Face Detection From Color Images Using a Fuzzy Pattern Matching Method

Haiyuan Wu, Qian Chen, and Masahiko Yachida

Abstract—This paper describes a new method to detect faces in color images based on the fuzzy theory. We make two fuzzy models to describe the *skin color* and *hair color*, respectively. In these models, we use a perceptually uniform color space to describe the color information to increase the accuracy and stableness. We use the two models to extract the skin color regions and the hair color regions, and then comparing them with the prebuilt *head-shape models* by using a fuzzy theory based pattern-matching method to detect face candidates.

Index Terms—Face detection, fuzzy pattern matching, perceptually uniform color space, skin color similarity, hair color similarity, head shape model.

1 Introduction

FACE detection from images is a key problem in human computer interaction studies and in pattern recognition researches. It is also an essential step in face recognition. Many studies on automatic face detection have been reported recently. Most of them concentrate on quasi-frontal view faces [3], [4], [5], [6], [7]. This is because the prior knowledge of the geometric relation with regard to the facial topology of frontal view faces can help the detection of facial features and it also makes the face modeling with a generic pattern possible. However, the quasi-frontal view assumption limits the kind of faces that can be processed.

A representative paradigm detects faces with two steps:

1) locating the face region [4], [9], [6], or assuming that the location of the face part is known [3], [5], [6], [7] and
2) detecting the facial features in the face region based on edge detection, image segmentation, and template matching or active contour techniques.

One disadvantage of step 1 is that the face location algorithm is not powerful enough to find out all possible face regions while remainning the false positive rates to be low. Another disadvantage is that the facial-feature-based approaches rely on the performance of feature detectors. For small faces or low quality images, the proposed feature detectors are not likely to perform well. Another paradigm is the visual learning or neural network approach [8], [10], [16], [11], [14]. Although the performance reported is quite well, and some of them can detect nonfrontal faces, approaches in this paradigm are extremely computationally expensive. A relatively traditional approach of face detection is template matching and its derivations [15], [12], [13]. Some of them can detect nonfrontal faces. This approach uses a small image or a simple pattern that represents the *average face* as the face model. It does not perform well for cluttered scenes. Face detection based on deformable shape models was also reported [17]. Although this method is designed to cope with the variation of face poses, it is not suitable for generic face detection due to the high expense of computation.

This paper describes a new face detection algorithm that can detect faces with different sizes and various poses from both indoor and outdoor scenes. The goal of this research is to detect all regions that may contain faces while remaining a low false positive output rate. We first develop a powerful skin color detector based on color analysis and the fuzzy theory, whose performance is much better than the existing skin region detectors. We also develop a hair color detector, which makes possible the use of the hair part as well as the skin part in face detection. We design multiple head-shape models to cope with the variation of the head pose. We propose a fuzzy theory based pattern-matching technique, and use it to detect face candidates by finding out patterns similar to the prebuilt head-shape models from the extracted skin and hair regions.

2 Detecting Skin Regions and Hair Regions

2.1 Perceptually Uniform Color Space

The terms *skin color* and *hair color* are subjective human concepts. Because of this, the color representation should be similar to the color sensitivity of human eyes to obtain a stable output similar to the one given by the human visual system. Such a color representation is called the *perceptually uniform color system* or UCS. Many researchers have proposed conversion methods from the Commission Internationale de l'Éclarirage's (CIE) *XYZ* color system to UCS. Among them, the $L^*u^*v^*$ and $L^*a^*b^*$ color representations were proposed by G. Wyszecki. Although they are simple and easy to use, both of them are just rough approximations of UCS. The psychologist Farnsworth proposed a better UCS through psychophysical experiments in 1957 [2]. In this color system, the MacAdam ellipses that describe the just noticeable chromatic difference become circles with approximately the same radius (see Fig. 1). This indicates that two colors, with an equal distance as perceived by human viewers, will project with an equal distance in this color system, and that is the feature we wanted.

We first convert the RGB color information in images to CIE's *XYZ* color system:

$$\begin{cases} X = 0.619R + 0.177G + 0.204B \\ Y = 0.299R + 0.586G + 0.115B \\ Z = 0.000R + 0.056G + 0.944B \end{cases}, \quad \begin{cases} x = \dfrac{X}{X+Y+Z} \\ y = \dfrac{Y}{X+Y+Z} \end{cases} \tag{1}$$

where Y carries the luminance information, and (x, y) describe the chromaticity. Then we convert the chromaticity (x, y) to the Farnsworth's UCS with a nonlinear transformation.[1] The result of this conversion is represented by a tuple value (u_f, v_f). The values of (u_f, v_f) of all visible colors are in the range of:

$$\begin{cases} u_f \to [0, 91] \\ v_f \to [0, 139] \end{cases}$$

2.2 Skin Color Distribution Model

In conventional methods, all visible colors are divided into two groups: One is the "skin color," and the other is not. However, con-

• H. Wu is with the Department of Mechanical and System Engineering, Kyoto Institute of Technology, Matsugasaki, Sakyo-ku, Kyoto 606-8585, Japan. E-mail: wuhy@ipc.kit.ac.jp.
• Q. Chen is with the Department of Design and Information Sciences, Faculty of Systems Engineering, Wakayama University, 930 Sakaedani, Wakayama, 640-8510, Japan. E-mail: chen@sys.wakayama-u.ac.jp.
• M. Yachida is with the Department of Systems and Human Science, Graduate School of Engineering Science, Osaka University, 1-3 Machikaneyama-cho, Osaka, 560-8531, Japan. E-mail: yachida@sys.es.osaka-u.ac.jp.

Manuscript received 16 July 1997; revised 2 Mar. 1999. Recommended for acceptance by D. Kriegman.
For information on obtaining reprints of this article, please send e-mail to: tpami@computer.org, and reference IEEECS Log Number 107728.

1. A C program to perform this conversion can be found at: http://www.sys.wakayama-u.ac.jp/~chen/ucs.html.

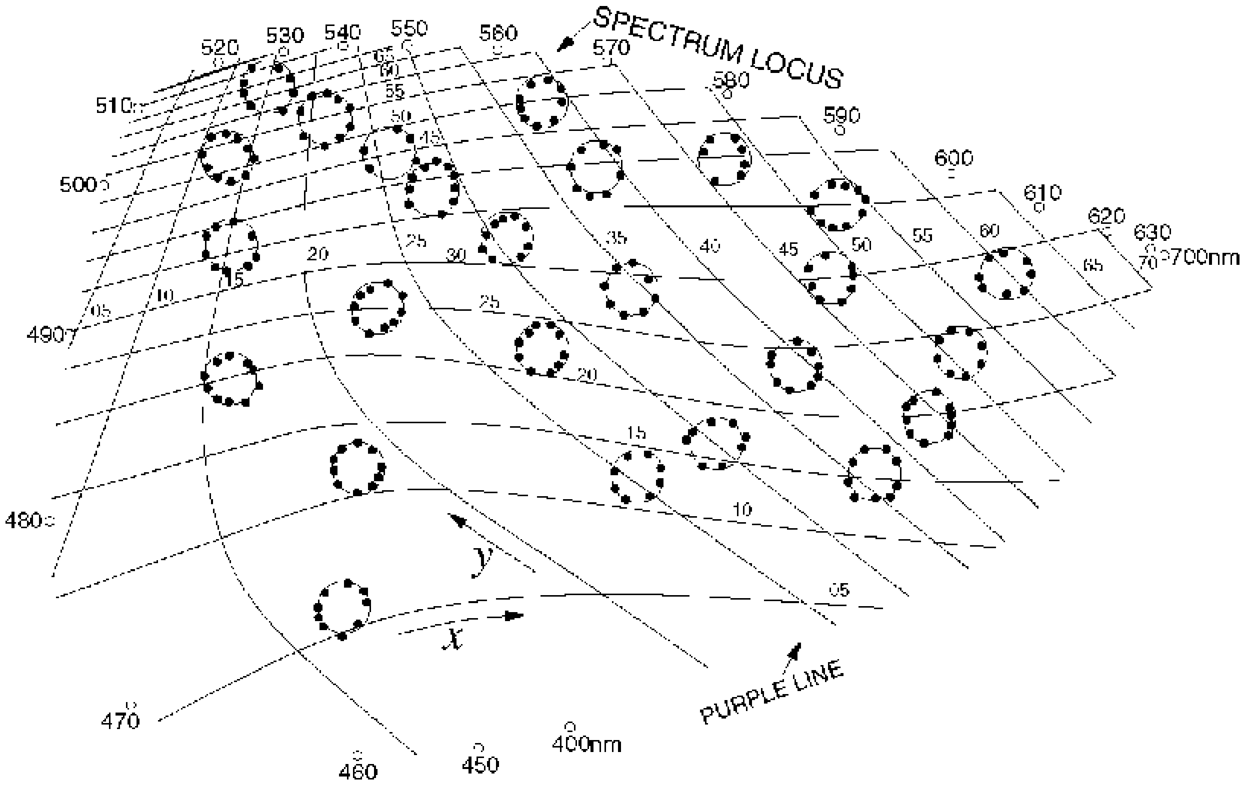
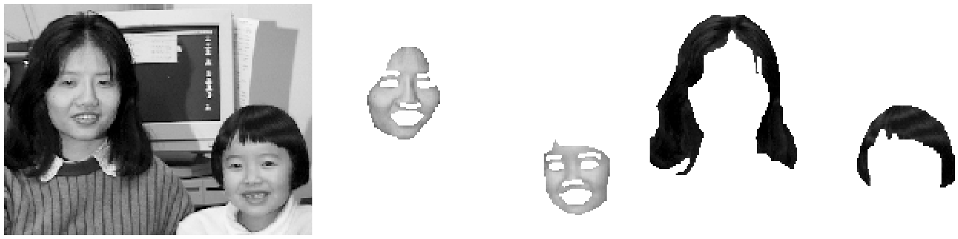


Fig. 1. Nonlinear transformation of the 1931 CIE chromaticity diagram where the transformed MacAdam's ellipses are very close to circles of equal size (from Farnsworth, 1957).



(a) (b) (c)

Fig. 2. An image used to build the SCDM and HCDM.

sider two colors near the boundary of the skin part. Although the difference between them is almost unnoticeable by a human viewer, one is regarded as "skin color" and the other is not. This is unnatural and is considered as one of the reasons of instability in conventional methods for skin color detection. We assign a value within [0.0, 1.0] to each point in the color space to indicate how much a visible color looks like the skin color. We call this value as *skin color likeness* and use a table to describe the skin color likeness of all visible colors. We call it the Skin Color Distribution Model, or simply SCDM. The SCDM is a fuzzy set of *skin color*. We use a large image set containing faces to investigate the distribution of color of the human skin region in order to build the SCDM. Fig. 2a shows a sample image. The procedure to build the SCDM is as follows:

1) Manually select skin regions in each image (see Fig. 2b).
2) Prepare a table of 92 × 140 entries to record the two-dimensional chromatic histogram of skin regions, and initialize all the entries with zero.
3) Convert the chromaticity value of each pixel in the skin regions to Farnsworth's UCS, and then increase the entry of the chromatic histogram corresponding to it by one.
4) Normalize the table by dividing all entries with the greatest entry in the table.

2.3 Hair Color Distribution Model

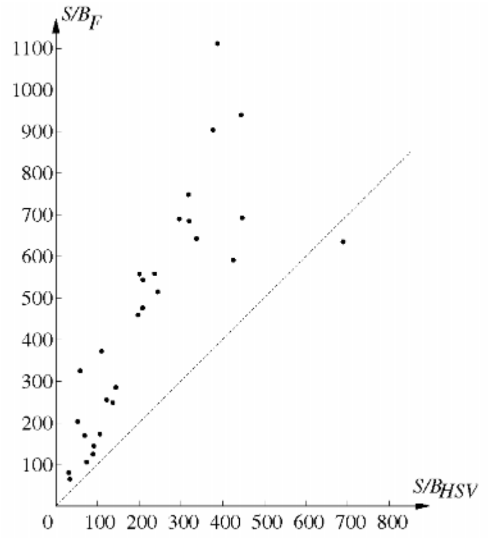
We use a model similar to SCDM to describe the hair color. We call it the Hair Color Distribution Model, or simply HCDM. The HCDM describes the hair color likeness of all visible colors. Because hair regions often show low brightness and the chromaticity estimation of low brightness color is not stable, we use the luminance information as well as chromaticity to describe the hair color. The HCDM is a function of three variables: the luminance Y and the chromaticities (u_f, v_f).

$$HCDM(Y, u_f, v_f) = HCDM_y(Y) \times HCDM_c(u_f, v_f). \tag{3}$$

where $HCDM_y$ and $HCDM_c$ are histograms of the luminance and chromaticity of hair regions respectively. We first investigate the distribution of color on the hair region in sample images (see Fig. 2c) in the luminance and chromaticity space, then we build $HCDM_y$ and $HCDM_c$ similarly as we build the SCDM.

Image		Skin	Background	S/B
1	F	0.5668	0.0023	248.5
	HSV	0.2287	0.0016	136.3
2	F	0.6224	0.0078	80.0
	HSV	0.3247	0.0110	30.5
3	F	0.6263	0.0031	203.1
	HSV	0.3450	0.0066	52.1

(a)



(b)

Fig. 3. The comparison results of the skin color detection using different color systems.

2.4 Skin Color Detector and Hair Color Detector

We use SCDM and HCDM to extract the skin color region and the hair color region, respectively, as follows. The results are the skin/hair color likeness of each pixel in the input image. We call them the Skin Color Similarity Map (or SCSM) and Hair Color Similarity Map (or HCSM).

$$\begin{cases} SCSM = SCS(p) = SCDM\big(u_f(p), v_f(p)\big) \\ HCSM = HCS(p) = HCDM\big(Y(p), u_f(p), v_f(p)\big) \end{cases} \quad (4)$$

where $Y(p)$, and $(u_f(p), v_f(p))$ are the luminance and chromaticity of pixel p in the input image, $SCS(p)$ and $HCS(p)$ are the skin color likeness and the hair color likeness of pixel p, respectively.

To investigate the effectiveness of using Farnsworth's UCS, we build two SCDMs with the same sample image set. One is our original SCDM, the other is the same as our SCDM, except that the color space is replaced by the HSV (Hue/Saturation/Value) color system. We prepare 29 test images and select the skin region by human viewers. We then estimate the average SCS values of the skin regions (we call it "Skin"), and of the nonskin regions (we call it "Background") for each test image with the two SCDMs. The results are summarized in Fig. 3. Fig. 3a shows the representative results of three images. The item "F" or "HSV" indicates that the results are given by our SCDM or by the SCDM using the HSV color system. The item "S/B" indicates the ratio of the "Skin" value to the "Background" value. In Fig. 3b, the horizontal axis indicates the S/B value given by our SCDM, and the vertical axis indicates the S/B value given by the SCDM using the HSV color system. Each dot in Fig. 3b shows the two S/B values estimated from one same image. The better skin color detector should give a higher "Skin" value and a lower "Background" value. In Fig. 3b, the S/B_Fs are greater than the S/B_{HSV}s for all the test images except one. This demonstrates the effectiveness of using the perceptually uniform color space in skin color detection.

3 Head-Shape Model

We ignore the detail of facial features and consider the face as a pattern composed of a skin part and a hair part. We abstract the appearance of faces in images into five kinds of pattern:

1) frontal view,
2) left side view,
3) right side view,
4) left diagonal view, and
5) right diagonal view.

Accordingly we make five head-shape models. Each head-shape model is a two dimensional pattern consisting of $m \times n$ square cells. We assign two properties to each cell: The skin proportion M_F and the hair proportion M_H, which indicate the ratios of the skin area or of the hair area within the cell to the area of the cell.

We build the head-shape models with the following procedure:

1) Collect images containing frontal faces, and the faces rotated to the left (and to the right) by 15, 30, 45, 60, 75, and 90 degrees.
2) Manually select the rectangular face region, the skin part, and the hair part in it, then divide it into $m \times n$ square cells.

(a) (b) (c) (d) (e)

Fig. 4. The primitive head-shape models.

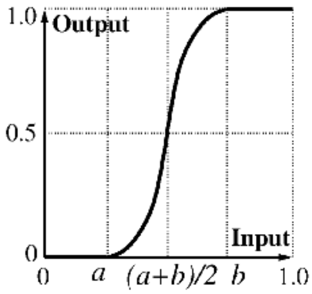


Fig. 5. The *S* type standard function.

3) Use the frontal-view face images and the images containing faces rotated to the left and to the right by 15 degree to calculate the average M_F and M_H for each cell. Then use them to build the frontal-view head-shape model.
4) Similarly, use the images containing faces rotated to the left (or to the right) by 30 and 45 degrees to build the left (or right) diagonal view head-shape model. Moreover, use the images containing faces rotated to the left (or to the right) by 60, 75, and 90 degrees to build the left (or right) side-view head-shape model.

Fig. 4 shows the head-shape models. The frontal-view model contains 10×13 cells, while the others contain 10×12 cells.

4 Fuzzy Pattern Matching

In the image correlation or template matching approach, the template (pattern model) must be a small image. In other words, the template must contain the same kind of information as the input image. In this research, we detect faces by comparing the head-shape models with the SCSM and HCSM. Because the head-shape models, SCSM and HCSM, describe different kinds of information, the image correlation or template matching approach can not be applied directly. Here, we describe a new pattern matching method for such cases based on the fuzzy theory. We call it *fuzzy pattern matching*. We first develop a method based on the fuzzy theory to estimate the skin proportion and the hair proportion from the average SCS and the average HCS of a square region. We also use the fuzzy theory to estimate the degree of similarity between the square regions in images and the cells in head-shape models.

4.1 Proportions of Skin Color Area and of Hair Color Area

In the case that the skin (or hair) color region are represented in binary images, the skin (or hair) color area can be estimated by counting the number of skin (or hair) color pixels. However, this is not the case in our research. To compute the proportion of the area of the skin (or hair) color part in a square image region, we first calculate the average skin hair color similarity a_s (or the average hair color similarity a_h) in the square region:

$$\begin{cases} a_s = \dfrac{\sum_{p \in region} SCS(p)}{n^2} \\ a_h = \dfrac{\sum_{p \in region} HCS(p)}{n^2} \end{cases} \tag{5}$$

where n is the size of the square region in pixels.

We define two fuzzy sets R_S and R_H: R_S (or R_H) is the fuzzy set of $A_S \ni a_s$ (or $A_H \ni a_h$), which is defined by a fuzzy membership function μ_{A_S} (or μ_{A_H}):

$$\mu_{A_S} : R_S \to [0,1]; \text{ or } \mu_{A_H} : R_H \to [0,1]. \tag{6}$$

R_S (or R_H) is used to describe the relationship between the average skin (or hair) color similarity a_s (or a_h) and the proportion of the skin (or hair) color part in a square region of the input image. We use two S type standard functions to represent μ_{A_S} and μ_{A_H}. An S type standard function is defined by the following equation:

$$S(x; a, b) = \begin{cases} 0 & x \le a \\ \dfrac{2(x-a)^2}{(b-a)^2} & a < x \le \dfrac{(a+b)}{2} \\ 1 - \dfrac{2(x-b)^2}{(b-a)^2} & \dfrac{(a+b)}{2} < x \le b \\ 1 & b < x \end{cases} \tag{7}$$

where $0 \le a \le 1$, $0 \le b \le 1$, and $a \le b$. The parameters a and b control the shape of the function (see Fig. 5). When a is close to b, the function will behave like a step function. If a is set to a big value, the output of the function will decrease, and if b is set to a small value, the output will increase.

In this research, we choose (a, b) to be (0.0, 0.6) for μ_{A_S} and (0.0,0.75) for μ_{A_H}. These are determined through experiments so that the proportions of the skin color area and of the hair color area given by the functions become similar to the one given by human viewers. Thus, the skin color proportion (R_S) and hair color proportion (R_H) can be estimated by the following equations:

$$\begin{cases} R_S = \mu_{A_S}(a_s) = S(a_s; 0.0, 0.6) \\ R_H = \mu_{A_H}(a_h) = S(a_h; 0.0, 0.75) \end{cases} \tag{8}$$

4.2 Fuzzy Pattern Matching Based on Two-Term Fuzzy Relation

To estimate the similarity between a square region in the input image and a cell in a head-shape model, we need some methods to compare the properties of the square region in the image (R_S and R_H) and the properties of the cell in a head-shape model (M_F and M_H). In the fuzzy theory, the degree of similarity between two sets of real number x_1 and x_2 is described by *two-term fuzzy relation*. It can be expressed by:

$$AE(x_1, x_2) = e^{-a|x_1 - x_2|^b}, \tag{9}$$

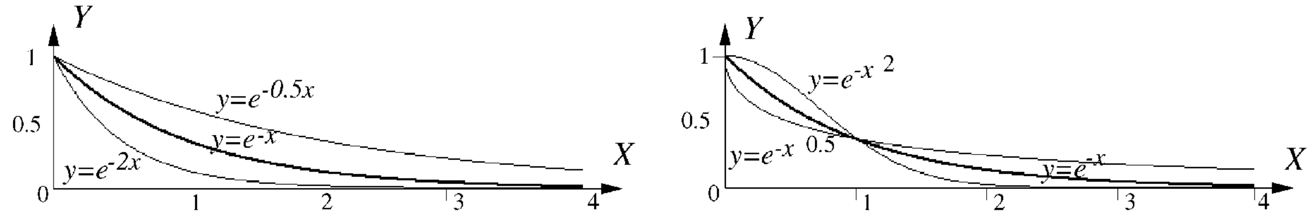


Fig. 6. The shape of the function e^{-ax^b}.

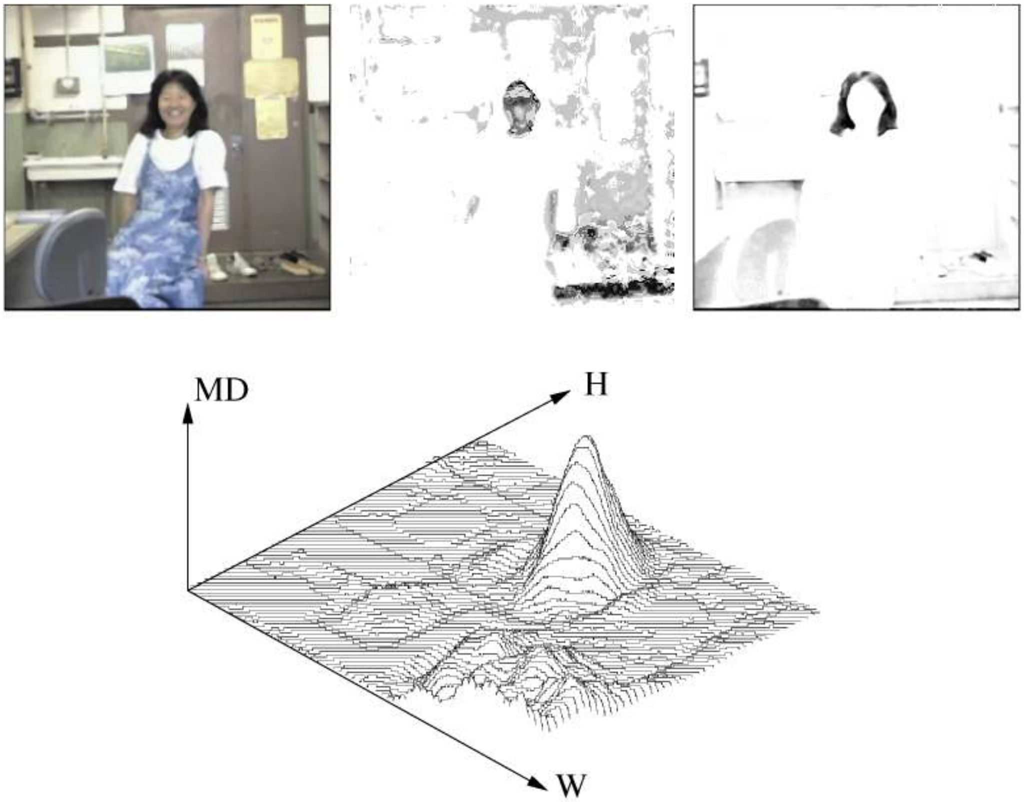


Fig. 7. An MMD obtained by comparing the skin-color similarity map and the hair-color similarity map with the head-shape models.

TABLE 1
TOTAL EXPERIMENTAL RESULTS

Face size (pixels)	Number of faces	Correctly detected faces	false positive	Detection rate(%)
Bigger than 100×120	25	25	0	100
Bigger than 50×60	124	120	3	97
Bigger than 20×24	74	67	15	90

where $a > 0$, and $b > 0$. The parameters a and b control the shape of the function (see Fig. 6).

To estimate the similarity between (R_S, R_H) and (M_F, M_H), we define the distance between them as the following:

$$\left|(R_S, R_H) - (M_F, M_H)\right| = \sqrt{(R_S - M_F)^2 + (R_H - M_H)^2}. \quad (10)$$

Thus, the degree of similarity between square regions in the image and the cells in the head-shape model can be calculated with the following equation, according to (9).

$$\begin{aligned} match(square, cell) &= AE(R_{S,H}, M_{F,H}) = e^{-a\left|(R_S, R_H)-(M_S, M_H)\right|^b} \\ &= e^{-a\left((R_S - M_F)^2 + (R_H - M_H)^2\right)^{0.5b}} \end{aligned} \quad (11)$$

We define the matching degree between a rectangular part in the image and a head-shape model as the sum of the degree of similarity between all cells in the model and the corresponding square regions in the image rectangle:

$$Match(rect, model) = \frac{\sum_{square \in rect} match(square, cell)}{m \times n}, \quad (12)$$

where m and n are the number of rows and columns of cells in a head-shape model.

To detect faces with different sizes and various poses, we compare all rectangular regions of the given size with the head-shape models. Each rectangular region is divided into $m \times n$ square subregions, each of them corresponding to a cell in the head-shape model. In this research, we let the size of the square subregion vary from one pixel to N pixels, where

$$N = \frac{\text{The height of image}}{\text{The number of cells in a column of the head shape model}}. \quad (13)$$

Therefore, there will be multiple matching degrees at the same position in an image. Each of them describes the matching degree of a rectangular region of a particular size. We select the one with the highest matching degree as the matching degree at the position and build a matrix to record the matching degree at all positions in an image. We call this matrix as *map of matching degree*, or simply MMD. It also carries the information about the size of the rectangle region and the kind of the head-shape model giving that matching degree.

We let a and b in (11) vary from 0.1 to 10 and use them to estimate the MMDs for various images. Then we select $a = 0.5$ and $b = 1$ that give the best MMDs. The "best" here means that the MMD shows high values in the face regions and low values in the non-face regions.

Fig. 7a shows an input image. Fig. 7b and Fig. 7c are gray-scale images that indicate the SCSM and HCSM estimated from

Fig. 8. Experimental results of face-candidate detection.

Fig. 7a, respectively. Fig. 7d shows the MMD. In the figure, the *W*-axis and the *H*-axis are the horizontal axis and the vertical axis of the image plane, and the *MD*-axis indicates the matching degree. One can see a "mountain" appearing at the position where the face exists. The matching degree (*Match*(*rect*, *model*)) in (12) can be considered as the likeness between the rectangular part (*rect*) and a face. We treat the rectangular image regions having the likeness greater than a given threshold as face candidates. We use 0.7 as the threshold in this research. All the local maximum of MMD greater than this threshold value are considered as face candidates. A higher threshold value will increase the reliability of the detected faces, but will also fail to detect some real faces. On the other hand, if a lower threshold is used, all faces in an image may be detected successfully, but many nonface regions may also be detected as faces.

5 Experiments and Results

We implemented our method on a PC compatible computer to construct a semi-real-time face detection system. The system is composed of a PC with a 266 MHz Pentium II, a full-color image capture card and a common video camera. All adjustable parameters or selectable modes of the video camera such as white balance, gain and so on are set to auto. We built two sets of SCDM and HCDM, one for the Asians and the other for the Caucasians. The SCDM and HCDM can be switched from one set to the other. The automatic model selection has not been implemented currently. We used seven-image sequences (five men and two women) to build the head-shape models.

We first tested our algorithm on 97 still color images, which are not in the image database used for building SCDM and HCDM. The images consist of indoor scenes under fluorescent light, and under the mixed illumination of fluorescent light and sunlight, as well as outdoor scenes. Many of them are from TV. There are 223 faces in the test image set. Among them, 186 are Asian faces, and the others are Caucasian faces. The face size varied from 20×24 pixels to 200×240 pixels. The experimental results are summarized in Table 1.

We also tested the system on live video sequences and movie videos. The processing speed was about 2.5 frames per second, and the system worked quite robustly and stably.

Some experimental results are shown in Fig. 8. The white rectangles in the figure indicate the detected face candidates. The upper one is the image *N7* (musician) from the *Graphic technology-Prepress digital data exchange-Stand colour image data, ISO/JIS-SCID*. The following images are picked up from the videotapes taken at the demonstration site of the *IEEE Third International Conference on Automatic Face and Gesture Recognition*. The last four images are from a video movie. Many of them contain faces of different races, and each face has a different pose.

As shown in the experimental results, the proposed method sometimes fails to detect the real face. Reasons under concern include the following:

1) Illumination: Because we use color to detect the skin part and the hair part of faces, the variance of the illumination color will affect the detection result. However, by using the automatic white balance mode of the video camera, and by using the stable behavior of the UCS color system and the fuzzy representation of skin/hair color, the change of the illumination color does not affect our method much, unless there is strong illumination of highly saturated color light.
2) Occlusion: If a face is largely occluded, the cells in head-shape models corresponding to the occluded part of the face will give low output, thus the total matching degree may not be high enough to let the face be detected.
3) Adjacent faces: If two or more faces are too close, the skin parts or hair parts of them may be merged together. The shape of the resulting skin-hair pattern may be very different from the one for a single face.
4) Hairstyle: Faces with special hairstyles, such as skinhead, or wearing a hat, may fail to be detected. This is because the shape of the skin-hair pattern of such a face in the image may become quite different from our head-shape model.

Our method may also give some false positives under some conditions. The most important reason is that we only use the shape of the skin-hair pattern and ignore all the details about facial features during the face detection. Due to this, one may make a "face" by putting his/her hand on a piece of black cloth. This is why we call the result of the detected faces as face candidates. There are cases that some objects such as brown paper or unpainted wood may show skin color. If there are some dark objects around them, they may also be detected as faces. Checking if there are facial features in these face candidates can help delete all these false faces.

In our method, the face detection is performed several times, each time we only try to detect faces of a specified size. There may be multiple partially overlapped rectangular regions that are considered as face candidates. We select the one having the highest matching degree as the face candidate and ignore the rest. If there are more than one rectangle having the same matching degree, we select the biggest one. This operation, as well as the fact that sometimes the background may be detected as hair mistakenly, would often cause the faces to be detected larger than they actually are.

6 Conclusion

This paper has described a new approach to detect the face in images. Because we use a perceptually uniform chromatic system and the fuzzy theory based models to describe the skin color and the hair color, our method can detect skin regions and hair regions much more accurately and stably than conventional approaches. It helps both increases the face detection rate and reduces the false positive rate. We have developed a new pattern recognition method called fuzzy pattern matching, which makes possible the pattern detection using a pattern description model carrying different kinds of information from the input image. This gives the flexibility in designing the head-shape model. Thus we could create head-shape models that describe the essential features of the head shape. All these make the face like patterns distinctive from others.

Compared with the existing face detection approaches, the skin color detection method is much more accurate and efficient. The multiple head pose models allow us to detect faces of various poses. By not looking at the details of facial features, our method will not be affected by small, local changes in a face. Therefore, the proposed approach is not sensitive to image noise or the change of facial expression and head-pose and is very robust. The experimental results showed that our approach could detect faces successfully in an uncontrolled environment with complex background. Compared with neural network based approaches, this method is much faster and the performance is also not bad. For each frame of image (320×240 pixels), our method compares over 500,000 rectangular regions with the five head-shape models within 0.5 second on a PC.

References

[1] Q. Chen, H. Wu, and M. Yachida, "Face Detection by Fuzzy Pattern Matching," *Proc. Fifth ICCV*, pp. 591–596, 1995.

[2] G. Wyszecki and W.S. Stiles, *Color Science*. New York: John Wiley & Sons, Inc, 1967.

[3] S.Y. Lee, Y.K. Ham, and R.-H. Park, "Recognition of Human Front Faces Using Knowledge-Based Feature Extraction and Neuro-Fuzzy Algorithm," *Pattern Recognition*, vol. 29, no. 11, pp. 1,863-1,876, 1996.

[4] C.H. Lee, J.S. Kim, and K.H. Park, "Automatic Human Face Location in a Complex Background Using Motion and Color Information," *Pattern Recognition*, vol. 29, no. 11, pp. 1,877-1,889, Nov. 1996.

[5] X. Jia and M.S. Nixon, "Extending the Feature Vector for Automatic Face Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 17, no. 12, pp. 1,167-1,176, Dec. 1995.

[6] E. Saber and A. Tekalp, "Face Detection and Facial Feature Extraction Using Color, Shape and Symmetry Based Cost Functions," *ICPR'96*, pp. 654-658, 1996.

[7] P. Sinha, "Object Recognition via Image Invariants: A Case Study," *Investigative Ophthalmology and Visual Science*, vol. 35, pp. 1,735-1,740, Sarasota, Fla., May 1994.

[8] P. Juell and R. Marsh, "A Hierachical Neural Network for Human Face Detection," *Pattern Recognition*, vol. 29, no. 5, pp. 781-787, 1996.

[9] Y.H. Kwon and N. da Vitoria Lobo, "Face Detection Using Templates," *ICPR'94*, pp. 764-767, 1994.

[10] A.J. Colmenarez and T.S. Huang, "Face Detection With Information Based Maximum Discrimination," *Proc. CVPR'97*, pp. 782-787, 1997.

[11] H.A. Rowley, S. Baluja, and T. Kanade, "Neural Network-Based Face Detection," *CVPR'96*, pp. 203-208, 1996.

[12] M. Lew and N. Huijsmanns, "Information Theory and Face Detection," *ICPR'96*, pp. 601-605, 1996.

[13] T. Leung, N. Burl, and P. Perona, "Finding Face in Cluttered Scenes Using Labeled Random Graph Matching," *ICCV'95*, pp. 637-644, 1995.

[14] R. Vaillant, C. Monrocq, and Y. Le Cun, "Original Approach for the Localization of Objects in Images," *IEEE Proc. Vis. Image Signal Processing*, vol. 141, no. 4, Aug. 1994.

[15] Y. Dai and Y. Nakano, "Face-Texture Model-Based on SGLD and Its Application in Face Detection in a Color Scene," *Pattern Recognition*, vol. 29, no. 6, pp. 1,007-1,017, June 1996.

[16] E. Osuna, R. Freund, and F. Girosi, "Training Support Vector Machines: An Application to Face Detection," *Proc. CVPR'97*, pp. 130-136, 1997.

[17] A. Lanitis, C.J. Taylor, T.F. Cootes, and T. Ahmed, "Automatic Interpretation of Human Faces and Hand Gestures Using Flexible Models," *Proc. Int'l Workshop Automatic Face- and Gesture-Recognition*, pp. 98-103, 1995.