspace), was proposed in Geng *et al.* (2007). In their study, the aging pattern was defined as a sequence of images that represent the aged face, so the idea was to model this pattern. A representative subspace was used to determine the aging pattern for a face image by projecting the image in the subspace so that the face image can then be reconstructed and at the same time the location of that face image in the aging pattern will reveal its age. The AGES method is an interesting work that achieved respectable results based on 2D facial aging estimation.

The method described in the study of Lee *et al.* (1999) uses aging simulation and cloning in a family of four people (father, mother, son and daughter). This study differs from the other studies stated in this section due to its approach of using 3D virtual faces that were reconstructed from the four family members by extracting their shapes and textures and mixing them. For mixing 3D heads between the family members, a method was generated to conduct 3D shape interpolation and 2D morphing using triangulation. Then eventually, based on the identification of the feature points, wrinkles within facial animation and aging were created.

For facial aging process, a dynamic model was presented in Edwards *et al.* (1998) for simulation. A high resolution face model was considered and expanded with age and hair features. The system focuses on three facets that occur due to aging: changes in the appearance of hair style and shape, wrinkles appearance and the effects of aging on facial components.

## METHODOLOGY

**2-d facial aging approach:** The 2D FA approach that can predict the length, number and position of the forehead wrinkles is divided into three main stages as shown in Fig. 1

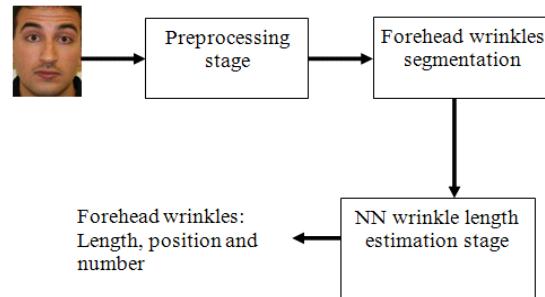


Fig. 1: 2D FA flowchart

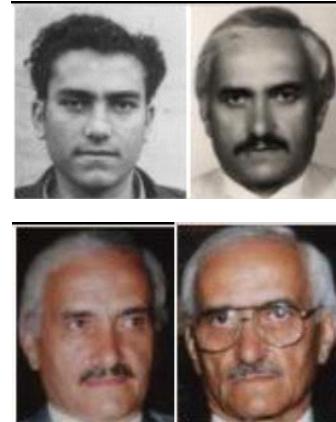


Fig. 2: Sample image for the same person

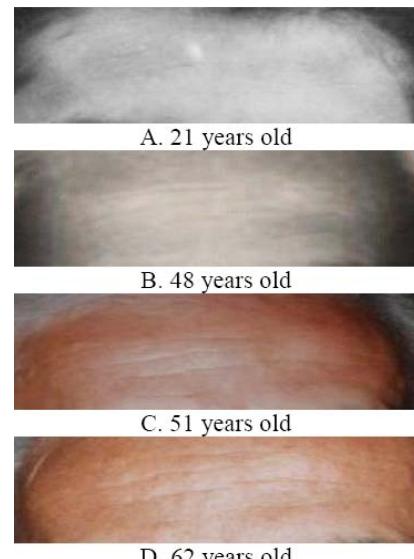


Fig. 3: Cropped forehead areas

**Preprocessing stage:** For this study, the FG-NET Database was used. This database is a 2D aging database that contains 1002 face images of 82 people.

Due to the limitation of the database that was mentioned in the previous section, it was necessary for the

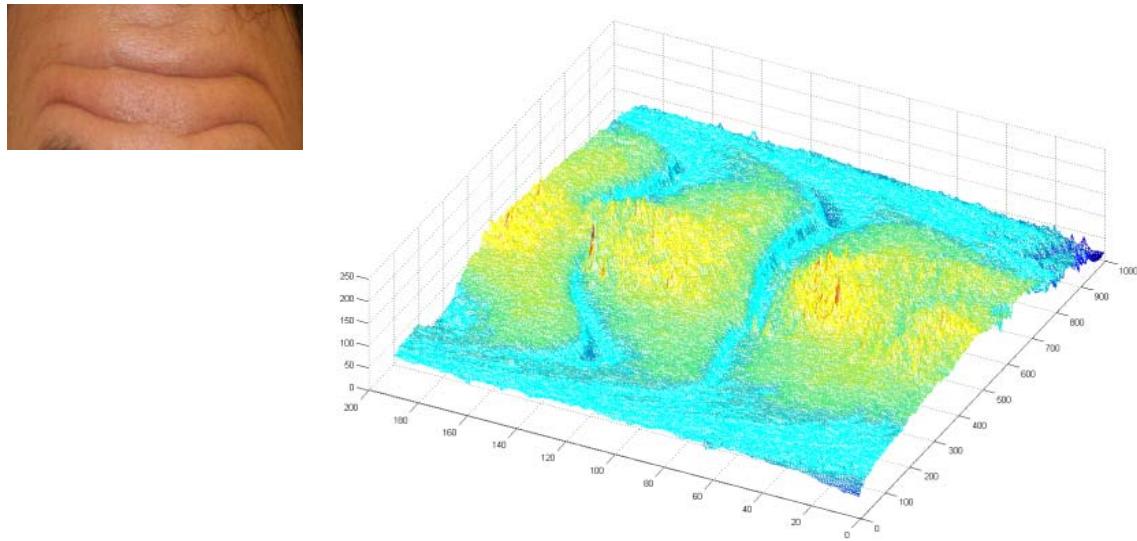


Fig. 4: Wrinkle representation in 3D mesh

authors of this study to be selective, i.e., best images were chosen for the experiments. For further enhancement, the selected images were filtered using Matlab R2008a to gain sharpness. Figure 2, shows a sample of four selected images of the same person at different age spans.

The four images, from left to right, are at the age of 21, 48, 51 and 62, respectively. Using Matlab again, the forehead areas of the 4 images were cropped as in Fig. 3. This process was done on all selected images to have a dataset ready to be used in the experiments.

**Forehead wrinkles segmentation:** In any segmentation process, the region of interest should be determined initially. Therefore, in our study, the forehead wrinkles are the objects of interest that are to be extracted. So, the proposed segmentation process for this method was divided into three main steps.

**Forehead wrinkles threshold:** The main goal for this step is to find the suitable threshold value that can be used to accurately separate the wrinkled regions from the background. Choosing the threshold value is one of the most difficult problems in 2D FA since the wrinkles do not seem to appear accurately in 2D images as shown in the Fig. 4.

Therefore, a Row-by-Row Threshold (RRT) method is used to find a precise local threshold value for each image row as in the study of (AbuBaker *et al.*, 2005). This method presents an excellent result in extracting the breast skin in the mammogram images (AbuBaker *et al.*, 2005; AbuBaker, 2008). In this method, a minimum gray level value (excluding the background) is assumed as an initial point to start the process. Then, the averages for the gray levels above and below the initial value are

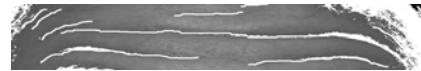


Fig. 5: Threshold forehead without setting the background to zero

computed separately. Finally, the algebraic difference between the two means is added to the initial value. The computed value is considered as the initial value to the next iteration and so on. The process will end when the mean difference becomes almost equals to zero. The mean error method is implemented for each histograms row. As a result, each row has its own threshold value. Hence, the number of a threshold values that are generated is equal to the number of image rows. This method is implemented to forehead wrinkle region and can accurately extract all the wrinkles in the image as shown in Fig. 5.

## RESULT AND DISCUSSION

**Implementing morphological and connected component labeling approaches:** The morphological erosion process is applied as a next step in order to remove or reduce the area size of the small white region surrounding the separation between the threshold objects. In some cases, the wrinkles are touch or partially covered with hair as in this case, so erosion process is used to separate these two objects and at the same time it eliminated small white regions.

Finally, the wrinkle size is the last filter to accurately detect the wrinkles in the forehead. This filter is design based on the following steps:

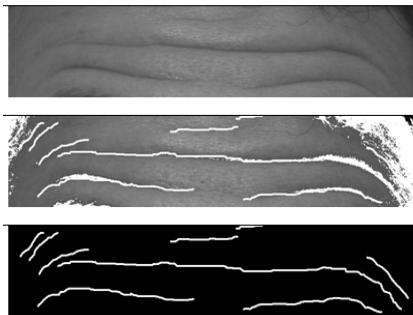


Fig. 6: (A) Original gray level forehead, (B) threshed forehead, (C) result of implementing morphological erosion and CCL

- A novel One Scan Connected Component Labeling (OSCCL) algorithm (AbuBaker *et al.*, 2007) is implemented on the images resulted from the erosion process. The main objective of the OSCCL is to give a unique label for each object in FA image as shown in Fig. 6 Then the area for each object is computed in pixels.
- The algorithm was adjusted so that wrinkles only are preserved after the detection step. Wrinkles of the sizes smaller than 10 pixels or greater than 1600 pixels are left out during detection since the maximum continues wrinkle size is 1630 pixels. So, any object exceeded these areas will be set to zero otherwise it will have a value of 255 as shown in Fig. 6.
- In this stage, the number and length of the forehead wrinkles are determined. Number of wrinkles is calculated after implementing the size filter as presented earlier. So the remaining objects (wrinkles) are calculated in the image to indicate the number of wrinkles in the image. All the tested images have the same resolution which is 10 mm pixel size. Therefore, the wrinkle length is also calculated in this stage since number of pixels for each wrinkle is stored in the CCL algorithm.

**3-D wrinkle length estimation:** Each wrinkle in the real life is a 3D wrinkle or curve wrinkle, whereas, the length in the previous section is calculated using 2D image. So the curvature of the wrinkle is not considered in calculating the length of the wrinkle.

In this section, the neural network will be design and trained to convert the length of the wrinkle from 2D to 3D as will be presented in the following subsections.

**Data collection:** Maya 2008 was used in order to form the 3D curves. Since the cropped 2D foreheads and the 3D forehead model are available, texturing can be started by first uploading both 2D and 3D foreheads to the Maya

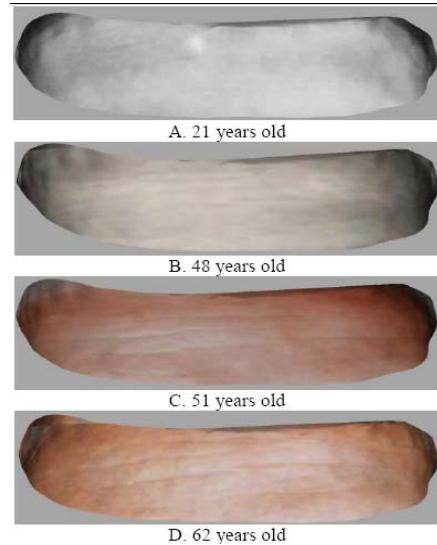


Fig. 7: 3D texture result

environment, then mapping the 2D image of the forehead to the 3D forehead object.

For the forehead images that are shown in Fig. 3, the texturing results are as the following:

The difference between Fig. 3 and 7 can now be spotted. The images in Fig. 3 are simply 2-dimensional images but after mapping them to the 3-dimensional object, viewing them in the 3D environment became possible. The whole point of this process is generating 3D curves from the actual wrinkles. Textures will then be removed, resulting in realistic curves (wrinkles) constructed on the 3D face model.

Since, the length of the 2D and 3D wrinkles are measured, training and learning matrices for the neural network is specified based on the number of cases which are 100 faces. These faces are divided to five categories according to age as the following: 21-30, 31-40, 41-50, 51-60, 61-70. So the wrinkle length for the faces in each category is calculated and stored in an input matrix. As a result, five input matrices with different dimensions are generated based on the number of wrinkles in each category. In the same manner, the wrinkle length is calculated in 3D as in the study of Mehdi *et al.* (2009) and Mehdi (2011) to produce five output matrices with different dimensions.

**Learning neural network:** The values of the input matrices are arranged in training vectors in a manner similar to the Jackknife technique (Fukanga, 1990), where 70% of the data were used for the NN training phases and the remaining 30% were used for the NN testing phases.

Five parallel neural networks is design according to the age of the person. The topology of each of the NN

## CONCLUSION

This study presents the ongoing effort to extract the length, position and number of a forehead wrinkle using a neural network in 2D facial images. The proposed method was divided into three main stages. The first stage is preprocessing stage, where the forehead of each face was cropped manually in order to detect the wrinkles. Then the row-by-row threshold process was carried out in order to segment the wrinkles in the forehead images. After that, the CCL with morphological erosion process were carried out in order to reduce the number of false objects and could accurately detect the wrinkles in the forehead image. Finally, the neural network is used to convert the 2D length of the wrinkles to their corresponding lengths in 3D images.

The algorithm was objectively compared with the 3D detection algorithm based on the age categories and the length, position and number of forehead wrinkles. The evaluation showed a good performance for the 2D detection algorithm in estimating the number of wrinkles with their positions and lengths for each forehead.

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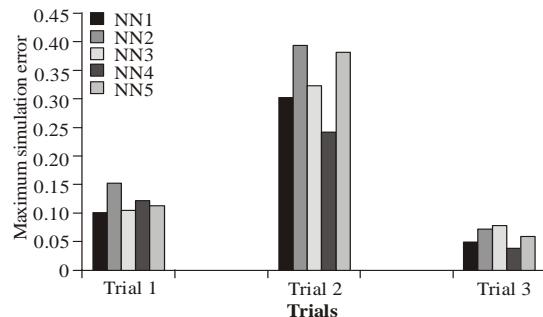


Fig. 8: NN evaluation chart, trial 1 uses 3 hidden nodes, trial 2 uses 10 hidden nodes, trial 3 uses 5 hidden nodes

consists of one input node, hidden layer and one output node. To find the optimum topology (i.e., the optimum number of hidden nodes in the hidden layer), several feedforward NN structures were trained using the training data to find the minimum training error, as shown in Fig. 8 As a result, it is found that the feed forward NN with one hidden layer and five nodes produce the minimum errors.

**Evaluating the proposed methodology:** One hundred faces from FG-NET database are used in this objective evaluation. The position, length and the number of the forehead wrinkles is produced in 2D and 3D images. A comparison is carried out with our proposed 2D position, length and number of the forehead wrinkles detection algorithm using neural network and 3D forehead wrinkle detection that is proposed in Mehdi *et al.* (2009) and Mehdi (2011). The average error rate for each age category is calculated based on the detected wrinkle length, number and position. The reference data for each image is the result obtained from 3D detection algorithm as shown in Table 1.

From Table 1 it is clear that the 2D detection algorithm can successfully estimate the number of wrinkles, length and position with minimum error. Also, it is noticed that the minimum error were in ages from 41 and above. This is feasible since the depth of the wrinkles in these ages is much deeper than the people in age 40 and less. So, extracting the wrinkles in the threshold process will be more accurate for the people of 41 and above.

Table 1: 2D average error for each age category based on 3D detection algorithm

	21-30	31-40	41-50	51-60	61-70
Length	0.133	0.0845	0.0696	0.0541	0.0132
Number	0.070	0.0340	0.0129	0.0050	0.0010
Position	0.090	0.0740	0.0285	0.0139	0.0090

Therefore, finding the length, number and position of the wrinkles will be more accurate than people who are of the age 40 or less.

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