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A New Skin Color Detection Approach based on Fuzzy Expert System

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Abstract

One of the most important applications of intelligent systems in medicine is using expert systems to help with the diagnostic-treatment decision making process. Designing a new Fuzzy Expert System is aimed at for detecting human skin from other materials intelligently. Skin detection is a challenging problem, because certain factors such as brightness change, a complicated background, and objects with colors similar to that of human skin represent the obstacles thereof. The dataset used in this research was adopted from the UCI accredited database having 245057 records, with each record having four fields. The skin is made up of R, G, and B color space segmentation obtained from the facial images of both genders in different age and racial groups. The results achieved show that this system has managed to detect human skin with 80% accuracy using the help of expert's knowledge on human skin detection such as dermatologists and digital image processing experts.

Keywords: Expert System, Fuzzification, Fuzzy Logic, Fuzzy Rules, Human Skin Detection, Intelligent Detection

1. Introduction

In the real world, the human perceives and utilizes many concepts in a fuzzy manner (meaning inaccurate, unclear, and vague). For instance, even though words and concepts such as warm, cold, long, short, old, young, etc. do not denote a certain specific number, the human mind understands all of them quickly and with astonishing flexibility and employs them in its decision makings and deductions. While the machine merely understands numbers and works with precision. The variables in nature or in calculations are of two types: Quantitative values that can be represented by a number, and Qualitative values that are expressed on the basis of a feature. In a fuzzy set, each of these traits is defined by means of the membership function and a value between zero and one is assigned to it.

In the present decade, it has become prevalent to use soft computing in many applications from normal everyday tasks to the most complex creative processes of the human. One of its applications is necessary in medicine, i.e. the use of Fuzzy Expert System for helping with the diagnostic-treatment decision making process as well as determining the skin type. Skin is one of the unique features of humans. Skin detection has applications in various fields such as identification and identity confirmation based on facial characteristics, security and military applications, video conferences, camera remote control, skin tracking in video, managing pictorial information banks, information access, etc.

In what follows, previous works will be reviewed. In the third section, the applied method and the components of a proposed Fuzzy Expert System is described. In the fourth section, practical results and the research achievements will be evaluated and in the end, a conclusion will be drawn.

2. Lecture Review

RGB correspond to the three primary colors: red, green and blue, respectively. To reduce the dependence on

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lighting, the RGB color components are normalized so that sum of the normalized components is unity $(r + g + b = 1)$. Since the sum of these components is 1, the third component does not hold any significant information and is normally dropped so as to obtain a reduction in dimensionality. It has been observed that under certain assumptions, the differences the skin-color clusters in *rgb* space have relatively lower variance than the corresponding clusters in RGB and hence are shown to be good for skin-color modeling and detection[13,14]. Due to the above advantages, *rgb* has been a popular choice for skin-detection and has been used by Bergasa et al.[15], Brown et al.[16], Caetano and Barone[17], Oliver et al.[18], Kim et al.[19], Schwerdt and Crowley[20], Sebe et al.[21], Soriano et al.[22], Storring et al.[23],Wang and Sung[24], Yang and Ahuja[14],Yang et al.[13], Iraji[29]. The CIE (Commission Internationale de l'Eclairage) system describes color as a luminance component Y, and two additional components X and Z. CIE–*XYZ* values were constructed from psychophysical experiments and correspond to the color matching characteristics of human visual system. This color space has been used by Brown et al.[16], Chen and Chiang[25], Wu et al.[26].

This dataset was first compiled by Rajen Bhatt, Abhinav Dhall, IIT Delhi. In 2009, they presented a paper titled "Efficient Skin Region Segmentation using Low Complexity Fuzzy Decision Tree Model" in the Indian IEEE conference called INDICO[1]. In the same year, they presented a paper titled "Adaptive Digital Makeup" in the International Symposium on Visual Computing (ISVC). Leonid Sigal et al.[2] put forward a novel method for skin segmentation in real time systems and video conferences. This segmentation enjoyed a fairly reliable performance despite the great variety of skin types. This approach was effective even in brightness changes; in addition, the Markov's method is used in this study[3]. Bouzerdoum presented an algorithm for skin region segmentation in color images using color and edge information. For the first time, the color regions of skin were used for human skin color detection using Bayesian model[4]. Rodrigo Verschae et al. performed skin regions segmentation with high processing speed through examining the neighboring pixels[5]. Junwei Han et al. used a new method to solve the skin segmentation problem. At first, a general skin model was developed given a gesture of video sequences. The data were then gathered from several frames automatically. In the end, an SVM classification was used for skin pixel detection on the basis of active learning[6]. Mohammad Shoyaib et al. carried out skin detection using color distance map[7]. In another research, a novel facial recognition algorithm was introduced which was a hybrid of skin color segmentation and main components analysis which are named SCS-PCA[8]. K. K. Bhoyar et al. used a classifier called novel neural network symmetric to detect skin pixels from non-skin ones in color images[9]. Data mining methods such as k-means were also used for skin detection and considerable results were achieved[10]. Hamid A. Jalab used a cluster pixel model in this paper for skin segmentation under particular environmental conditions. The proposed model can overcome the sensitivity to brightness conditions and changes in complex backgrounds[11]. The review paper by P. Kakumanu et al. on skin detection and modeling is recommended for further study[27]. Finally, one of the best results associated with the issue is achieved by a fuzzy system which is combined by support vector machine (FS-FCSVM)[28].

3. Methods

Fuzzy systems are knowledge-based or rule-based systems. The heart of a fuzzy system is a knowledge base comprised of if-then fuzzy rules. An if-then fuzzy rule is an if-then expression certain parts of which are specified by a continuous membership function.

3.1 Fuzzy Expert System

Fuzzy logic appeared first among novel calculation approaches in 1965, when Professor Lotfizadeh developed the fuzzy set theory. The word "fuzzy" means inaccurate, unclear, and vague. Although fuzzy systems describe indefinite and unclear phenomena, fuzzy theory itself is a precise theory[12].

Our real world is much more complicated than one could come up with a precise description and definition for it. Therefore, an estimated, or in other words, fuzzy description should be introduced for a model which is acceptable and analyzable. With the progression toward the information era, major importance is placed on human knowledge. Hence, a hypothesis is required that can formulate human knowledge systematically incorporating it into engineering systems along with other mathematical models.

The knowledge needed for numerous problems under study takes one of the following distinctive forms:

- Objective knowledge, such as mathematical models, equations, and formulas that are developed in advance and are employed for solving conventional physics, chemistry, or engineering problems.
- Personal knowledge, such as information that can be to some extent described and expressed linguistically, but cannot be typically quantified using traditional mathematics. This type of knowledge is called tacit knowledge. Whereas both types of knowledge are required in practice, fuzzy logic endeavors to coordinate these two types in an orderly, logical, and mathematically plausible manner.

3.2 Proposed System

This research aimed at developing an intelligent fuzzy system for skin detection. The system can detect skin by receiving the components of an object. In this section, the design stages of FESDSkin are described and studied. By means of a dataset, this system has data matrix with dimensions of 4*245057 in which the first three columns are R, G, and B (X2, X1, and X3 features) and the values of the fourth column are class labels (1 for skin, 2 for non-skin) where skin detection is performed by introducing the three components R, G, and B. For higher system flexibility, MATLAB 6.2.2 was used for designing and implementing FESDSkin.

3.2.1 Fuzzification

Converting a variable with precise value into to a fuzzy quantity is called fuzzification. In this section, the data are analyzed and for each input of the membership functions, data range and type are explained. At first, system input and output should be introduced and then, proper if-then rules should be employed. To design membership functions and the specific features of each of them, experts' knowledge in different fields should be used. Advising experts were selected from two different types of expertise. The first group was dermatologists, because they are familiar with different human skin types, skin diseases, and characteristics of different skin types. The second group was digital image processing experts, because they constantly work with the facial skin of different humans and are familiar with the most subtle color details. The proposed system has three inputs called R (red color feature), G (green color feature), and B (blue color feature) and an output called Skin (skin feature). Figure 1 is an overview of the proposed fuzzy expert system.

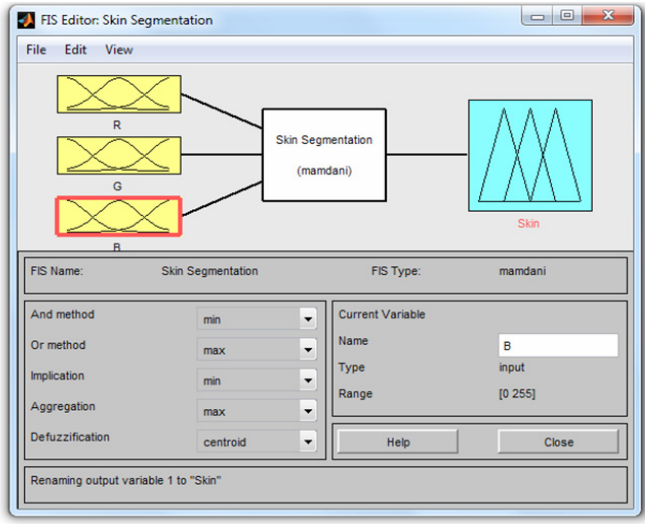


Figure 1. An overview of the proposed fuzzy expert system.

In this system, MIN operator, MAX operator, MIN, and MAX are used respectively for fuzzy AND, OR, intersection operator, and union function. The defuzzification method is center of gravity.

At first, in order for the correlation between the columns to be known, regression and correlation analyses are separately conducted on both columns of the dataset. The three colors are directly correlated indicating that if the value of the first column increases, the second and third columns react accordingly and increase.

3.2.1.1 Red Color Input

This component and input has the following charac teristics:

The first column, i.e. red color, starts from 26, its lowest value and reaches 225, its highest value. The lower the number is belong to the darker the color and vice versa. According to the experts' view, this field can be divided into six membership functions. It should, of course, not be forgotten that these functions share values with one another. Triangular functions were selected in order for the calculations to be carried out more simply and in a shorter period of time. Figure 2 shows the six input membership functions of the R component.

- Minimum: 26.
- Maximum: 225.
- Average: 113.87.
- Color R (Very Bold, Bold, Median, Pale, Very Pale, Very very Pale).

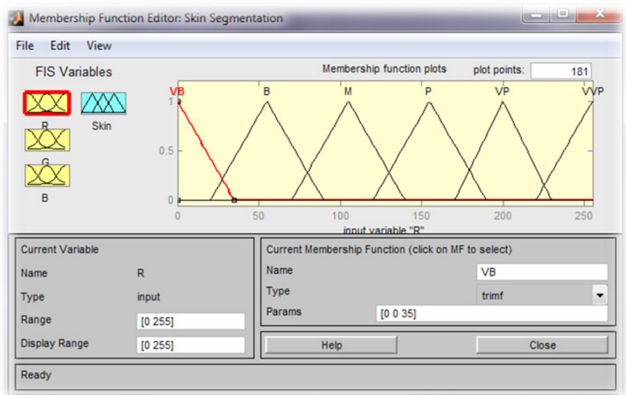


Figure 2. The six input membership functions of the R component.

In what follows, the equations used in this fuzzification may be seen (Equations 1).

Very Bold = (0, 35)

$$f_{VeryBold}(x,0,0,35)\begin{cases} 0 & x \le 0 \\ \dfrac{x-0}{0-0} & 0 \le x \le 0 \\ \dfrac{35-x}{35-0} & 0 \le x \le 0 \\ 0 & 35 \le x \end{cases}$$

Bold = (20, 90)

$$f_{Bold}(x,20,55,90)\begin{cases} 0 & x \le 20 \\ \dfrac{x-20}{55-20} & 20 \le x \le 55 \\ \dfrac{90-x}{90-55} & 55 \le x \le 90 \\ 0 & 90 \le x \end{cases}$$

Median = (70, 140)

$$f_{Median}(x,70,105,140)\begin{cases} 0 & x \le 70 \\ \dfrac{x-70}{105-70} & 70 \le x \le 105 \\ \dfrac{140-x}{140-105} & 105 \le x \le 140 \\ 0 & 140 \le x \end{cases}$$

Pale = (120, 190)

$$f_{Pale}(x,120,155,190)\begin{cases} 0 & x \le 120 \\ \dfrac{x-120}{155-120} & 120 \le x \le 155 \\ \dfrac{190-x}{190-155} & 155 \le x \le 190 \\ 0 & 190 \le x \end{cases}$$

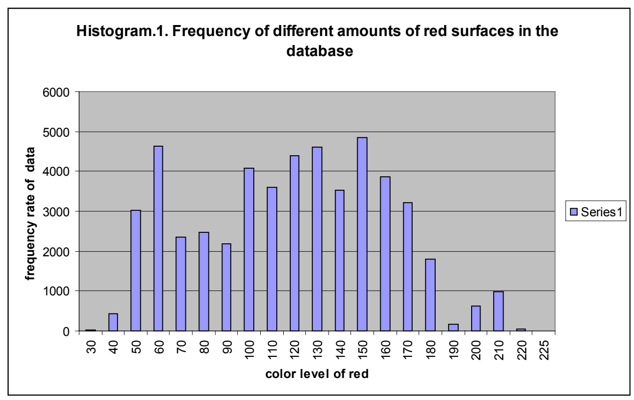
Very Pale = (170, 230)

$$f_{VeryPale}(x,170,200,230)\begin{cases} 0 & x \le 170 \\ \dfrac{x-170}{200-170} & 170 \le x \le 200 \\ \dfrac{230-x}{230-200} & 200 \le x \le 230 \\ 0 & 230 \le x \end{cases}$$

VVery Pale = (220, 255)

$$f_{VVeryPale}(x,220,255,255)\begin{cases} 0 & x \le \\ \dfrac{x-70}{105-70} & 70 \le x \le 105 \\ \dfrac{140-x}{140-105} & 105 \le x \le 140 \\ 0 & 140 \le x \end{cases}$$

Equations 1



The above diagram (Histogram 1) demonstrates the abundance of the different levels of the red color in data base samples. It is perfectly clear that abundance in levels below 50 and over 180 is much lower than other levels.

3.2.1.2 Green Color Input

In view of the data bank, this component has the following characteristics:

- Minimum: 56.
- Maximum: 230.
- Average: 146.60.
- Color G (Very Bold, Bold, Median, Pale, Very Pale, Very very Pale).

Investigations indicate that the best state for this component is having six triangular membership functions. The existence of these membership functions causes increased detection accuracy, because human skin detection

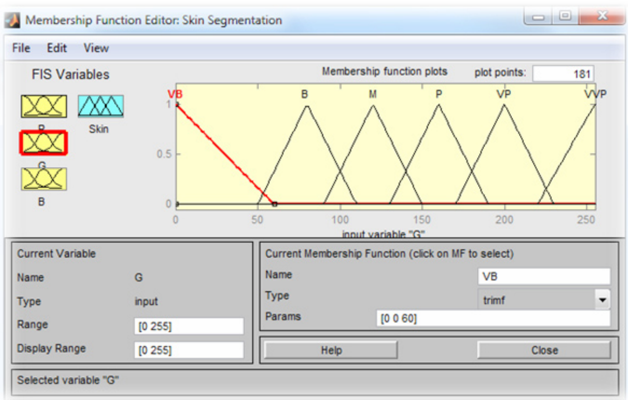


Figure 3. The six input membership functions of the G component.

is a difficult challenging problem owing to the innate characteristics of the skin. Whereas human skin generally has a small percentage of green, the value range of the "Very Bold" membership function was considered bigger (Figure 3).

In what follows, the equations used in this fuzzification may be seen (Equations 2).

Very Bold = (0, 60)

$$f_{VeryBold}(x,0,0,60)\begin{cases} 0 & x \le 0 \\ \dfrac{x-0}{0-0} & 0 \le x \le 0 \\ \dfrac{60-x}{60-0} & 0 \le x \le 0 \\ 0 & 60 \le x \end{cases}$$

Bold = (50, 110)

$$f_{Bold}(x,50,80,110)\begin{cases} 0 & x \le 50 \\ \dfrac{x-50}{80-50} & 50 \le x \le 80 \\ \dfrac{110-x}{110-80} & 80 \le x \le 110 \\ 0 & 110 \le x \end{cases}$$

Median = (90, 150)

$$f_{Median}(x,90,120,150)\begin{cases} 0 & x \le 90 \\ \dfrac{x-90}{120-90} & 90 \le x \le 120 \\ \dfrac{150-x}{150-120} & 120 \le x \le 150 \\ 0 & 150 \le x \end{cases}$$

Pale = (130, 190)

$$f_{Pale}(x,130,160,190)\begin{cases} 0 & x \le 120 \\ \dfrac{x-120}{155-120} & 120 \le x \le 155 \\ \dfrac{190-x}{190-155} & 155 \le x \le 190 \\ 0 & 190 \le x \end{cases}$$

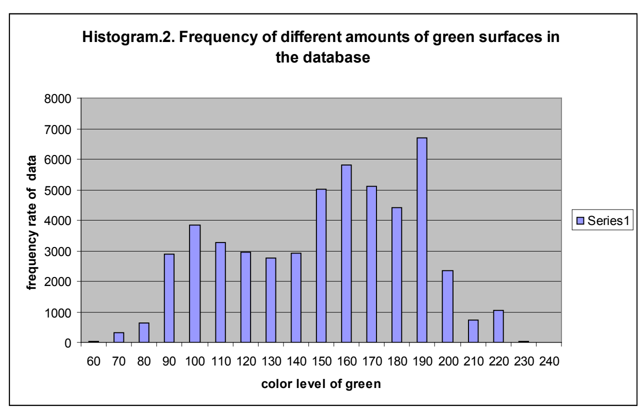
Very Pale = (170, 230)

$$f_{VeryPale}(x,170,200,230)\begin{cases} 0 & x \le 170 \\ \dfrac{x-170}{200-170} & 170 \le x \le 200 \\ \dfrac{230-x}{230-200} & 200 \le x \le 230 \\ 0 & 230 \le x \end{cases}$$

VVery Pale = (220, 250)

$$f_{VVeryPale}(x,220,255,255)\begin{cases} 0 & x \le \\ \dfrac{x-70}{105-70} & 70 \le x \le 105 \\ \dfrac{140-x}{140-105} & 105 \le x \le 140 \\ 0 & 140 \le x \end{cases}$$

Equations 2



The above diagram (Histogram 2) shows the abundance of the different levels of green existing in data bank samples. According to the diagram, the abundance of the levels below 90 and over 200 is less than that of other levels. The greatest abundance was also between the levels 150 to 200.

3.2.1.3 Blue Color Input

In view of the data bank, this component has the following characteristics:

- Minimum: 106.
- Maximum: 255.
- Average: 203.99.
- Color B (Very Bold, Bold, Median, Pale, Very Pale).

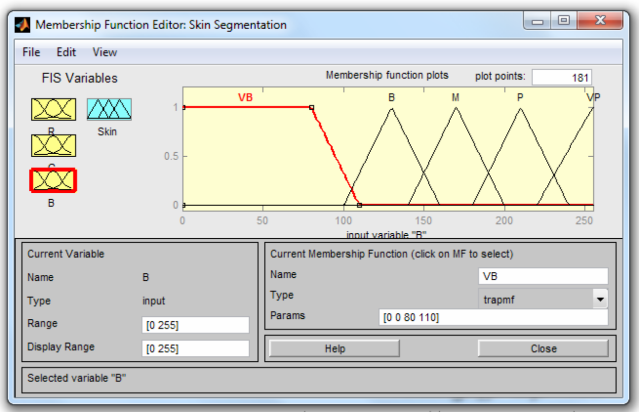


Figure 4. The five input membership functions of the B component.

The color blue consists of five membership functions, one trapezoidal and four triangular. According to the experts' view, the "VB" membership function enjoys a wider range, because human skin lacks this level of blue and all these levels may easily be summarized in one function. Figure 5 is the blue color input of this expert system.

Very Bold = (0, 110)

$$f_{VeryBold}(x,0,0,80,110)\begin{cases} 0 & x \le \\ \dfrac{x-0}{0-0} & 0 \le x \le 0 \\ 1 & 0 \le x \le 80 \\ \dfrac{110-x}{110-80} & 80 \le x \le 110 \\ 0 & 110 \le x \end{cases}$$

Bold = (100, 160)

$$f_{Bold}(x,100,130,160)\begin{cases} 0 & x \le 100 \\ \dfrac{x-100}{130-100} & 100 \le x \le 130 \\ \dfrac{160-x}{160-130} & 130 \le x \le 160 \\ 0 & 160 \le x \end{cases}$$

Median = (140, 200)

$$f_{Median}(x,140,170,200)\begin{cases} 0 & x \le 140 \\ \dfrac{x-140}{170-140} & 140 \le x \le 170 \\ \dfrac{200-x}{200-170} & 170 \le x \le 200 \\ 0 & 200 \le x \end{cases}$$

Pale = (180, 240)

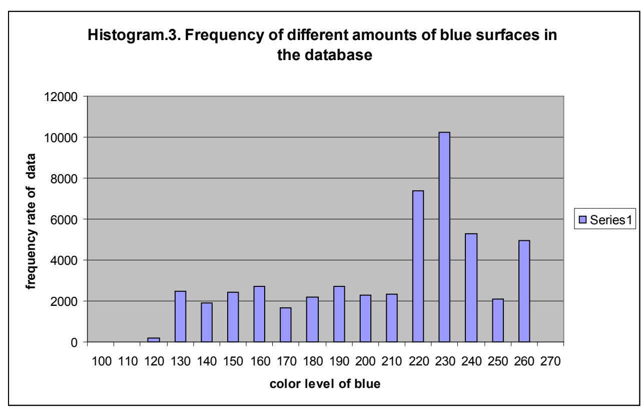
$$f_{Pale}(x,180,210,240)\begin{cases} 0 & x \le 180 \\ \dfrac{x-180}{210-180} & 180 \le x \le 210 \\ \dfrac{240-x}{240-210} & 210 \le x \le 240 \\ 0 & 240 \le x \end{cases}$$

Very Pale = (220, 250)

$$f_{VeryPale}(x,220,\ 255,\ 255)\begin{cases} 0 & x \le 220 \\ \dfrac{x-220}{255-220} & 220 \le x \le 255 \\ \dfrac{255-x}{255-255} & 255 \le x \le 255 \\ 0 & 255 \le x \end{cases}$$

Equation 3

As can be seen above, fuzzification equations of the blue color component are demonstrated (Equation 3).



Histogram 3 shows the variations rate of the abundance of blue color levels. According to the diagram, dark levels, i.e. levels below 220, have lower abundance in comparison with those between 220 and 240. This is quite evident, because human skin color lacks dark blue levels.

3.2.1.4 Output of System

This function is the most important component of a fuzzy system, because particular care should be exercised upon its definition. This function is comprised of four triangular membership functions, each of which demonstrates the membership degree of the respective object to human skin. In fact, the system output is a number between 0 and 100. The greater this value, the more the object resembles human skin. Figure 5 shows these four membership functions. The output membership function has the following characteristics:

- HSkin (Very Low, Low, Mid, High).

3.2.2 Fuzzy Rules

Fuzzy rules are a set of fuzzy variables interacting by the above operators. They constitute conditions and the response to the conditions leads to certain decisions. In a fuzzy rule, merely the membership value from conditions is attributed to the decision. In this section, given the correlation relation, the relation is linear and direct in a way that if the value of the first column increases, the second and third columns react accordingly and increase. Oppositely, as could be seen in the previous section, the lowest and highest values of each column and field were determined. Now, fuzzy rules can be implemented considering the correlation relation and the high and low values of each field.

It should be noted that fuzzy rules should be developed under experts' supervision and according to their knowledge. Otherwise, the results wouldn't be satisfactory. In the proposed system, 32 fuzzy rules were used. In what follows, a number of these rules are selected randomly.

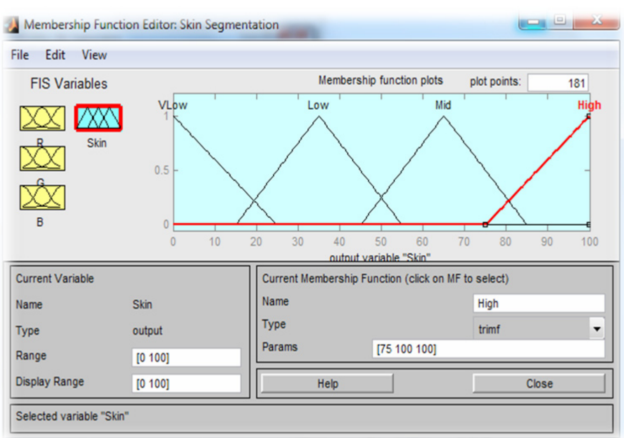
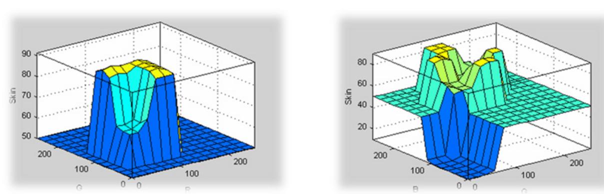


Figure 5. shows these four output membership functions.

Table 1. The numbers of fuzzy rules are selected randomly

✓	1. If (R is B) and (G is B) and (B is B) then	(Skin is Mid) (1)
✓	2. If (R is M) and (G is M) and (B is M) then	(Skin is Mid) (1)
✓	3. If (R is P) and (G is P) and (B is P) then	(Skin is Mid) (1)
✓	8. If (R is M) and (G is M) and (B is B) then	(Skin is High) (1)
✓	9. If (R is B) and (G is M) and (B is M) then	(Skin is Mid) (1)
✓	10. If (R is M) and (G is B) and (B is M) then	(Skin is High) (1)
✓	11. If (R is M) and (G is M) and (B is P) then	(Skin is High) (1)
✓	12. If (R is M) and (G is P) and (B is M) then	(Skin is High) (1)
✓	21. If (R is VP) and (G is P) and (B is VP) then	(Skin is High) (1)
✓	22. If (R is VP) and (G is VP) and (B is P) then	(Skin is High) (1)
✓	23. If (R is VB) and (G is VB) and (B is VB) then	(Skin is VLow) (1)
✓	24. If (R is VVP) and (G is VVP) and (B is VP) then	(Skin is VLow) (1)
✓	25. If (R is B) and (G is VB) and (B is VB) then	(Skin is VLow) (1)
✓	30. If (R is B) and (G is B) and (B is VP) then	(Skin is VLow) (1)
✓	31. If (R is VP) and (G is B) and (B is B) then	(Skin is VLow) (1)
✓	32. If (R is B) and (G is VP) and (B is B) then	(Skin is VLow) (1)

In Figure 6, the three-dimensional relationship between system inputs may be observed. These images can be extracted after registering fuzzy rules and the system's strengths and weaknesses can be figured out by use of them.



input : x(R) vs y(G) input : x(G) vs y(B)

Figure 6. The three-dimensional relationship between system inputs.

4. Experimental Results

In this section, a number of values within the dataset are randomly selected and the proposed system is tested. A sample of system testing may be seen in Figure 7. Given the below inputs, it has managed to estimate the similarity to human skin as much as 68.2%. This data has activated rule no 1.

- Test 1
  Fild1(R) = 74
  Fild2(G) = 85
  Filde3(B) = 123

The result is almost acceptable, because this data actually pertains to a sample of human skin. System testing was conducted at two stages: The first stage, test samples were selected from the bank in a way that all of the rules were exercised and their performance validity was evaluated. At the second stage, a series of special samples was presented to the system under specialists' supervision and the results were examined by experts. This stage improved the rules and resolved the problems of the proposed system.

- Test 2
  Fild1(R) = 81
  Fild2(G) = 87
  Filde3(B) = 130

As can be seen in Figure 8, rule no. 1 and 7 are fired and the output is 75.3% demonstrating the degree of similarity to skin.

- Test 3
  Fild1(R) = 142
  Fild2(G) = 142
  Filde3(B) = 196

Efforts were made upon system testing to use inputs that activate more rules, so that the resultant of several rules would also be evaluated and tested. As can be seen in Figure 9, rules no. 3, 15, 13, and 16 are fired and the output is 72.2% demonstrating the degree of similarity to skin.

- Test 4
  Fild1 (R) = 125
  Fild2 (G) = 157
  Filde3 (B) = 228

According to the Figure 10, rules no. 14, 3, and 17 are activated and the output is 69.3% demonstrating the degree of similarity to skin. So far, the system is tested using values that certainly resembled human skin to a great extent. In what follows, samples will be selected with other different values, so that system performance would be tested and evaluated also in presence of non-skin data.

Figure 7. A sample of system testing by R = 74, G = 85, B = 123.

Figure 8. A sample of proposed system testing by R = 81, G = 87, B = 130.

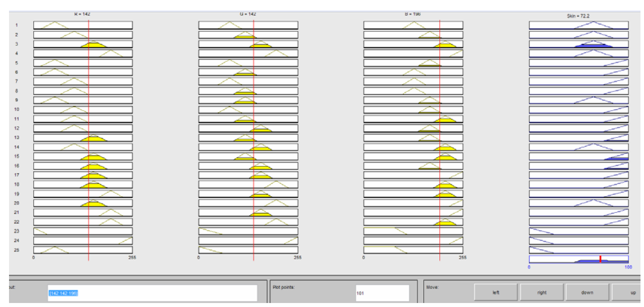


Figure 9. A sample of proposed system testing by R = 142, G = 142, B = 196.

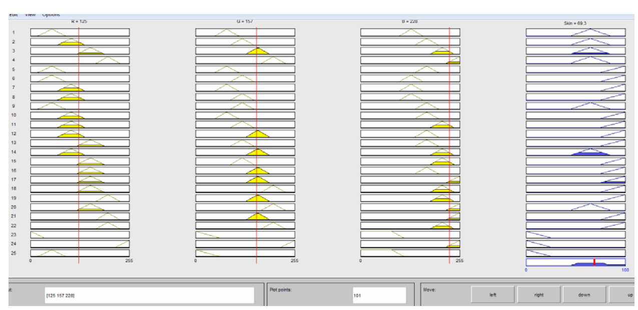


Figure 10. A sample of proposed system testing by R = 125, G = 157, B = 228.

- Test 5
  Fild1 (R) = 33
  Fild2 (G) = 34
  Filde3 (B) = 25

As can be seen (Figure 11), rule no. 25 is activated and the output is 10.1% indicating that this test does not resemble skin. This is a good instance of the high accuracy of system performance and it can be realized that fuzzy rules and inputs are properly selected and designed.

- Test 6
  Fild1 (R) = 66
  Fild2 (G) = 17
  Filde3 (B) = 9

As can be seen (Figure 12), rule no. 25 is activated and the output is 8.69% indicating that this test does not resemble skin.

- Test 7
  Fild1 (R) = 101
  Fild2 (G) = 77
  Filde3 (B) = 71

It can be seen clearly (Figure 13), rule no. 29 is activated and the output is 8.13% indicating that this test does not resemble skin. In this test, the data might resemble skin data at a superficial glance, but it turns out after testing that this data does not pertain to human skin.

Figure 11. A sample of proposed system testing by R = 33, G = 34, B = 25.

Figure 12. A sample of proposed system testing by R = 66, G = 17, B = 9.

Figure 13. A sample of proposed system testing by R = 101, G = 77, B = 71.

In view of the tests performed on the system, the results are as follows:

Table 2. Performance results of the proposed system testing for twenty logical random data samples

Value	R G B	True	False
Lt1	140 160 210	✓	
Lt2	160 140 200	✓	
Lt3	200 220 200	✓	
Lt4	53 84 160	✓	
Lt5	40 100 180	✓	
Lt6	70 110 100		✓
Lt7	80 140 130	✓	
Lt8	98 123 142	✓	
Lt9	100 130 100		✓
Lt10	221 204 212	✓	
Lt11	175 190 236	✓	
Lt12	144 166 231	✓	
Lt13	113 148 221	✓	
Lt14	181 178 134		✓
Lt15	137 149 153		✓
Lt16	180 178 130		✓
Lt17	82 84 32	✓	
Lt18	255 255 255	✓	
Lt19	125 161 221	✓	
Lt20	98 147 223	✓	
Accuracy of system		**80 %**	

- Considering the number of the rules developed, the system is capable of detecting HSkin from non-Skin; that is, if the system encounters human skin values, it will consider it to be over 50% and if facing non-skin, it will consider it to be below 50%.
- The system appears to be successful in all test values pertaining HSkin.

In what follows, twenty logical random data samples are fed to the system to examine the performance. The results may be seen in Table 2.

5. Conclusion

Fuzzy expert systems offer a comprehensive technique with very high potentials to detect human skin from other materials. This system can simulate human experience and knowledge from complex decision makings using approximate information and in environments with uncertainty. This fuzzy system operates in accordance with particular characteristics for detecting human skin. According to the input data, detection is categorized as *very low*, *low*, *median*, and *high*. In view of the results obtained, the proposed system managed to perform detection with 80% accuracy. The specialists considered this result to be acceptable. It is not claimed that the proposed system has the best performance. The authors would like to propose the application of neural networks along with fuzzy systems for better results and that the system would be able to detect the values more deterministically.

6. References

1. Bhatt RB, Dhall A, Sharma G, Chaudhury S. Efficient Skin Region Segmentation Using Low Complexity Fuzzy Decision Tree Model. Proceedings of the IEEE-INDICON; Ahmedabad, India. 2009 Dec. 16–18; p. 1-4.
2. Dhall A, Sharma G, Bhatt R. Adaptive Digital Makeup. Proceedings of International Symposium on Visual Computing (ISVC), Las Vegas, Nevada, USA. 2009. Nov 30–Dec 02. p. 728–36.
3. Sigal L, Sclaroff S, Athitsos V. Estimation and Prediction of Evolving Color Distributions for Skin Segmentation Under Varying. Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2000); 2000.
4. Phung SL, Bouzerdoum A, Chai D. Skin Segmentation Using Color and Edge Information. Proceedings of 2003 IEEE; 2003.
5. Ruiz-del-Solar J, Verschae R. Robust skin segmentation using neighborhood information. Proceedings of 2004 IEEE; 2003.
6. Han J, Award GM, Sutherland A, Wu H. Automatic Skin Segmentation for Gesture Recognition Combining Region and Support Vector Machine Active Learning. Proceedings 7th International Conference on Automatic Face and Gesture Recognition (FGR'06)–IEEE; 2006.
7. Abdullah-Al-Wadud M, Shoyaib M, Chae O. A Skin Detection Approach Based on Color Distance Map. Proceedings of Hindawi Publishing Corporation EURASIP. Journal on Advances in Signal Processing. 2008.
8. Lang L, Weiwei GU. The Face Detection Algorithm Combined Skin Color Segmentation and PCA. Proceedings of 2009 IEEE; 2009.
9. Bhoyar KK, Kakde OG. Skin Color Detection Model Using Neural Networks and its Performance Evaluation. Proceedings of Journal of Computer Science. 2010; 6(9)963–8. ISSN: 1549-3636.
10. Ng P, Chi-Man P. Skin Color Segmentation by Texture Feature Extraction and K-mean Clustering. Proceedings of 2011 IEEE Third International Conference on Computational Intelligence, Communication Systems and Networks; 2011.
11. Naji SA, Zainuddin R, Jalab HA. Skin segmentation based on multi pixel color clustering models. Proceedings of 2012 Elsevier Inc; 2012.
12. Available from: www.fa.wikipedia.org/wiki/History of 13. Fuzzy Logic.
13. Yang J, Lu W, Waibel A. Skin-color modeling and adaptation. ACCV98; 1998.
14. Yang MH, Ahuja N. Gaussian Mixture model for human skin color and its application in image and video databases. Proceedings of SPIE: Conference on Storage and Retrieval for Image and Video Databases. 1999; 3656:458–66.
15. Bergasa LM, Mazo M, Gardel A, Sotelo MA, Boquete L. Unsupervised and adaptive Gaussian skin-color model. Image and Vision Computing. 2000; 18(12):987–1003.
16. Brown D, Craw I, Lewthwaite J. A SOM based approach to skin detection with application in real time systems. BMVC01; 2001.
17. Caetano TS, Barone DAC. A probabilistic model for the human skin-color. ICIAP01; 2001. p. 279–83.
18. Oliver N, Pentland A, Berard F. Lafter: Lips and face real time tracker. CVPR97. 1997.
19. Kim SH, Kim NK, Ahn SC, Kim HG. Object oriented face detection using range and color information. AFGR98; 1998.
20. Schwerdt K, Crowely JL. Robust face tracking using color. AFGR00; 2000.

21. Sebe N, Cohen T, Huang TS, Gevers T. Skin detection, a Bayesian network approach ICPR04; 2004.
22. Soriano M, MartinKauppi JB, Huovinen S, Laaksonen M. Adaptive skin color modeling using the skin locus for selecting training pixels. Pattern Recognition Letters. 2003; 36(3):681–90.
23. Stoerring M, Koeka T, Anderson HJ. Granum E. Tracking regions of human skin through illumination changes. Pattern Recognition Letters. 2003; 24(11).
24. Wang JG, Sung E. Frontal-view face detection and facial feature extraction using color and morphological operations. Pattern Recognition Letters. 1999; 20:1053–68.
25. Chen C, Chiang SP. Detection of human faces in colour images. IEEE Proceedings of Vision Image and Signal Processing. 1997; 144(6):384–8.
26. Wu H, Chen Q, Yachida M. Face detection from color images using a fuzzy pattern matching method. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1999; 21(6):557–63.
27. Kakumanu P, Makrogiannis S, Bourbakis N. A survey of skin-color modeling and detection methods. Pattern Recognition Letters. 2007; 40:1106–22.
28. Juang, Chia-Feng, Shih-Hsuan C, Shen-Jie S. Fuzzy system learned through fuzzy clustering and support vector machine for human skin color segmentation. Systems, Man and Cybernetics, Part A: Systems and Humans. IEEE Transactions on 37. 2007; 6:1077–87.
29. Iraji, Saber M, Yavari A. Skin color segmentation in fuzzy ycbcr color space with the mamdani inference. American Journal of Scientific Research. 2011;7:131–7.