Age Range Estimation Based on Facial Wrinkle Analysis Using Hessian Based Filter

Husniza Razalli, Rahmita Wirza O.K. Rahmat, Fatimah Khalid and Puteri Suhaiza Sulaiman

Abstract Aging is a normal process that has an effect on different parts of the human body under the influence of various biological and environmental aspects. The most prominent changes that occur on the face are the form of the skin wrinkles, which are the main objective of this research. Specific wrinkle detection is an important task in face textural analysis. Previously, some researchers have been proposed the age range estimation based on wrinkle analysis in literature, but poor localization limits the performance of the whole age estimation process. This is because, when less number of wrinkles are detected or extracted, it will consequently affect the process to estimate the correct age. Therefore, we address this issue to enhance age range estimation method using a new approach to extract correct facial wrinkles for further analysis. We propose a method to extract facial wrinkle in face image using Hessian based filter (HBF) for age estimation. In other word, this research focus on age range estimation method based on facial wrinkle analysis extracted from facial image obtained from FG-NET database using hessian based filter. The proposed filter is theoretically straightforward, however, it significantly increases the wrinkle analysis result compared to previous methods. The result shows that HBF successfully obtained higher accuracy with over 90 % estimation rate.

Keywords Age range estimation · Wrinkle analysis · Wrinkle density · Hessian based filter

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1 Introduction

The human face contains a lot of information related to personal characteristics, including identification, emotion, age, gender and race. This information has been used extensively in face recognition and verification systems which are capable of interpreting the facial information found in human-to human communication [1, 2, 3]. Currently, the research related to age range estimation using face images is more important than ever, because it has many applications, such as an internet access control, underage cigarette-vending machine use [1, 4], age-based retrieval of face images [4], age prediction systems for finding lost children and face recognition robust to age progression. In the human aging process, two biophysical change or growth happen on the face [5], which are;

- The craniofacial bony aging due to a relative change in bone expansion and loss most probably refers to face shape, and
- The change of face texture and elasticity of the skin.

During adult aging, from adulthood to old age, the most perceptible change becomes skin aging (texture change). The shape change still continues, but less dramatically, mostly due to typical patterns in skin and tissue [6]. Originally shown in [7] and also in [8], Fig. 1 shows six face sketches, each of which associated with age of 30, 40, 50, 60, 70 and 80 years old, respectively. Biologically [8], as the face matures and ages with loss of collagen beneath skin as well as gravity effects, the skin becomes thinner, darker, less elastic, and more leathery. A dynamic wrinkles and blemishes due to biologic aging gradually appear. Dynamic wrinkles and folds due to muscle motion become more distinct. In the areas of deeper attachment, such as cheeks, eyelids, chin, and nose, elasticity of muscles and soft tissues gets weak and fat continues depositing. In other areas, fat may atrophy or be absorbed. These changes lead to the downward descent or sagging of the skin, such as double chin, dropping cheek, and lower eyelid bags [9]. The bony framework underneath the skin may also deteriorate to accelerate the development of skin aging, such as wrinkles, creases, and droops. In addition, face aging during this age period may cause the loss of flexible control of facial muscles so that the facial movements and behaviors may also change unintentionally [5]. In other words, face aging throughout this age era suitably can be measure based on wrinkle analysis. The

Fig. 1 Face aging sketches from 30 to 80 years with 10 years per sketch, originally shown in [8], also in [7]

wrinkle and skin features are generally appeared by high frequency components on face images and easily distinguishable to human eyes, however it is a challenging task for computer vision systems to detect them automatically. Therefore, traditionally edge detector or high frequency images are used to extract local features.

2 Existing Method

Most of the researchers focus on edge detection in order to extract wrinkle in estimating the age of a person through wrinkle analysis process. Dehshibi et al. [10] and Shima et al. [11] estimates facial age using hybrid of geometric features extraction and wrinkle analysis. In their wrinkle analysis process, they used canny edge detector to extract wrinkles. Based on the extracted wrinkles, they calculated the density of the wrinkles. Meanwhile Jiang et al. [12] proposed the classification of the skin aging level at the lower eyelid regions. The wrinkles analysis process used in this work was also based on canny edge detector and used wrinkle density and intensity as measurements. Wrinkles are measured as line segment series. Wrinkle should not be confused with edge. Edge is the border between two areas while wrinkle is a line that is either darker or lighter than their neighbourhood. Therefore, edge detection methods such as Canny are not suitable for wrinkle detection because it will produce wrinkle boundaries, not the wrinkle. Based on this statement, wrinkle density and intensity obtained from canny edge detected probably give inaccurate wrinkle analysis results and leading to reduction of age estimation accuracy.

Batool and Chellappa [2] proposed a stochastic wrinkle detection method based on marked point process (MPP). They employed a second derivative linear filter to extract line structures from an image, and penalized an overlap of wrinkle segments. However, their solution strongly depends on the initial condition, and fails to detect complex patterns of wrinkles.

In this work, we propose a new method for extracting facial wrinkle from a face image using Hessian based filter (HBF) and use these extracted wrinkles to estimate the age range. We focused on the problem of classifying an adult age range (age around 19–70) since wrinkles happening during these period. And as a nature process, wrinkle only occur when a person reaching adulthood period. Furthermore, this research was based on the publicly available FG-NET (Face and Gesture Recognition Research Network) aging database which contained 1,002 color and grayscale images of persons from 0 to 69 years of age [13].

The rest of this paper is organized as follows. Section 2 provides step by step methodology of the proposed work. Section 3 demonstrates an experimental setup while, Sect. 4 describes experimental results. Finally, conclusions are drawn in Sect. 5.

3 Methodology

The proposed facial age range estimation method using HBF is briefly outlined in this section. The technique starts with the input of face image from FGNet database. This technique comprises four major processes which are; Wrinkle Region of Interest (ROI) Localization, Wrinkle Detection and Extraction, Wrinkle Density Calculation and Age Range Classification as illustrated in Fig. 2.

This proposed method will recognize person's age group based on their face image. The range between subsequent age groups is 10 years, which mentioned in [5] this age gap give maximum result to wrinkle progression during aging. The ranges of the age are grouped as below;

- R1—Range 1 age 19–30,
- R2—Range 2 age 31–40,
- R3—Range 3 age 41–50 and
- R4—Range 4 is for 51+

3.1 *Wrinkle ROI Localization*

During age progression, wrinkles on faces become more and more clear. The wrinkles on human face become more prominent when he or she getting older. Aged people often have clear wrinkles on the following areas of the face [14]:

- The forehead has horizontal furrows.
- The eye corners have crows' feet.
- The cheeks have obvious cheekbones, crescent shaped pouches, and deep lines between the cheeks and the upper lips.

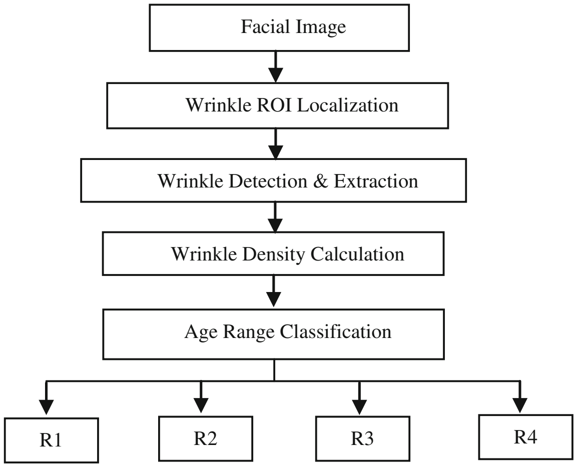

Fig. 2 Block diagram for age range estimation process using Multi-SVM Classification

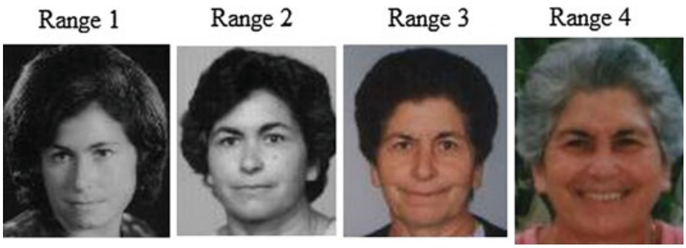

Fig. 3 Sample images in FG-NET database for every age range

However, according to [15] the upper ROI face wrinkles increase the performance of age estimation and as mentioned in [12], skin aging tendency can be indicated well using lower eyelid region since this area possesses important information for aging level identification. Based on these two statements, only selected ROI are used to detect and extract the wrinkle, which are forehead area and lower eyelids area. The measurement of the area is carried out based on region of the eye as describe in Fig. 3. We labeled the forehead box as A, lower eyelid for left eye as B and lower eyelid for the right eye as C. The height of all ROI areas is determined by the height of eye region, denoted by ‘n’. The width for ROI area A and B is also the same with the width of the eye region. By contrast, the width of ROI area A is 3 times of that of the width of the eye region width. The definition of ROI areas is defined in Eq. (1) and (2):

$$Area\,B = Area\,C = Area\,of\,Eye \tag{1}$$

$$Area\,A = EyeHeight * (EyeWidth * 3) \tag{2}$$

The ROI is also selected based on consideration about the nature of face and circumstances that may occur during detection, such as if we choose the area around mouth, we should consider the gender of the sample. This is because we try to extract the wrinkle pixels, most of older male samples in our FG-NET database consist of the face with mustache and beard which will disturbed the result of the detection. Therefore, in order to reduce the number of error detection we only consider the above-mentioned ROI areas in our proposed algorithm.

3.2 Wrinkles Detection and Extraction

Wrinkles are considered as stochastic spatial arrangements of line segment sequences. Wrinkle should not be confused with edge which refers to the border between two areas. By contrast, wrinkle is a line that is either darker or lighter than their neighbourhood as shown in Fig. 1. Therefore, edge detection methods such as

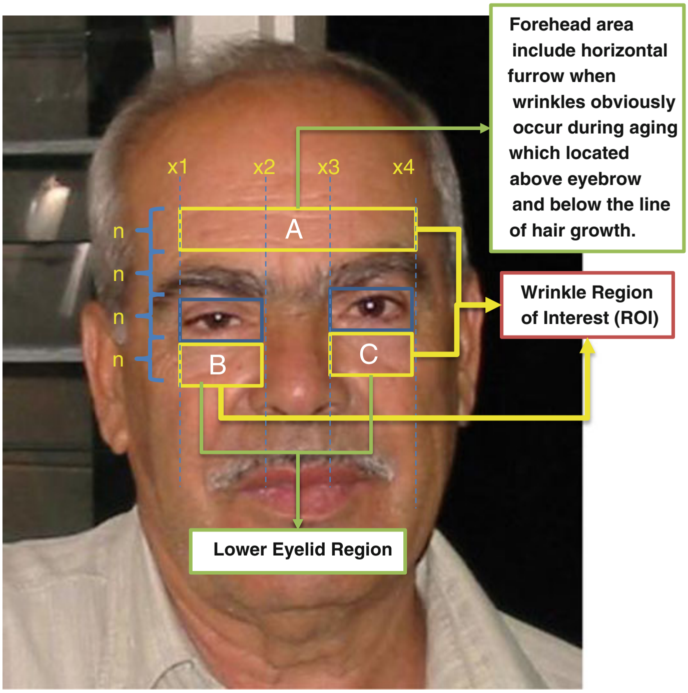

Fig. 4 The selected areas of facial wrinkles for HBF analysis

Canny and Sobel are not suitable for wrinkle detection because it will only produces wrinkle boundaries, not the wrinkle.

The HBF is applied in order to extract wrinkles from selected ROI of facial wrinkles as shown in Fig. 4 where the HBF with the scale range, scale ratio and correction constant parameter was used according to the selected facial, as cited from [15]. Here, the HBF with [1 1] scale range, and 1 scale ratio were chosen. This was done after some empirical analysis with the method, where these settings exhibited the best performance.

After extracting the wrinkle from selected ROI areas of the facial images, Wrinkle Extraction Process can be applied on facial images. In this stage, several steps are used to obtain exact wrinkles pixels as describe in Fig. 5. Firstly, the input of wrinkle ROI will be converted to grayscale image. Then, Hessian Based Filter [16] is applying to the grayscale image to get the wrinkle edge likeliness (Fig. 6).

After that, morphological operation was used to remove unwanted pixels which are considered as a noise. Finally, the wrinkle pixels result was passed to another process which is equivalent to measuring the density of wrinkles.

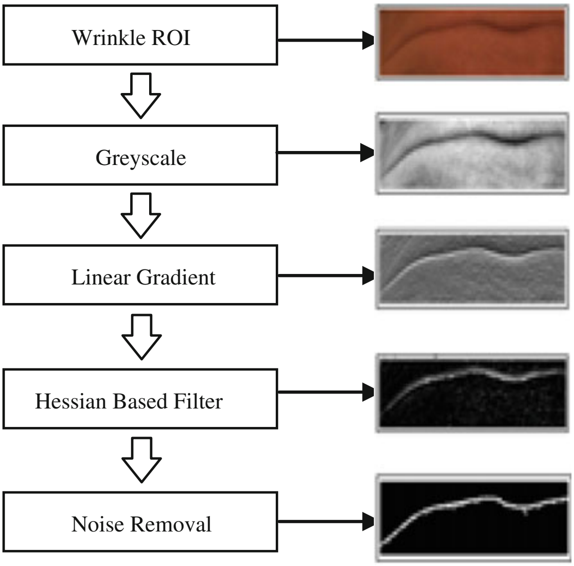

Fig. 5 Block diagram for wrinkle extraction process using HBF

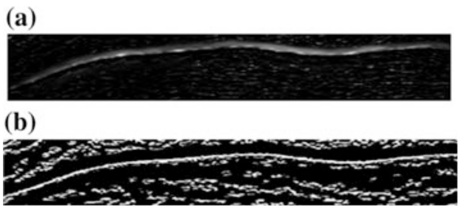

Fig. 6 **a** Wrinkle edge using Hessian Based Filter, **b** Wrinkle edge using Canny Edge Detector

3.3 Calculate Wrinkle Density

In our proposed method, the binary wrinkle image from ROI A image after noise removal process is taken as the input. The function returns 1 when it finds wrinkle pixels in the input image and returns 0 elsewhere. The wrinkle density $\mathrm{WD_A}$ in area A is defined as:

$$\mathrm{WD_A} = \frac{|WA|}{|PA|} * 100 \tag{3}$$

where WA stands for the total of all wrinkles pixels in area A, PA is the set of all pixels in area A.

Table 1 Average wrinkle densities for selected wrinkle ROI

Age range	Wrinkle ROI		
	Area A	Area B	Area C
Range 1	8.09	11.60	10.70
Range 2	9.55	12.80	12.40
Range 3	13.20	14.80	13.90
Range 4	15.40	18.20	16.40

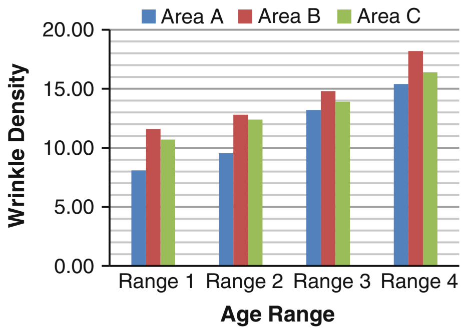

Fig. 7 Distribution of average wrinkle densities in selected ROI for every age range

In order to measure the effectiveness of our method, we firstly find the wrinkle density pattern from 100 adult face images with age around 19–60 years old obtained from FG-NET database. The wrinkle density then grouped according to its age range. After that, the average wrinkles density associated with every age range is calculated for all selected ROI. These values are listed in Table 1.

From Table 1 we distribute the wrinkle densities in a graph to clarify the pattern of the extracted wrinkle density during age progression using our proposed method as shown in Fig. 7.

From the figure, we can observe the pattern of the wrinkles progression during aging and we can conclude that those seleted ROI contributed to wrinkle analysis.

3.4 Age Range Classification

For the classification process, modified Multi Support Vector Machine (Multi-SVM) developed by Mishra [17] was chosen because it is designed for binary class problems which select the optimal linear decision hyper-plane. In SVM based classification, each data point in the dataset is represented by a k-dimensional vector with n-ratios. Assuming, each data point belongs to only one of two classes, the SVM Separate the dataset with a k-1 dimensional hyper-plane with maximum separation between the two classes. The same data point and process goes to Multi-SVM classifier. However, in Multi-SVM assumes, each data point belongs to one of more than two classes as shown in Fig. 7. This phase is used as an experimental setup to measure the accuracy of the proposed age range estimation method. Detail explanation about classification process is discussing in the next section.

4 Experimental Setup

The proposed age range estimation based on facial wrinkle analysis using hessian based filter is evaluated on the FG-NET aging database. Out of 1002 face images from 82 subjects with the age ranging between newborns up to 69 years, only 180 proper frontal images with no spectacles, no beard and moustache and no extreme facial expression were chosen, which are selected randomly from different ages range between 19 and 69 years old. We use the Multi-SVM classifier to estimate the age range of the facial image as describe in Fig. 8.

The n ratios are the densities for all ROI, and the data is split into training and testing sets with k rows. The ¼ k data as a training set which is used for generating the classification model and the ¾ k data as a testing set is used to test the classification performance of the classifier. As it is shows in Fig. 5, the classifiers categorize the images into four age groups as mentioned earlier.

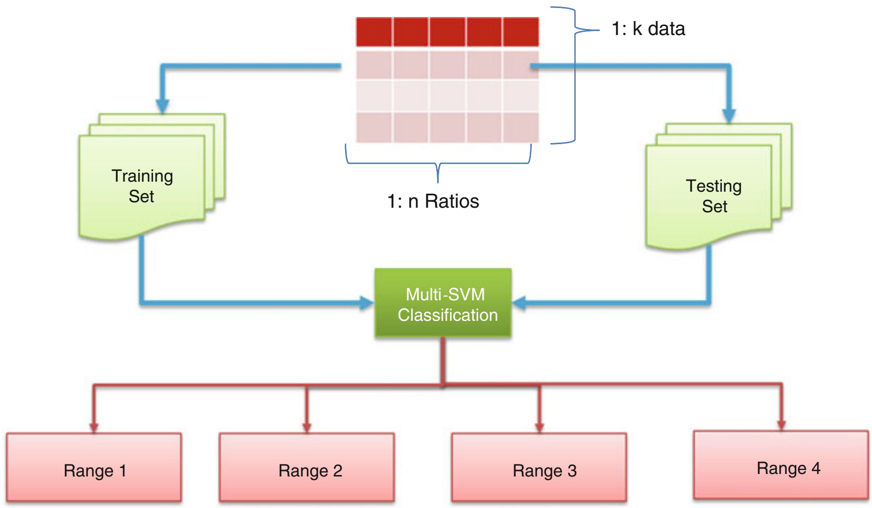

Fig. 8 Block diagram for age range estimation process using Multi-SVM Classification

Table 2 Estimation rate for the propose age range estimation method

Ground truth	Total image	Detected image	Accuracy (%)
Range 1	89	83	93.25
Range 2	48	42	87.50
Range 3	25	23	92.00
Range 4	18	17	94.44

Table 3 Performance comparison of Hessian Based Filter (HBF) with the work of other researchers

Ground truth	Accuracy (%)
Canny Edge Detector proposed by [10, 11, 12]	82.356
Proposed HBF	91.798

5 Result and Discussion

This section presents the experimental results for the age range estimation method based on facial wrinkle analysis extracted from facial image using HBF. Wrinkle analysis proposed in this work was compared with the method proposed in [10, 11]. The results are listed in Tables 2 and 3.

From the results, this method successfully classifies the face images acquired from FG-NET database into preferred ranges using Multi-SVM classifier with higher accuracy of estimation rate (%). The average accuracy of our proposed method also demonstrates a promising result compare to others.

6 Conclusion

In this work we extract the wrinkles on upper face region using HBF and then calculate the wrinkle density to measure the age range of a person's face. We experimented with different wrinkle analysis method proposed by previous work to compare accuracy of the age range estimation method. Although higher estimation rate achieved by using our proposed estimation method, this approach can be beneficial in hybrid features extraction method since it can reduce the need of unwanted features and decrease time execution. However, the drawback is the image have to be frontal (without tilt) with no facial accessory, radial lighting condition and consideration of image quality.

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