This article can be cited as P. Moallem, B. S. Mousavi and S. Sh. Naghibzadeh, Fuzzy Inference System Optimized by Genetic Algorithm for Robust Face and Pose Detection, International Journal of Artificial Intelligence, vol. 13, no. 2, pp. 73-88, 2015.

Fuzzy Inference System Optimized by Genetic Algorithm for Robust Face and Pose Detection

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ABSTRACT

A human face detection method for color images is presented in this paper, which is pose, size and position independent, and has the priority of classifying detected faces in three groups: frontal, near frontal and profile, according to their pose. This system is a fuzzy rule base one, optimized by genetic algorithm. In the first stage, skin color regions are selected in the input image. Within each skin area, lip pixels and ear texture are searched, and applied as features to identify face candidates in the skin regions. Summarizing all obtained information along by skin region shape and lip area position relative to skin area, four inputs are computed for fuzzy inference system, and face areas as well as their poses would be introduced. The proposed method is tried on various databases, including HHI, Champion, Caltech, Bao and IMM databases. Achieved results show a remarkable detection rates compared to other methods, for various face poses. 96.8%, 95.3% and 87.8% correct detection rates are achieved, respectively for frontal, near frontal and profile face images over 1298 face image samples.

Keywords: Face and Pose Detection, Fuzzy Inference System, Genetic Algorithm.

Mathematics Subject Classification: 62H35, 03B52.

Computing Classification System: I.4.7, I.4.8, I.5.1

1. INTRODUCTION

Identifying the location of all human faces in the image, called face detection, is a well-known pattern recognition problem. This task has received considerable attention due to its wide range of applications such as personal identification and access control, model-based video coding, face recognition, intelligent human-computer interaction and low-band width communication for video phone (Huang et al. 2011). Moreover, the face detection is a challenging problem. The wide range of allowable facial pattern variation in images is the key issue and difficulty in face detection. The detection performance may be affected by the presence or absence of glasses, bread, mustaches, imaging condition, camera characteristics and occlusion (Yang et al. 2002).

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In the spite of all above mentioned difficulties, extensive research has been conducted on various aspects of face detection by machines. Most detection systems carry out the task by extracting certain properties of a set of training images acquired at predefined poses in an off-line setting. These systems typically scan through the entire image at every possible location and scale to locate faces. The extracted properties can be either manually coded or learned from a set of data as adopted in the recent systems that have demonstrated acceptable results (Ali et al. 2011).

Repeating the detection process, a pyramid of images whose resolutions are reduced by a factor, is performed to detect faces at different scale (Rowley et al. 1998). By means of certain visual cues (e.g. color and motion) as pre-processing steps, the procedure speed would be increased (Schneiderman and Kanade 2004). A large number of proposed face detection methods can be grouped as: pixel-base (Sung and Poggio 1998), parts-based (Heisele et al. 2007), local edge features (Fleuret and Geman 2001), Haar wavelets (Papageorgiou and Poggio 2000), and Haar-like features (Dollar et al. 2007) methods. The recent systems with Haar-like features have shown acceptable empirical results in detecting faces under occlusion.

Also face detection can be formulated as a pattern recognition problem. As a result, numerous algorithms have been proposed to learn their generic templates such as eigenface and statistical distribution, such as neural network, fisher linear discriminant, sparse network of winnows, decision tree, Bayes classifier, support vector machine, and AdaBoost (Viola and Jones 2004).

Skin-color analysis has been the key feature in many above mentioned face detection algorithms in color images. Hsu et al. (2002) proposed a face detection algorithm based on a lighting compensation technique and a nonlinear transform that can be applied in a wide range of the skin-color. Unfortunately, this algorithm could not detect faces with all kind of poses. In fact, many of studies in the face detection domain are dedicated to a special kind pose. However, Jing and Chen (2009) proposed a system to detect face under various environment and poses, which combines the shape, color, and lighting distribution information.

In this paper a robust pose independent algorithm is proposed which has a priority of estimating face poses besides locating them in color images. To design more efficient system, after detecting face area, it will be classified as frontal, near frontal or profile. Pose estimation is very important in many face processing works including face modeling and face recognition. In general, face pose may present human physical states such as sleeping and concentration. As a result, it is very useful in many real-life applications, such as monitoring attentiveness of drivers or automating camera management (Liu et al. 2000). Moreover, head pose information is utilized to obtain cognitive cues about the user, such as the possible intention or gaze (Murphy-Chutorian and Trivedi 2009), and thus provides the means for the application to interact with the user in natural communication contexts such as in meetings (Ba and Odobez 2009). Humans can easily use the head pose information of other individuals for various cognitive tasks, such as detecting where one is used by Gurbuz et al. (2012).

Proposed method consists of several stages. In the first step, the skin regions are introduced in an input image. Through each of the separated skin regions, the face features, which are include lip and ear texture, are searched to materialize a robust pose/expression/lighting condition independent algorithm to locate faces and estimate poses in color images. This system is a fuzzy rule base one, optimized by genetic algorithms (GA).

Fuzzy set theory provides a framework to materialize a fuzzy rule base system which contains the selection of fuzzy rules, membership functions, and the reasoning mechanism. Such a system has been applied to many disciplines such as control systems, decision making and pattern recognition (Sivanandum et al. 2007), and in

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this paper it is supposed that such a system could overcome the complexity of the face detection problems, mainly are known as: variable conditions and diversity of human faces; as well as uncertainty of the basic face features.

However, it is often difficult for a human expert to define the fuzzy sets and fuzzy rules, used by these systems. GA as well as other well-known optimization algorithms have proven to be a useful method to optimize membership functions of fuzzy sets used by these fuzzy systems (Sivanandam and Deepa 2008, Bastos-Filho 2011, Precup et al. 2011, Zavoianu 2013, Hefnawy 2014). Following sections describe different stages of the proposed method in details.

Section 2 presents the skin color segmentation system including color space and skin color classification. Then Section 3 describes the proposed Fuzzy Inference System (FIS) face and poses detecting algorithm, its inputs/outputs and design. Some implementation results on various databases including frontal, near frontal and profile face images are presented in Section 4, and compared to various known robust algorithms to show the effectiveness of the proposed scheme. Last section is dedicated to the conclusion and future work.

2. SKIN COLOR SEGMENTATION

Skin color provides computationally effective and robust information against rotations, scaling, and partial occlusion. Therefore, it can be utilized as complimentary data to other features, such as shape and geometry, to build an accurate face detection system (Kakumanu et al. 2007). To apply this unique feature to detect faces in color images, firstly the suitable color space should be selected. Then, after modeling the color distribution, the way of color segmentation processing would be introduced. Different sections of our skin color segmentation algorithm are as follows:

2.1. Color Space

Color model selection is a primary step in the skin color classification. The RGB color space is the default one for most available image format and other color spaces could be obtained from a linear or non-linear transformation from RGB. Most widely used color spaces for the skin detection include: basic color spaces (RGB, normalized RGB, CIE-XYZ), perceptual color spaces (HIS, HSV, HSL, TSL), orthogonal color spaces (YCbCr, YIQ, Yuv, YES), and perceptually uniform color spaces (CIE-Lab and CIE-Luv) (Vezhnevets et al. 2003).

In the RGB color space, brightness and color information are coupled together, so it is not suitable for color segmentation under unknown lighting conditions. The transformation of RGB to perceptual color spaces is invariant to high intensity at white lights, ambient light and surface orientations relative to the light source. Hence, it has an acceptable performance to model the skin color. Since the output format used by digital camera or capturing equipment is usually either YCbCr or RGB, to avoid the extra computation required in conversion, the YCbCr color model is utilized in this work, which has the advantage of separating intensity component (Y) from the chroma components (Cb and Cr).

As the intensity is the main difference of various skin colors, in many skin classification researches, the intensity component is omitted. Simply discarding luminance information affects the model's accuracy. So, to obtain an optimum color space, different fraction of color space components are tried, and (1/3Y, Cr, Cb) is applied as the best to classify skin color.

2.2. Skin Color Classification

2.2.1. Designing Fuzzy Inference System

After transforming the input image in to the selected color space, the next step is searching the skin pixels, through the image. The fuzzy rule base system is designed in this stage.

Mamdani fuzzy system used is a 1-input, 1-output system applying the Euclidean distance between the color of each pixel to the average skin color sub-space as an input, and the likelihood of being skin pixel as an output. *Subtractive clustering* (Priyono and Ridwan 2005) is applied on input space (contain 150,000 skin and non skin pixels) to decide on the number of membership functions (MF's) and rules. Utilizing the obtained four clusters information and experimental knowledge, input and output MF's are designed. The semantic meaning assigned to each cluster for better understanding. The achieved rule in the skin segmentation FIS is:

IF input is Z, THEN output is Z
where $Z \in$ {Skin, Rather Skin, Low Probability Skin, Non-Skin}.

This system results in the skin-likelihood image, which is the gray-scale image whose gray values represent the likelihood of the pixel belonging to the skin. There should be an appropriate threshold to create a binary image by setting skin pixels to 1 and all other ones to 0.

2.2.2. Optimizing by GA

GA's are search algorithms their operations of GA are initialization, fitness evaluation, selection, mutation and crossover (Sivanandam and Deepa 2008). Each population consists of a number of chromosomes. In initialization, all the chromosomes in the population will be initiated with random values. Crossover produces new chromosomes that have some parts of both parent's genetic material. In GA, mutation modifies elements in the chromosomes randomly with low probability. The main role of mutation is to provide a guarantee that the probability of searching any individual will never be zero and to recover good genetic material that may be lost through the action of selection and crossover. A simple genetic algorithm can be summed up in seven steps as follows:

1) Start with a randomly generated population of n chromosomes.
2) Calculate fitness of each chromosome.
3) Select a pair of parent chromosomes from the initial population.
4) With a probability P_{cross} (the .crossover probability of the .crossover rate.), perform crossover to produce two offspring.
5) Mutate the two offspring with a probability P_{mut} (the mutation probability).
6) Replace the offspring in the population.
7) Check for termination or go to step 2.

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In this paper GA is used to obtain optimum MF shapes of fuzzy system. MFs and the threshold value are firstly designed empirically, as described in previous stage. GA, then applied to optimize fuzzy system MFs and select the suitable threshold. Our empirical knowledge is utilized to reduce the searching space and expedite the process. So, the MFs shapes are chosen according to previous designed system and the parameters of MFs plus the threshold are utilized as the inputs of the GA, whose fitness function defines by comparing the whole detected skin pixels in the image (*D*) with the actual number of these pixels (*A*). The fitness value, which should be minimized, is computed as follows:

$$\text{If } D = 0 \text{ then } \textit{Fitness} = 1, \text{ else } \textit{Fitness} = |1-A/D|$$

In this paper, the GA parameters are selected as follows:

Initial population = 100

Crossover coefficients= 0.8

Mutation coefficient (mutation is done in an un-uniform) = 0.03

Migration coefficient = 0.15

The obtained input and output MFs are shown in Fig. 1.

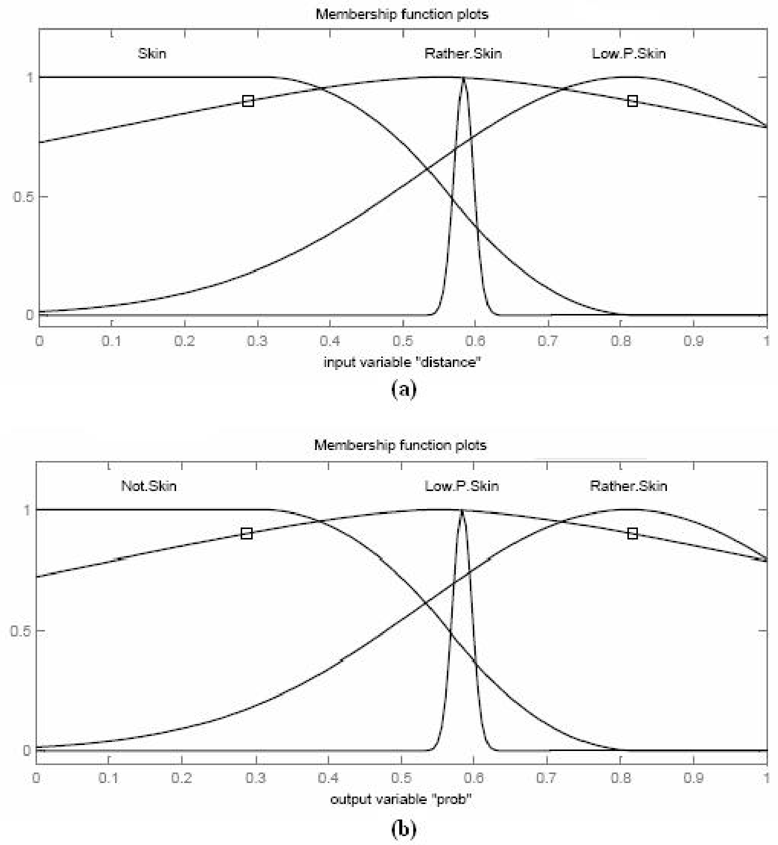

Figure 1. a) input MF and (b) output MF of skin color classification system

The threshold sets to 50% which means that the pixels with 50% or more probability are regarded as the skin pixels and, the binary image is formed. A morphological image processing, consists of filling holes and opening followed by closing, is accomplished on the binary image, to acquire separated and connected skin regions

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(Szeliski 2010). After labeling the connected components, each region is applied as the input for the next step. An example of applying this system on a sample image is illustrated in Fig. 2.

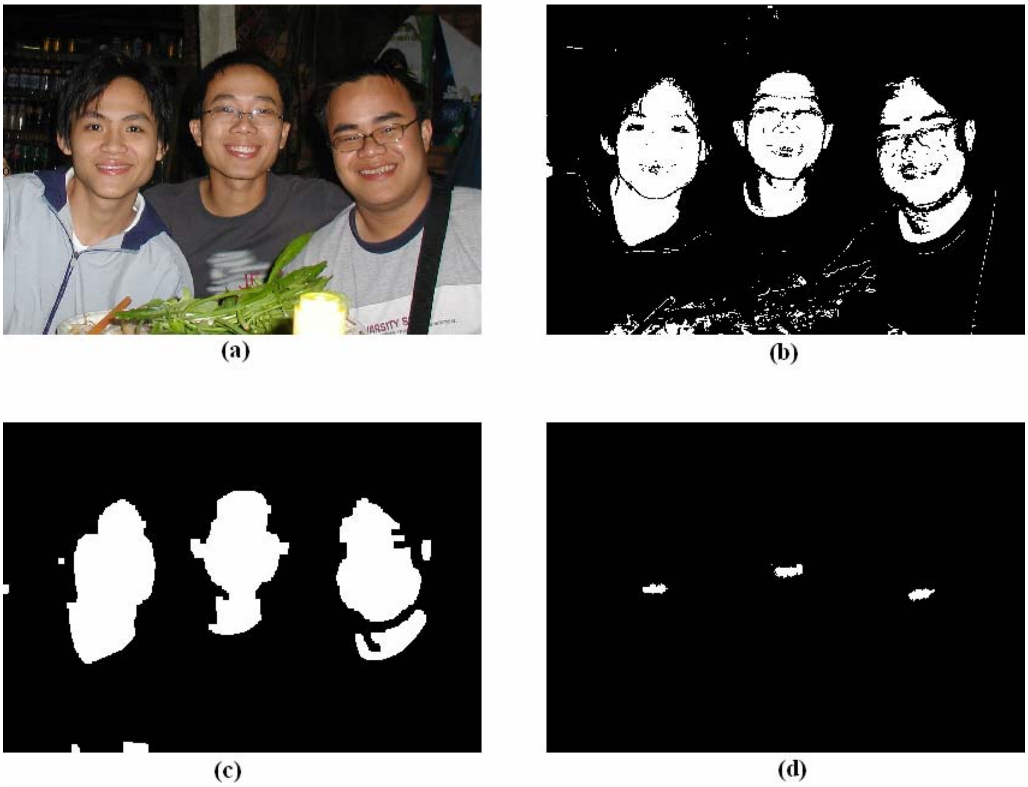

Figure 2. (a) input image, (b) detected skin pixels, (c) obtained result after morphological image processing, (d) detected lip area in each skin region

3. FACE and POSE DETECTION ALGORITHM

To select face blobs in the skin regions and reveal their corresponding pose, some facial feature should be checked. Although searching lip pixels is found more reliable, compare to other characteristics, it cannot be so useful for profile faces. Looking for ear texture is chosen as the robust method to find profile faces. Applying these features a fuzzy inference system is materialized, having the ability of detecting faces with different poses.

3.1. Defining FIS Inputs/Outputs

Three inputs and three outputs are defined for this system. Designing the precise system and reduce the false positive to the lowest possible value, are the main criteria in inputs/outputs selecting. The FIS inputs are as follows:

First input checks the skin area to locate the lip region. As the lip and eyes areas show the lowest intensity, within the face area, pixels owning the lowest intensity in the lower half of skin region are probably lip pixels. To confirm these pixels, color information is applied, either.

The normalized RGB color space, which has shown the best results in finding lip area, is utilized to look for lip pixels (Dargham and Chekima 2006). Equation (1) is computed as the first input of FIS:

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$$A = \frac{\sum_{i=1}^{i=n} r - \sum_{i=1}^{i=n} g}{n} \quad (1)$$

where *A* is the first input of fuzzy system and *n* is the number of low intensity pixels, detected in the lower half of skin region.

This value can be applied to locate lip area. Using GA, whose fitness function compares the whole detected lip pixels in the sample image with the actual number of these pixels and attempts to minimize the difference, 0.78 achieved as the best threshold value. Filling the holes and erosion plus opening by reconstruction (Kakumanu et al. 2007), are the morphological processing performed in binary image. Fig. 2 shows an example of obtained lip areas.

Second input is defined for profile faces detecting. Searching lip pixels could not be sufficient to locate profile faces. After investigating various characteristic, ear texture is found as the more suitable feature for these cases.

First of all, the ear location is estimated by its relative position to nose tip. The suggested process of finding nose tip by Yan and Bowyer (2007) is modified to be size invariant. The new process is as follows:
Suppose (x,y) is the corresponding coordinate of a pixel in an image. In the proposed algorithm for locating the nose, *X* values along each row which we first encounter a white pixel in the binary image is searched. With the median of these values (X_{median}) the approximation *X* value of the face contour is obtained. Then, the median of *Y* values in the range of X_{median} is calculated (Y_{median}). In the last step, the *X* value of nose tip is introduced as the minimum *X* values in the range of:

$$Y_{median} - (\frac{n}{2}) < Y < Y_{median} + (\frac{n}{2}) \quad (2)$$

where *n* is the number of *Y* values in the range of X_{median}. This method avoids the possibility of locating hair or chin as the nose tip. After determining the *x* and y of the nose tip, the ear location is estimated. Since the *Y* values of the nose tip and the ear are close, a horizontal search space which its *Y* value is equal to Y_{nose} is enough. Therefore, the *X* value of the search space is between the *x* value of the nose tip and the last skin pixel, in the same *Y* value. On the other hand, the ear dimension is estimated using area of the detected face. In the search region of ear existence, the properties of texture are evaluated. Fig. 3 shows a sample image of the profile face, binary skin region and nose location, and finally, the search region for estimating ear location.

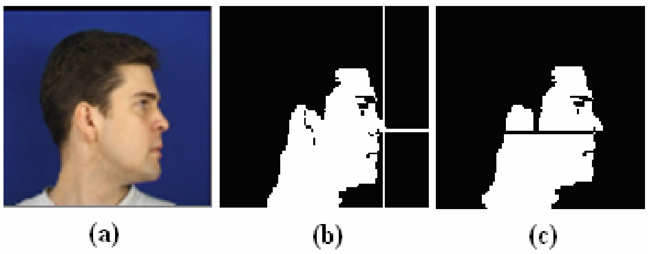

Figure 3. (a) main image, (b) skin region and nose tip position, (c) divide region to estimate ear area

After studying various texture classification methods (Hettiarachchi et al. 2014, Peters et al. 2013), Geometric Moment (GM), that is scale, position and orientation invariant, is chosen to evaluate ear area (Flusser 2006). A set of 10 ear images is collected to investigate the moment values. Two first moments, Φ_1 and Φ_2, are sufficient and more suitable to verify ear texture. Therefore, $\Phi_1+\Phi_2$ is computed as the second input of FIS.

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Third input reveals the similarity of skin region shape to an ellipse, to reduce the false positive of algorithm. Most template matching approaches are size dependent. So, instead of template defining, an estimated ellipse is drawn using area features (center of mass, maximum length line, minimum length line). For different head pose, the number of skin pixels that lie in this ellipse, could be approximated.

Fourth input (*D*) is the distance between the center of mass of skin region and the center of mass of lip region. As the pose estimation should be performed beside locate the faces, this input is defined to more accurate pose estimating. This input is also directly depend on face poses and varies with different turn angles.

Three outputs, called frontal, near frontal and profile, are considered for this FIS. They are respectively express the likelihood of a region being frontal, near frontal and profile face. Choosing suitable threshold for these outputs face areas would be introduced; in addition, they would be classified according to their pose. The block diagram of the proposed decision system is shown in Fig. 4.

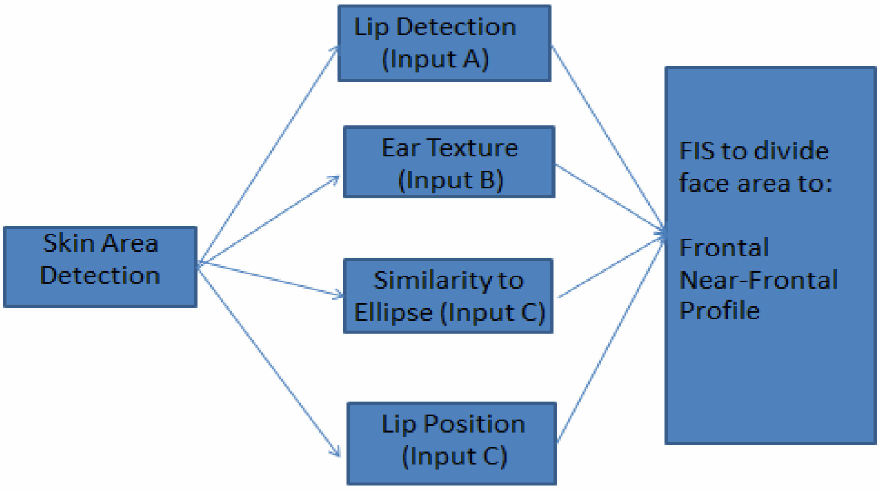

Figure 4. Block diagram of the proposed decision system

3.2. FIS Design

A Mamdani fuzzy inference system is designed based on described inputs and outputs. In the first stage, subtractive clustering is applied on input space, contain 150 non-face and face images with various poses, to decide on the number of membership functions. Assigned semantic meanings to clusters are as follows:

A: {Lip, Rather Lip, Non-Lip}

B: {Ear, Non-Ear}

C: {Frontal, Near Frontal, Profile}

D: {Frontal, Near Frontal, Profile}

Frontal Output: {Frontal, Non-Frontal}

Near Frontal: {Near Frontal, Non- Near Frontal}

Profile Output: {Profile, Non-Profile}

Applying the obtained clusters information and experimental knowledge, input and output MF's are designed. To achieve precise system with maximum flexibility a GA is applied over 52 randomly selected frontal, near frontal

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and profile face images, to design MFs and choose a threshold for face blobs selection. MF's parameters and three threshold values are computed as the GA inputs, and the defined fitness function attempts to maximize the likelihood of being face, with correct pose, for faces blobs. In Fig. 5 designed MFs are depicted. 65%, 59.5% and 63% of likelihood are selected to decide on frontal, near frontal and profile face regions, respectively.

4. EXPERIMENTAL RESULTS

4.1. Face Databases

As there is no standard image database to evaluate and compare face detection methods, most used databases with wide range of size, race, lighting condition, expression, pose and background are tried. These databases contain:

1. HHI face database including 206 face images (HHI Database 1998).
2. Champions face database including 227 face images (Campion Database 2001).
3. Bao database contains 150 one face images from various races, mostly from Asia, with wide range of size and pose (Bao Face Database 2001).
4. Caltech frontal face database, collected by Markus Weber at California institute of technology. There are 450 face images from 27 persons taken under different lighting, expression and background (Caltech Face Database 1999).
5. IMM face database contains 240 still images of 40 different human faces, including 7 female and 33 males with various facial expressions and poses (IMM Face Database 2002).
6. Due to the lack of profile face images in above databases, 25 profile faces images are added from (Yan and Bowyer 2007).

4.2. Obtained Results

The proposed algorithm is implemented under Matlab environment. To evaluate the performance of the proposed face detection system, some experiments are carried out with two first databases, separately. Table 1 shows the detection rates in HHI and Champion face databases, for the proposed method along by the result of Hsu et al. (2002), Jing and Chen (2009), Mousavi et al. (2008) and Moallem et al. (2011). The reported performances of the two first compared methods are extracted from Hsu et al. (2002), Jing and Chen (2009), since they also used HHI and Champion face databases. The two last compared methods are implemented in Matlab. In order to present a fair arbitration, we divide the face images to four different face poses in Table 1.

Table 2 compares the detection rates of the proposed method with the methods proposed by Ban et al. (2014) and Pan et al. (2013), for Bao, Caltech, IMM and CMU face databases. The reported detection rates of Ban et al. (2014) and Pan et al. (2013) methods are extracted from their reports, since they also used the same face databases. As it can be seen, the designed system could perform acceptably, compared to the other robust algorithms, for various poses.

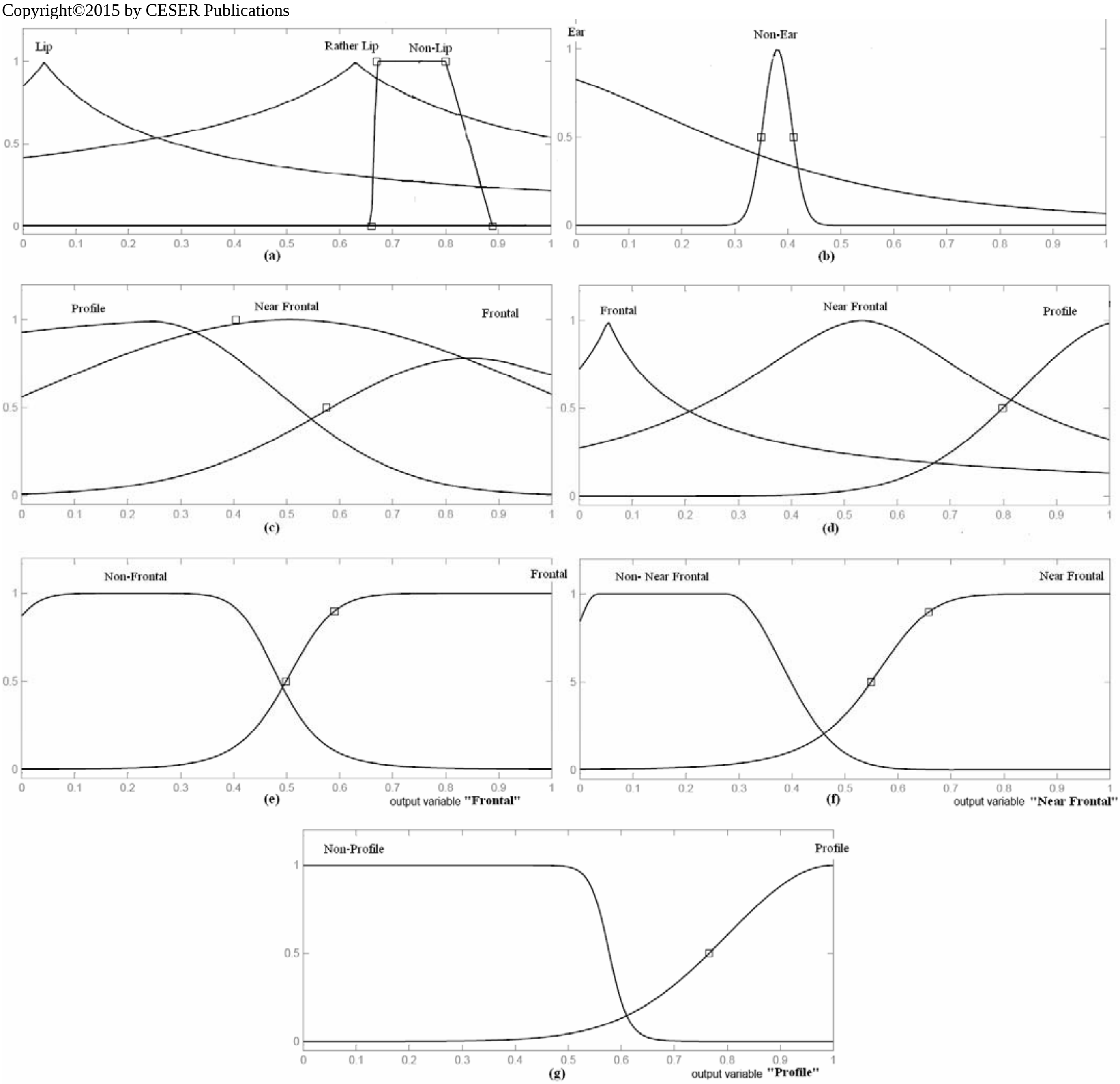

Figure 5. (a-d) inputs MFs, (e-g) outputs MFS of the proposed face detecting FIS.

In the last compared method (Moallem et al. 2011), four subsystems are applied which are tuned experimentally. Although, our new method show slightly lower detection rates in some cases, it has the advantage of applying one FIS to detect faces and poses, and obviously higher speed that is more suitable for real-time applications. The average processing times of the proposed algorithm and Moallem et al. (2011) algorithm, which are both implemented in Matlab environment, for the 296×448 images resolution on a 2.4 GHz Pentium 4, are about 0.5 and 1.5 seconds, respectively. Moreover, the proposed FIS is tuned automatically by GA, which made it much more flexible.

Table 1: Experimental Results on HHI and Champion Databases According to Different Poses

	HHI Database					Champion Database
Head Pose	Frontal	Near Frontal	Half Profile	Profile	Total	Total
No. of Image	66	54	75	11	206	227
Methods	Detection Rate (%)					
The Proposed	95.4	96.3	93.3	81.8	94.2	97.0
Jing et al. (2009)	92.4	98.1	92.0	90.9	93.7	95.1
Hsu et al. (2002)	88.4	90.7	74.7	18.2	80.6	91.6
Mousavi et al. (2008)	87.9	88.8	65.3	18.2	76.2	92.5
Moallem et al. (2011)	93.9	96.3	94.6	90.9	94.6	97.3

Table 2: Experimental Results on Bao, Caltech, IMM and CMU Face Databases

Database	Bao	Caltech	IMM	CMU
Methods	Detection Rate			
The Proposed	87.5	89	94.3	97.5
Ban et al. (2014)	65.9	65.4	77.4	58.7
Pan et al. (2013)	---	---	---	97.4

As there are just the images with one face and simple background in these databases, in the next experiment, the performance of the proposed method is investigated over all databases, including 1298 face images, which are divided in to three groups, according to their frontal, near frontal and profile pose. Obtained detection rates, which are summarized in Table 3, show that the proposed system can be used as a robust face and pose detection system in large databases which have high diversity on pose, expression and race. Fig. 6 shows examples of the system output.

Table 3: Summarized experimental results over all databases

Pose	Frontal	Near Frontal	Profile
Number of Images	1041	216	41
Detection rate	96.8	95.3	87.8

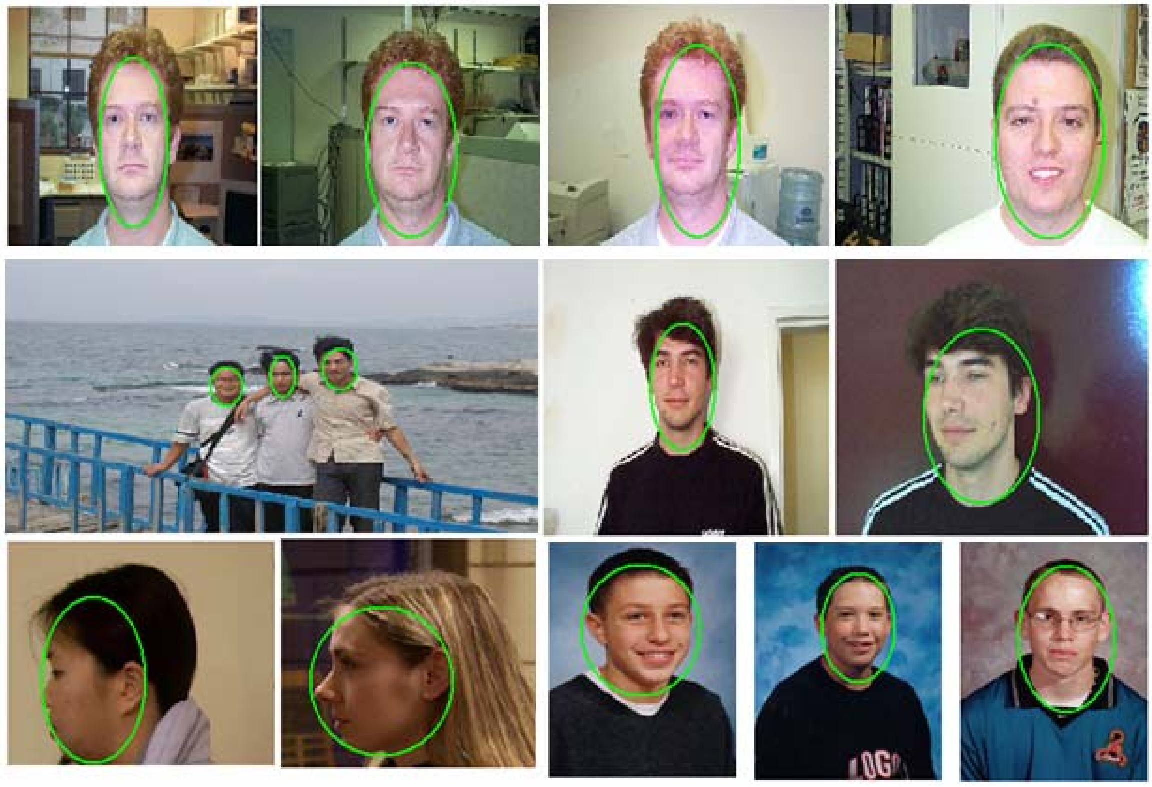

Figure 6. Examples of the outputs of the proposed FIS face detection

5. CONCLUSION and FUTURE WORKS

A novel system was proposed and described for face detection in color image. Two accurately tuned FIS's were employed. The first algorithm creates skin-likelihood image and selects skin blobs within an input image. In the second algorithm, along with the color information, intensity information, and approximated face shape for frontal/near frontal/profile faces, and ear texture properties were used to develop a pose independent FIS . In designing and tuning FIS, subtractive clustering was employed to decide on the number of MFs, and the optimum shape of MFs were achieved by the genetic algorithm. As a result, a robust fuzzy system is obtained which could detect faces with various pose, expression and race. Moreover, it could classify detected face areas in three groups: frontal, near frontal and profile, according to their pose.

To prove the efficiency of designed system, the obtained results were presented for HHI, Champion, Bao, Caltech, IMM, and CMU face databases and compared to six face detection algorithms. Moreover, the proposed system was applied on wide range of face images from different databases. The experimental results showed that the proposed system works well in detection of various poses. Detecting the profile, near frontal and frontal faces using a single algorithm, is remarkable advantage of the developed system. In addition, this algorithm could be utilized as the pose detection scheme as well.

On the other hand, the proposed system contains various subsystems, conclude in complexity increase. This feature, along with using fuzzy rule base algorithm, result in increasing execution time.

Simplifying the proposed system to use as a real-time one and estimating the face turn angle in images are the future plans.

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