Facial Age Estimation Using a Hybrid of SVM and Fuzzy Logic

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***Abstract*— This paper has presented a method of facial age estimation using a hybrid of Support Vector Machines (SVMs) and Fuzzy Logic (FL). The proposed method has taken facial features from wrinkles and skin color on the human face to estimate the age group and age in point. SVMs was used to estimate the five age-groups of human age. Then, FL was implemented to estimate the age in point corresponding in each group resulting from SVMs. For performance evaluation, k-fold cross validation was carried out using FG-NET and PAL databases consisting of 700 and 500 faces, respectively. The proposed method was evaluated in comparison with five advanced methods in literature. The results showed that the proposed method provided 88.84% and 90.88% of accuracy in aging group estimation in FG-NET and PAL databases, respectively. In addition, the proposed method reported 4.81 and 3.12 for MAE (mean absolute error) for point age estimation using FG-NET and PAL, respectively. In this regard, the proposed method provided the higher performance on accuracy and MAE superior to the compared methods.**

Keywords—Facial Age Estimation; Support Vector Machines; Fuzzy Logic

I. INTRODUCTION

Human face is very important to contact to each other. A human face has been used to estimate age by human for centuries. A human face is different from one another and different facial characteristics show their appearances [1] [2]. When a man became elder, facial structure on parts of skull will be expanded due to an increasing size of skull. Interval between important positions on face, such as the left eye and the right eye, skull, and nose and mouth [4], was the key features to estimate the age. In biology, facial aging occurs by repeated muscle movement and facial expression happened to be perpendicular to the direction of the facial muscles. For example, forehead has the horizontal direction, aging on eye's corner has the horizontal direction, and the aging under the eyes also has the horizontal direction [10]. Aging on cheek has the crosswise direction. In addition, skin color is also important to estimate the age. Facial scene, pellicle, freckle, and aging occur on skin. It effects on the skin and it is the melanin cell at the bottom layer of the skin that damaged by exposure of ultra-violet rays from the sun. The damaged thing will affect the skin that causes freckles overall tone of the skin to become uneven [10]. Deep aging on the surface caused by muscle, and deep forehead horizontal direction are significant. All of them depend on a human age.

As the age has increased, wrinkles on the forehead, areas under the eyes, areas between the left eye and the right eye and buckle areas become more apparent. At young age, the skin of face is youthful and smooth but when get older, the skin of the face has expansion of the follicle cells that make a human life to be different.

There are a variety of researches investigating the age estimation from the face based on several methods. Some heavily investigated the estimation of aging group; two age group [9], four age group [4], six age groups [5][6], and seven age groups [1][7] using Support Vector Machines (SVMs) [2][7], Neural Network [4], Extreme Learning Machine (ELM) [3], other focused on the estimation of ages in point using Support Vector Regression (SVR) [2][5], for example.

In general, there are five main components of age estimation shown in Fig. 1 as follows:

- Pre-processing: to crop the facial area from an input image in order to process in the next step.
- Feature extraction: to determine facial features such as wrinkles from important positions on face; forehead, left eye corner, right eye corner, left cheek, and right cheek. In addition, skin color feature was also key features.
- Age group classification: to estimate age group using machine learning techniques.
- Point age estimation: to estimate age in point using machine learning techniques.

This paper aimed to enhance accuracy of age estimation both age group and point age by using a hybrid of SVMs and Fuzzy Logic. It consists of 5 sections. Following this section, the proposed method was given in Section 2. Section 3 provided the experimentation. Results of the proposed method compared with the five state-of-the-art methods were given in Section 4. Section 5 summarize the research and future work.

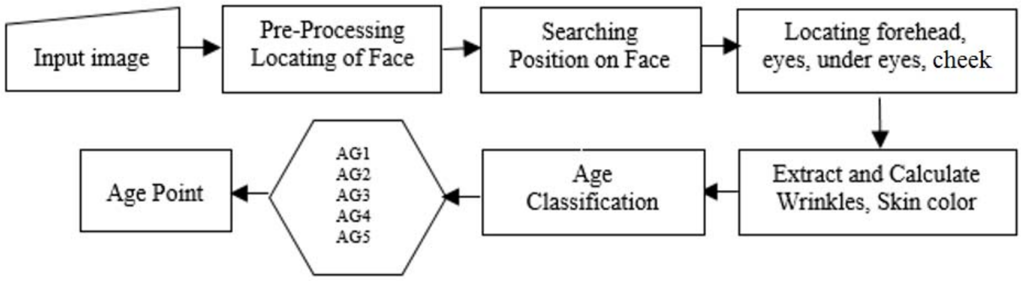


Fig. 1. Age estimation block diagram.

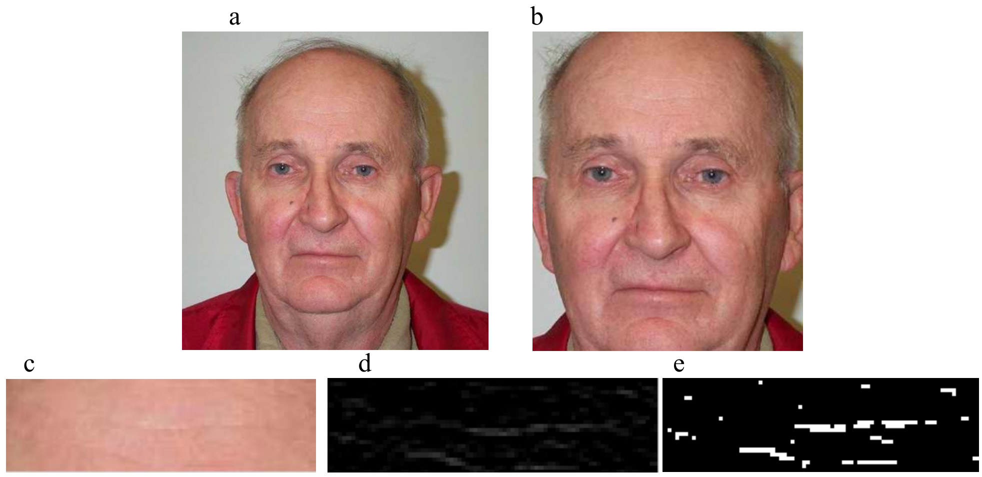


Fig. 2. Image pre-processing: (a) original image, (b) cropped face region, (c) original forehead, (d) edge detection by Sobel horizontal, (e) applying Gabor Filter.

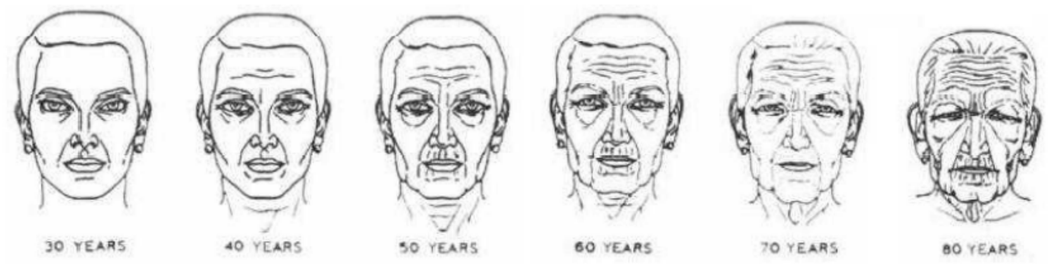


Fig. 3. Face aging sketches from 30 to 80 years with 10 years per sketch [10].

II. PROPOSE METHOD

The main process to estimate the age from a human face is to find attributes of aging. These attributes play a vital role as an important data to be classified age in groups and estimated age in points. A process of extracting attributes and estimating age has shown in following parts;

A. *Pre-processing*

In pre-processing method, we used standard color face pictures from FG-NET [11] and PAL [12] shown in Fig. 2(a). Fig. (b) showed the cropped face. Fig. 2(c) is the cropped forehead. After that, the picture will be changed from color to gray image to find edge using Sobel in horizon shown in Fig.2(d). The result from Fig.2(d) will be enhanced using Gabor filtering resulting in the enhanced edge in binary image shown in Fig.2(e). For other location on face, the same process was carried out to determine edge feature.

B. *Feature Extraction*

To find the main positions on face, we should know where the spots on face appeared. The aging we have chosen affects the estimation of age on face shown in Fig. 3. The main positions on face can tell us about aging of each range as shown in Fig. 4. Fig. 5 exhibited four important areas, such as, forehead, under the left and right eyes, on the corner of left and right eyes, and besides the left and right cheek.

C. Wrinkle Feature Extraction

Aging on face is very important to estimate age from face. This research utilized seven features of wrinkle shown in Fig. 4(a). Features on seven areas consisted of forehead, left eye corner, right eye corner, under left eye, under right eye, left cheek, and right cheek as shown in Fig. 5. The process to determined wrinkle began in calculating horizontal aging using the mask given in equation (1) followed by Gabor filtering [2], [3], [6], [7], and [8]. Then, the equation (2) was taken to modulate all seven edged features.

$$mask\left(\frac{\partial f}{\partial y}\right) = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{1}$$

$$f(x,y) = exp\left(-\frac{(x_0^2+\gamma^2 y_0^2)}{2\sigma^2}\right) \times cos\left(\frac{2\pi}{\lambda}x_0\right) \tag{2}$$

$$x_0 = xcos\theta + ysin\theta$$

$$y_0 = -xsin\theta + ycos\theta$$

D. Skin Color Feature Extraction

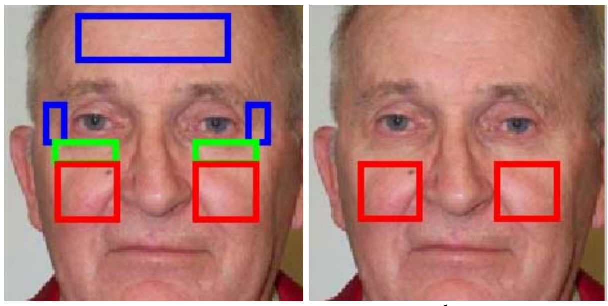
Besides wrinkle, skin color is also significant to distinguish the age [15]. This research took two positions into account for extracting skin color on face shown in Fig. 4(b) by converting the color system from RGB to HSV. Then, equations (3), (4), and (5) were implemented. In this regard, we were able to determine standard deviation of the picture by using the equation (6). Finally, we will obtain two more features from skin color, namely, the eighth and ninth features on the left cheek and the right cheek, respectively.

$$v = max, \tag{3}$$

$$s = \begin{cases} \frac{(max-min)}{max} & if \quad \max \neq 0 \\ 0 & if \quad \max = 0 \end{cases} \tag{4}$$

$$H = \begin{cases} -60, & if \ (s=0) \\ \frac{(G-B)}{(\max-\min)}\times 60, & if \ (R=max) \\ 2+\frac{(B-R)}{(\max-\min)}\times 60, & if \ (G=max) \\ 4+\frac{(R-G)}{(\max-\min)}\times 60, & if \ (B=max) \end{cases} \tag{5}$$

$$std = \left(\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{\frac{1}{2}} \tag{6}$$



a b

Fig. 4. (a) Seven areas for wrinkle analysis, and (b) Two areas for skin color.

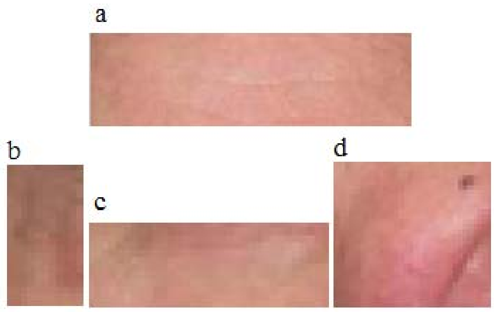


Fig. 5. (a) Forehead area, (b) Left eye corner, (c) Under left eye, and (d) cheek area.

E. Age group classification

SVMs is a popular machine learning technique in classification. It transformed original n dimensional data to higher dimension of features using kernel function. Even though SVMs was linearly binary classifier using maximal margin line as the classifier in nature, it can deal with multiclass using Decision Directed Acyclic Graph (DDAG) topology shown in Fig. 6. As earlier stated, kernel functions allowed SVMs to deal with non-linear classification. There were several kernel functions available in SVMs, such as linear, polynomial, quadratic, radial basis, Sigmoid, etc. Some kernel function were given in equation (7),(8),(9), and (10).

Linear

$$K(x_i, x_j) = x_i.x_j \tag{7}$$

Polynomial

$$K(x_i, x_y) = (x_i.x_j.\beta)^d \tag{8}$$

Radial Basis Function (RBF)

$$K(x_i, x_j) = exp\left(-\left\|x_i.x_j\right\|^2\right)/(2\sigma^2) \tag{9}$$

Sigmoid Function

$$K(x_i, x_j) = \tanh\left(y(x_i, x_j) + c\right) \tag{10}$$

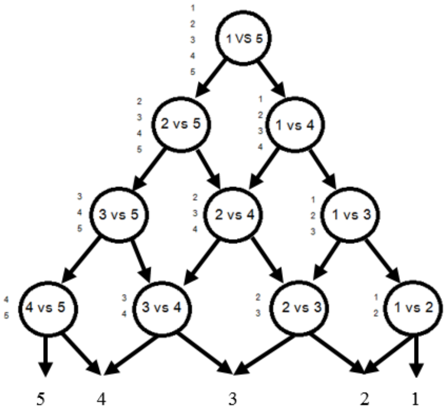


Fig. 6. Decision Directed Acyclic Graphs (DDAG).

In this research, SVMs was implemented using Decision Directed Acyclic Graph (DDAG) scheme for multiclass classification with Radial Basic Function (RBF) [13] as shown in Fig. 6. The experimentation utilized 10-fold cross validation in training-testing scheme to determine the five age groups of the test faces.

F. Fuzzy Logic

Following SVMs, the point age estimation was important. In this regard, Fuzzy Logic (FL) was popular in estimating the point age as shown in several algorithms in literature [2][5][15]. This paper presented a method to estimate the age-point with FL. The results of SVMs in each age group will become an input to FL. Input variables were wrinkle and skin color features and the output variable was the point age. All variables applied triangular membership functions for their terms. In this research, there were nine significant fuzzy inference rules being constructed from Table 1. To calculate the input 1, wrinkle, on FL, an original input features on face from 1 to 7 was considered. Pixel values in the image of binary of the feature 1-7 were determined. It was summed, and then divided by the maximum value of the feature 1-7. Then, it was normalized by being multiplied by ten as shown in equations (11) and (12). In addition, input 2, skin color, was determined using the previous eighth and ninth features as earlier stated in SVMs.

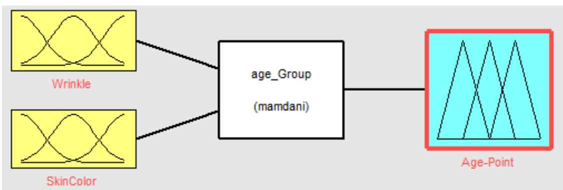


Fig. 7. Fuzzy logic diagram in age point estimation.

TABLE I. Nine rules for Fuzzy Logic.

Skin Color Wrinkle	**Low**	**Middle**	**High**
Low	Low	Low	Middle
Middle	Low	Middle	High
High	Middle	High	High

$$Input\ 1\ Wrinkle = \left(\frac{\sum(feature1{-}7)}{max(feature1{-}7)}\right) \times 10 \tag{11}$$

$$Input\ 2\ Skin\ Color = \left(\frac{\sum(feature8{-}9)}{max(feature8{-}9)}\right) \times 10 \tag{12}$$

III. EXPERIMENTATION

In experiment point of view, there were three parts to realize: the first part is database, the second part is the processes to extract features on face by finding wrinkle and skin color, the third part is the design of Support Vector Machines (SVMs) and Fuzzy Logic (FL).

For the first part, FG-NET [11] and PAL [12] databases were carried out in experimentation. They were the popular benchmark databases for estimating age from face [2] [5] [6] [7] [9]. The compared methods in this research utilized these databases in experimentation. The databases included 500 and 700 faces in PAL and FG-NET, respectively. Fig. 9 and Table 2 provided the database information.

The second part functioned on feature extraction. The proposed methods extracted nine features of the face consisting of wrinkles and skin color from the database. Sobel edge detection was implemented to find wrinkles in horizontal direction shown in Fig. 2(d). Then, Gabor filtering algorithm enhanced the resulting edges obtained from Sobel shown Fig. 2(e). Furthermore, a density feature of pixels in sixteen zones was considered. Each zone has the size of 4x4 pixel window. Then, we calculated a number of dark spots in each zone to become a feature. The proposed method consists of nine features shown in Table 3.

In the third part, SVMs was implemented to classify age into five groups consisting of AG1 for under 20 years, AG2 for 21-30 years, AG3 for 31-40 years, AG4 for 41-50 years, and AG5 for 51 years and over, shown in Fig. 8. Decision Directed Acyclic Graphs (DDAG) was implemented for multi-classification on SVMs. DDAG compared n(n-1)/2 times, which is ten, for five age groups shown in Fig. 6. To estimate age in point, FL was carried out mapping the input 1 (wrinkle) and input 2 (skin color) to the output (point age) using the specified membership functions as stated earlier and shown in Fig. 7.

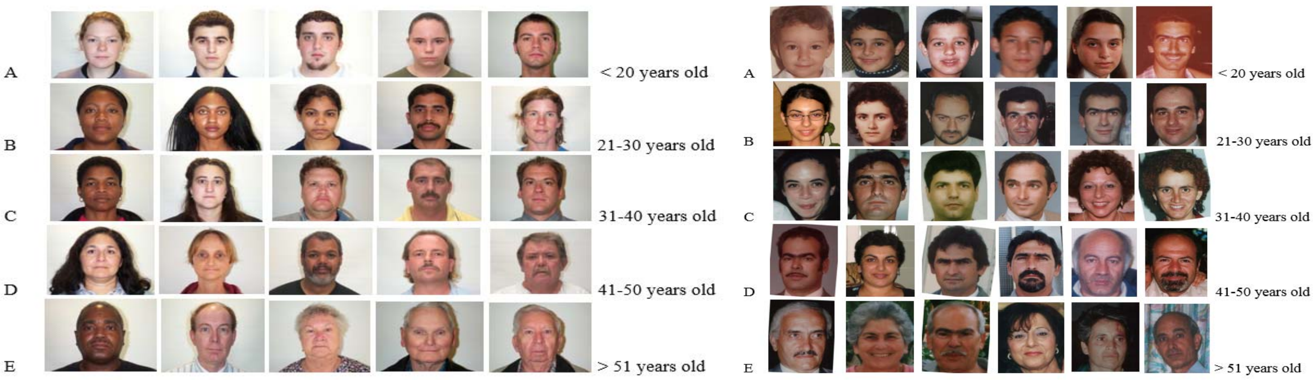


Fig. 8. Sample images in PAL and FG-NET databases: (A) group 1, (B) group 2, (C) group 3, (D) group 4, and (E) group 5.

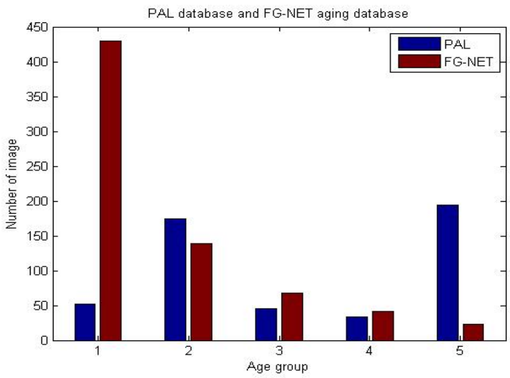


Fig. 9. Facial distribution on PAL and FG-NET databases.

TABLE II. Facial distribution on PAL and FG-NET databases.

Age Group	Age Rang	PAL database	FG-NET database
1	< 20	10.4 %	59.3 %
2	21-30	35 %	20 %
3	31-40	9.2 %	10 %
4	41-50	6.6 %	6 %
5	>51	38.8 %	4.7%

IV. RESULTS

This paper evaluated the proposed method in comparison with the five advanced methods in literature. In this regard, the same databases consisting of the same number of facial images were implemented. The compared methods consisted of [2] on PAL and [6][2][9][7][5] on FG-NET. For experimental design, the proposed method implemented the same group of age as each compared method. In addition, the proposed method presented the performance obtained by specified a number of age group. For the compared methods, [6] presented an automated age regression for personalized IPTV services, [2] proposed age estimation using a hierarchical classifier based on global and local feature, [9] presented hierarchical age estimation with dissimilarity-based classification, [7] presented human age estimation framework using different facial parts, and [5] proposed a hybrid constraint SVR for facial age estimation. The results were portrayed in Table (4) and (5). Table 4 portrayed the result of [2] compared with the proposed method using PAL to estimate age in point. In this respect, the proposed method significantly provided the better MAE; the lower the better. For the best proposed number of age groups, the proposed method gave the superior performance in MAE to the compared methods. The results were the same using FG-NET database as shown in Table 5.

TABLE III. Feature example for SVMs.

Image	F1 (wrinkle)	F2 (wrinkle)	F3 (wrinkle)	F4 (wrinkle)	F5 (wrinkle)	F6 (wrinkle)	F7 (wrinkle)	F8 (Skin Color)	F9 (Skin Color)
	0 0 2 2 1 0 0 0	0 2	0 4	0 0 0 5 0 1 6 0	1 0 0 2 2 2 3 0	8 8 0 6	5 6 1 3	15 1 1	11 1 0
	0 1 0 0 2 3 2 5	4 0	3 4	2 0 3 9 1 2 3 7	6 3 6 2 5 9 3 7	20 12 6 7	1 14 12 6	16 1 1	15 1 1
	0 8 4 0 5 13 13 4	4 4	2 6	0 0 0 2 0 0 3 7	1 1 0 0 7 5 0 0	5 19 19 6	16 1 4 18	10 2 1	11 1 1
	2 2 2 0 9 10 14 8	13 15	5 0	0 2 0 6 2 6 10 1	3 7 6 5 2 0 3 4	14 18 11 20	9 14 27 19	0 5 8	0 5 8
	5 11 4 0 7 4 8 13	14 16	1 10	5 0 0 2 0 4 5 4	2 0 1 2 6 7 0 0	15 5 24 40	11 18 37 19	0 6 9	8 2 9

Fig. 10. A 63-years-old man and 11-years-old boy in FG-NET.

TABLE IV. A comparison of the proposed method and the compared methods on PAL database.

Research	PAL database			
	Compared methods		*Proposed method*	
	age group (%)	age point (MAE)	age group (%)	age point (MAE)
Paper1 [2]	-	4.19	-	4.00
Proposed Method			90.88%	3.12

TABLE V. A comparison of the proposed method and the compared methods in FG-NET database.

Research	FG-NET database			
	Compared methods		*Proposed method*	
	age group (%)	age point (MAE)	age group (%)	age point (MAE)
Paper1 [6]	-	5.49	-	4.52
Paper2 [2]	-	4.65	-	4.12
Paper3 [9]	-	3.85	-	3.52
Paper4 [7]	-	3.17	-	3.10
Paper5 [5]	-	5.28	-	4.88
Proposed Method			88.84%	4.81

V. CONCLUSION

This paper presented the method to estimate the age group and point age using a hybrid of Support Vector Machines (SVMs) and Fuzzy Logic (FL). The investigating features consisted of facial wrinkles and facial skin color. For forecasting age groups, the proposed method using SVMs to forecast the age into 5 groups. Then, FL took output from SVMs as inputs to forecast the age in point in each group. For performance evaluation, 700 faces in FG-NET and 500 faces in PAL databases were implemented using 10-fold cross-validation in comparison with the five advanced compared methods in literature. In this regard, the proposed method provided 90.88% and 3.12 in PAL database for accuracy and mean absolute error (MAE), respectively. It was superior to the compared methods. In addition, the proposed method gave 88.84% and 4.81 in FG-NET for accuracy and MAE, respectively. The results showed the outstanding performance of the proposed method that outperformed the compared methods. This suggested us to continue finding the most powerful features and the improved method to enhance the performance on age estimation in future work.

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