Algorithm for Face Extraction Based on Lip Detection

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This paper proposes a new and simple algorithm for face extraction from a color image. The approach detects the lip region in a face object. First, the lip- and skin-color pixels in an image are extracted on the basis of statistical probability analysis. These lip- and skin-color pixels are segmented separately by using binary image processing techniques to produce lip- and skin-color regions. Each region that has a skin-color region and one or more lip-color regions as its subset regions is nominated as a face candidate. To detect only the face objects from the face candidates, the algorithm evaluates the values of seven pattern variables of those face candidates. A face candidate with all its seven pattern variable values within the valid range values of face object class is detected as a face object. Verifications of the proposed algorithm were provided by the experimental results that gave 91.8% detection of face objects from 104 sample images. This is significant for locating or detecting the faces in color images.

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Introduction

The segmentation and recognition of faces in scenes of various conditions that are relatively easy for humans but not for machine vision systems have been extensively studied during the last two decades. Related issues such as face detection, extraction of facial features, and recognition and identification of faces have attracted the interest of many disciplines such as computer vision,[1–3] pattern recognition,[4–6] artificial intelligence,[7,8] and neural networks.[9,10] Samal and Iyengar[11] and Chellappa, Wilson, and Sirohey[12] report literature surveys on human face recognition. The main reason of this curiosity is faces are the most interesting and important objects in scenes or images. They convey the identity, physical features, expression, and vitality of people. Contributing methods and systems with the capability to detect and/or recognize faces in images or scenes offer many practical applications in photographic processing, medical diagnosis, security systems, criminal identification, and human–machine interaction.

Much of the engineering literature reporting studies on human faces deals with the recognition of faces and extraction of facial features, and only a few deal with the segmentation of faces. Here, the segmentation of faces also means the detection or location of faces. Almost all of those studies work with input images with the locations of faces known a priori. In many cases when the location of a face in an image is unknown, first the system has to know the face is present and locate its position before the techniques of extraction of facial features and face recognition could be implemented. The segmentation of faces itself has many practical applications, for example, in image and photographic film processing,[13,14] detecting the presence of a face and tracking its location for warnings in security systems, compressing the whole image except facial region to reserve its quality in transmission, storage, and communication media,[2,17] and manipulating or animating the faces in still and video images.[18]

Various techniques for face extraction have been proposed in the literature,[6,14,19–24] and four of those are as follows: Govindaraju and colleagues locate the faces from newspaper photographs by matching the structural model of the face and the lines and arcs in the input image.[14] Craw, Ellis, and Lishman use template matching of model heads to extract the head outlines.[6] Turk and Pentland locate faces from motion images using motion detection and manipulation of the images in “face space.”[23] Yang and Huang locate human faces in a complex black and white picture using a hierarchical knowledge-based method that consists of three levels.[24] In a previous study, we proposed a new technique for extracting the faces from color images using knowledge-based multistep filtering.[25] This technique segments skin-color regions in a color image and then detects only the face objects in those regions based on shape information or mensuration parameters of face class. This technique performs badly in extracting face objects when skin-color regions merge with other skin-color objects, for example, objects made of wood, or cloth.

The objective of the current study also was to extract faces from color images using a new approach. In this study, we propose an algorithm for face extraction based on a simple idea. If a region has a skin-color region and a lip-color region as its subset regions, then the possibility exists that this region is a face object. In the following discussion, a region that has a lip-color and a skin-color region as its subset regions is called a “face candidate.” Because not all of the face candidates are face objects, consequently we have to evaluate and confirm the validity of each face candidate to be correctly classified to face class. To classify all face candidates, we evaluated seven pattern variables of the face candidates and extracted only face objects from face candidates by evaluating their seven pattern variable values. Because the approach was to extract the face object based on lip detection, in this article the term “face” was limited to a face object that has a lip region as its subset region, unless the same word is mentioned with an explicitly different meaning. Note that the face of interest in a color image usually has a lip region as its subset region.

The validity of this algorithm was verified by the experimental results that gave 91.8% extraction of face ob-

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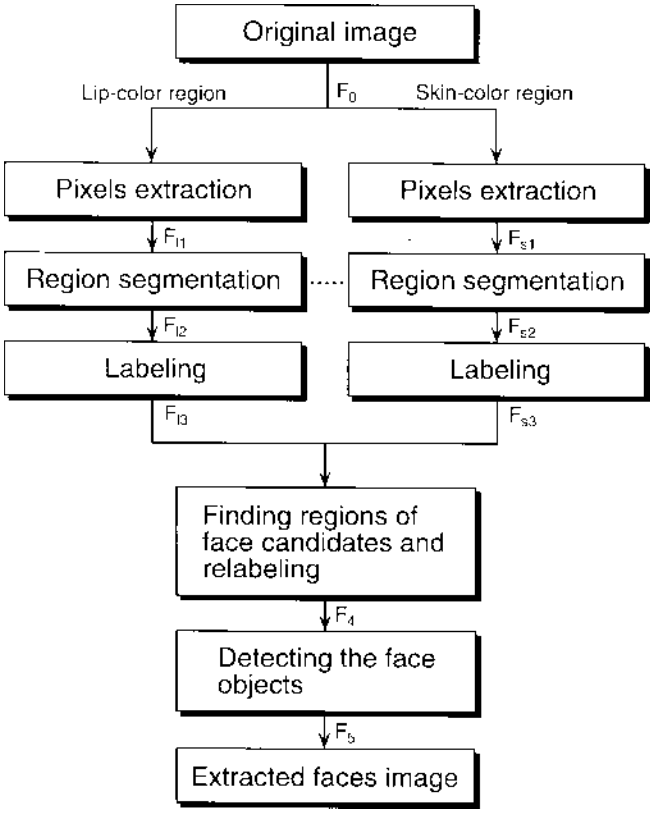


Figure 1. Block diagram of the method and experiments.

jects from 104 sample images, comprising 24 training images and 80 testing images. This technique is simple and automatic, and with some appropriate modifications could be applied to color images recorded with other imaging media such as photographic, still video camera, and digital camera images. This technique is significant as an alternative algorithm for locating or detecting face objects from a color image.

Method and Experiments

Figure 1 shows the block diagram of the method and experiments in the current study. As shown, lip- and skin-color regions are segmented and labeled separately. Regions of face candidates are determined by synthesizing lip- and skin-color regions in an image. The following subsections describe the procedure of the proposed algorithm.

Pixel Extraction. Pixel extraction was based on statistical probability analysis of ellipsoid distributions of pixel chromaticities in lightness intervals. Lightness was defined by

$$L = \frac{1}{\sqrt{3}}(R + G + B), \tag{1}$$

and red and green chromaticities by

$$r = \frac{R}{R+G+B}, \tag{2a}$$

$$g = \frac{G}{R+G+B}. \tag{2b}$$

The databases of chromaticities of lip- and skin-color pixels in lightness intervals were determined by measuring the R, G, and B values of sample pixels in the lip and skin regions of the original images F_o, respectively.

Red and green chromaticity distributions of samples of lip- and skin-color pixels can be expressed by the ellipsoid distribution equation[26,27]

$$2\left(1-\rho^2\right)Q(r,g) = \left(\frac{r-\bar{r}}{\sigma_r}\right)^2 - 2\rho\left(\frac{r-\bar{r}}{\sigma_r}\right)\left(\frac{g-\bar{g}}{\sigma_g}\right) + \left(\frac{g-\bar{g}}{\sigma_g}\right)^2, \tag{3}$$

where $Q(r,g)$ is a constant and ρ is the correlation coefficient.

$$\rho = \frac{\mathrm{cov}(r,g)}{\sigma_r\sigma_g} = \frac{E\{(r-\bar{r})(g-\bar{g})\}}{\sigma_r\sigma_g}. \tag{4}$$

Here, cov(r,g) is the covariance and $E\{(r-\bar{r})(g-\bar{g})\}$ is the expectation value. The curve $Q(r,g)$ equals constant is an ellipse, and $Q(r,g)$ represents the confidence level of ellipsoid distribution. For example, at $Q(r,g) = 1$, 2, and 3 the confidence levels are 63.2, 86.5, and 95%, respectively. Each interval lightness of lip- and skin-color pixels has one ellipsoid distribution. This study used this equation for extracting the lip- and skin-color pixels.

The algorithm extracted the lip- and skin-color pixels from image F_o. Chromaticities and lightness of all pixels in the image F_o were computed and analyzed with the databases of ellipsoid distributions of lip-color pixels that were determined earlier as the references for extracting the lip-color pixels. If a pixel in image F_o at a particular lightness interval had red and green chromaticities within the ellipsoid distribution of lip-color pixels at confidence level 90%, then this pixel was detected as a lip-color pixel, otherwise the pixel was considered a nonlip-color pixel. The detected lip-color pixel in the binary image result F_{l1} was considered a white pixel (logical value 1) and a black pixel (logical value 0) for a nonlip-color pixel.

The white pixels representing skin-color regions in the binary image F_{s1} were extracted from image F_o by a similar procedure as that used to extract the lip-color pixels mentioned above. If a pixel in the binary image F_{l1} and the pixel in the binary image F_{s1} at the same position (i, j) both had logical value 1 (white pixel), then the pixels at that position in the binary image F_{l1} and F_{s1} were considered black pixels.

Region Segmentation. To reduce the number of noise pixels and at the same time segment lip-color regions in image F_{l1} and skin-color regions in image F_{s1}, we implemented an iterative cross-binary median-filtering operation with a cross mask shown in Fig. 2. Each area of 3×3 pixels in image F_{l1} and F_{s1} was convoluted with this cross mask of 3×3 pixels. If the convolution result was greater than or equal to 3, which is when the number of white pixels in the binary image at positions of pixel “1” in the cross mask was greater than or equal to 3 pixels, then the pixel in the center of that area was set equal to 1 (white pixel), otherwise 0. This binary median filtering first was applied to image F_{l1} and then to image F_{s1}. After applying this filtering to both images, the white pixels at the same position (i, j) where both images F_{l1} and F_{s1} had white pixels at that position were set to be black pixels. Finishing the binary median filtering on the images F_{l1} and F_{s1} and deletion of white pixels of the same position, the algorithm repeated to do the binary median filtering on the image results F_{l1} and F_{s1} and delete the white pixels of the same pixel position in both images. This step was performed iteratively to output image F_{l2} and F_{s2}.

0	1	0
1	1	1
0	1	0

Figure 2. The mask for binary cross median filtering.

Finding the Face Candidate. The segmented lip-color regions in image F_{l2} and the segmented skin-color regions in image F_{s2} were labeled separately to produce images F_{l3} and F_{s3}, respectively. The term "face candidate" refers to the region that has a skin-color region and a lip-color region as its subset regions. Figure 3 illustrates how to find a region of a face candidate; a region that has skin-color and lip-color regions as its subset regions. Figure 3(a) is the labeled skin-color region image (F_{s3}) and Fig. 3(b) is the labeled lip-color regions image (F_{l3}). Figure 3(c) is the binary image (F_4) that resulted from an OR operation on binary images in Figs. 3(a) and 3(b). The connectivity analysis of lip and skin regions for finding the region of the face candidate was done by the following procedures: Each region in Fig. 3(c) was relabeled and its area size computed. One by one, the relabeled regions were evaluated. The relabeled region that had no intersection or that had area size of the intersection with the lip region in Fig. 3(b) equal to its area size was not face candidate. The relabeled region that had the intersection and that had area size of intersection with the lip region in Fig. 3(b) not equal to its area size was a face candidate. In Fig. 3(d), the region labeled by No. 2 is a face candidate.

Pattern Vector. There were three classes of regions or objects: face, nonface, and undefined. In this study, we only used two region classes; face and nonface. The undefined regions are face regions that merge with other skin-color objects, for example, hands, arms, clothes, and objects made of wood. The undefined region class was not classified any further. To classify the regions, we only need to detect the face objects from the face candidate regions. Regions that were not detected as face objects automatically were classified as nonface class.

The classification of face candidate regions was carried out by evaluating a pattern vector of seven pattern variables. Figure 4 shows the parameters for computing these pattern variables. To extract the faces from the face candidate regions, we applied the reasoning that the face class has a common range value for each of these pattern variables. Table I describes the seven pattern variables for extracting faces. The common range values of these seven pattern variables of the face class were observed and determined from the experiments on face objects in the training images.

Detecting the Face Objects. The flowchart in Fig. 5 illustrates the algorithm for classifying face candidate regions and detecting face objects. Assume we have N regions to be classified. One by one from the first to the N-th region, the region's pattern variable values are evaluated. If all of the region's pattern variable values are within the valid range values of pattern variables of face class, which

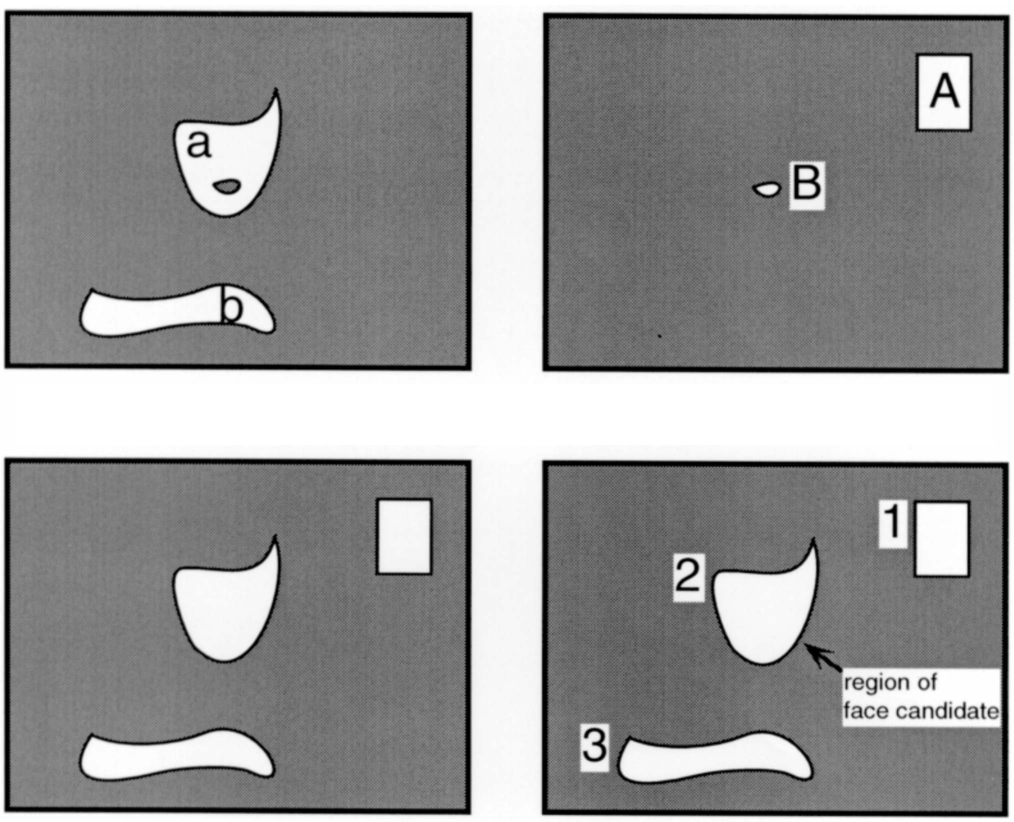


Figure 3. Method of finding face candidate regions: (a) labeled skin-color regions, (b) labeled lip-color regions, (c) resulted from OR operation on images in (a) and (b), and (d) relabeled new region images.

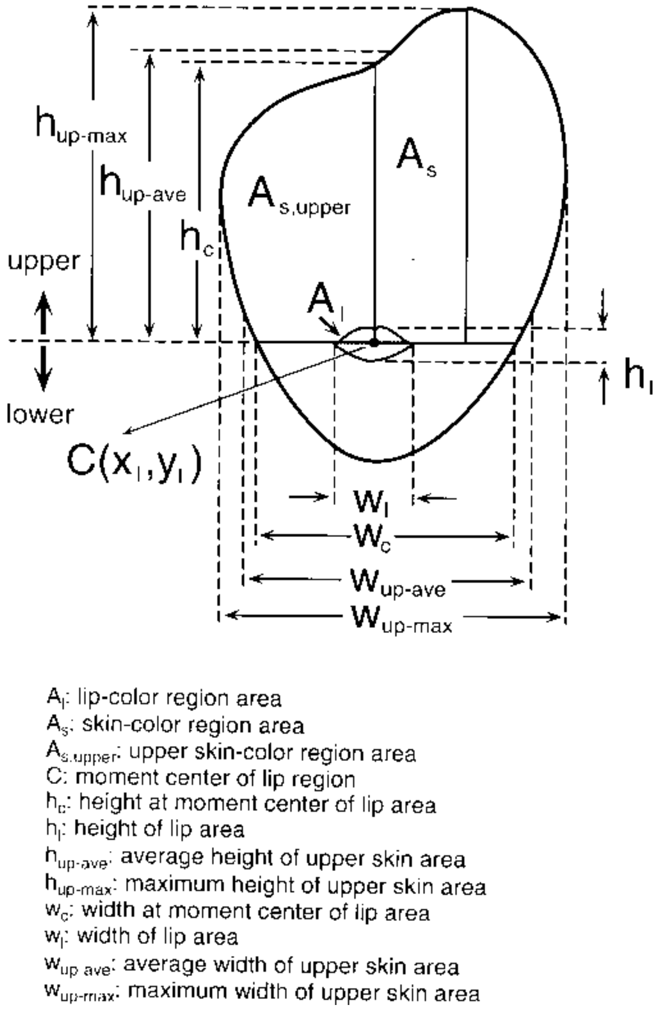


Figure 4. Parameters for computing pattern variables.

is when the region's pattern variable values pass all seven evaluation blocks, then this region is detected as a face class. If at least one of the region's pattern variable values is not within the valid range values of that pattern variable, the region is classified as nonface class.

Displaying the Extracted Face. There are many ways to extract or display the face object after detecting it. To display the face object from the original image, we simply determined the moment center of the face candidate region detected as a face object and computed the longest radius from that moment center to the farthest pixel in that region. The extracted face object was inside a white circle with radius equal to the longest radius computed earlier. Another way to display the face object is to make a circle with its center at the moment center of the lip-color region and radius equal to the maximum height of the upper skin-color region ($h_{\text{up-max}}$) as shown in Fig. 4. The extracted face object is inside the circle. This also can be shown by a rectangular mark or area.

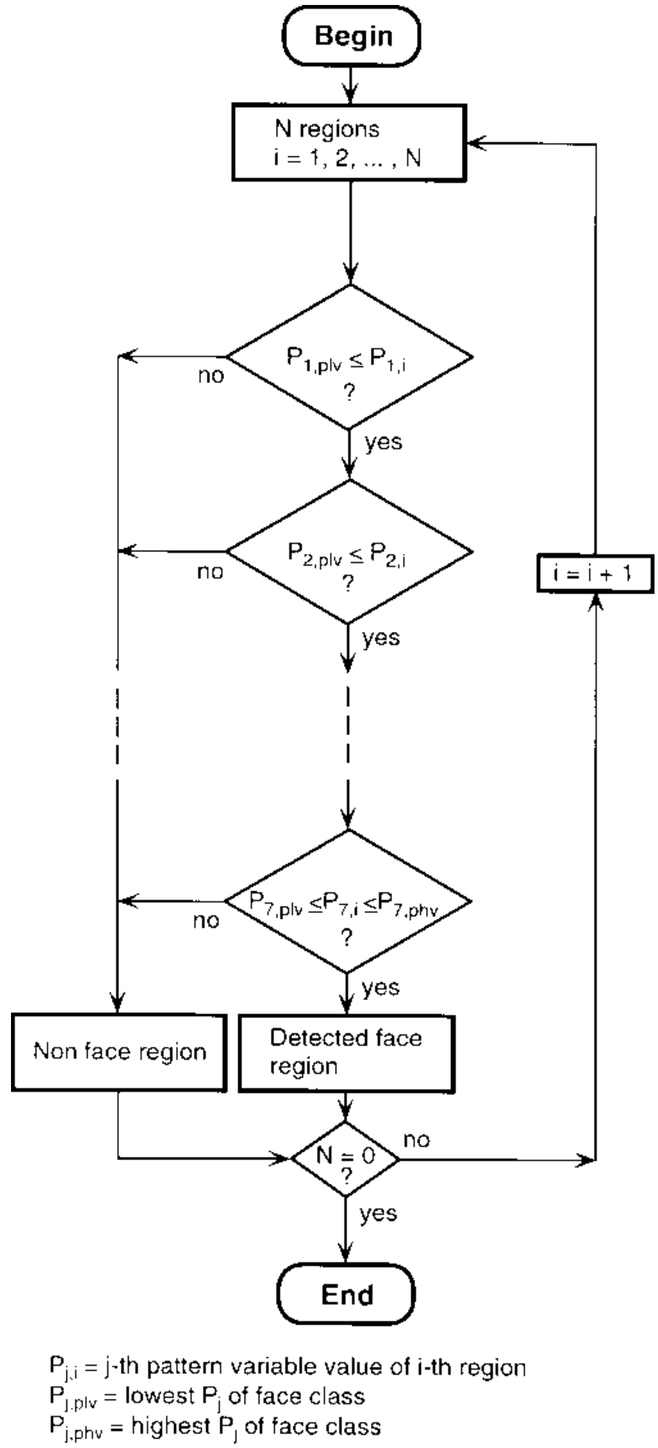


Figure 5. Algorithm for detecting faces.

Experimental Results and Discussion

Image Acquisition. In our experiments, we used color images recorded in Fuji Super G color negative film (ISO 100, daylight type) as image objects. The scenes of people in these images were taken by a simple compact Fuji Cardia camera. Most of the images were taken indoors. The camera used has automatic exposure control, incorporated flash, and a self-focusing system. Each negative film image of area size 2×3 cm^2 was sampled and quantified by a mechanical drum scanner (Model 2605, Abe Sekkei Inc., Japan) to be 400×600 pixels in 8 bit/pixel quantization level with red (R), green (G), and blue (B) filters. Both sampling pitch and rectangular aperture were 50 μm. The digital values of R, G, and B color components of the digitized image represent the image densities. We chose 104 digitized images for the experiments. In this study, 24 images were used for the training experiments and the other 80 images for testing experiments. The digitized images were processed by a workstation computer (Sun Sparc Station 2, Sun Inc., CA) using a program written in Standard C language.

TABLE I. Pattern Variables for Detecting Faces

No.	Pattern variable	Explanation
1.	$P_1 = A_s + A_1$	region area
2.	$P_2 = A_s + A_1/A_1$	region area/lip area
3.	$P_3 = A_{s,up}/w_{up\text{-}max} \times h_{up\text{-}max}$	upper skin area/upper rectangular area
4.	$P_4 = h_1/w_1$	height of lip/width of lip
5.	$P_5 = h_c/w_c$	height at moment center of lip area/ width at moment center of lip area
6.	$P_6 = h_{up\text{-}ave}/w_{up\text{-}ave}$	average height of upper skin area/ average width of upper skin area
7.	$P_7 = h_{up\text{-}max}/w_{up\text{-}max}$	maximum height of upper skin area/ maximum width of upper skin area

Ellipsoid Distributions of Lip- and Skin-Color Pixels. The ellipsoid distribution of lip-and skin-color pixel chromaticities in lightness intervals were determined statistically from the samples of lip- and skin-color pixel populations in the 24 training images. We sampled and measured the R, G, and B values from 500 samples of pixels in lip regions and 10,000 samples of pixels in skin-color regions of 24 training images. The R, G, and B values of these pixels were used to compute the lightness, red and green chromaticities for analyzing the ellipsoid distributions of lip- and skin-color pixels.

Lightness of lip-color pixels ranged from 220 to 330 lightness units. These pixels were categorized to 11 lightness intervals. Skin-color pixels ranged from 220 to 360 and had 14 lightness intervals. Both classes of pixels had interval ranges of 20 lightness units. The chromaticities of sample pixels at a particular interval of lightness were analyzed statistically, and the ellipsoid distribution of chromaticities in the lightness interval were determined. The result of sampling and analyzing the chromaticities of lip- and skin-color pixels are given in Figs. 6 and 7, respectively. These ellipsoid distributions were the databases for extracting lip- and skin-color pixels in the images of our experiments.

Face Extraction. In the training experiment, we did operations from pixel extraction to finding regions of face candidates on the 24 learning images to output image F_4. The system for detecting the face objects was formed from training on the face objects in these images. The seven pattern variables provided in Table I became the setting parameters that controlled the recognition of face objects. One by one, the face objects were fed into this system. Each time the system made an error detecting a face object, the range value of the relevant pattern variable was updated to accommodate the pattern variable value of the new face object. This step was carried out to the last face object in the learning image. The range values of these six pattern variables at the end of this recognition process were nominated as the common range values of the face object class. These range values were as follows,

$$\begin{aligned} P_2 &\geq 20.0 \\ P_3 &\geq 0.4 \\ P_4 &\leq 3.0 \\ 0.5 \leq P_5 &\leq 2.0 \\ 0.5 \leq P_6 &\leq 2.0 \\ 0.5 \leq P_7 &\leq 2.0 \end{aligned} \tag{5}$$

These ranges were used as the references for automatically classifying and detecting face objects from color images. The range value of the area pattern variable depends on the face object size and image size. Consequently, the area pattern variable could not be generalized for detecting the face object. In experiments, we concerned ourselves

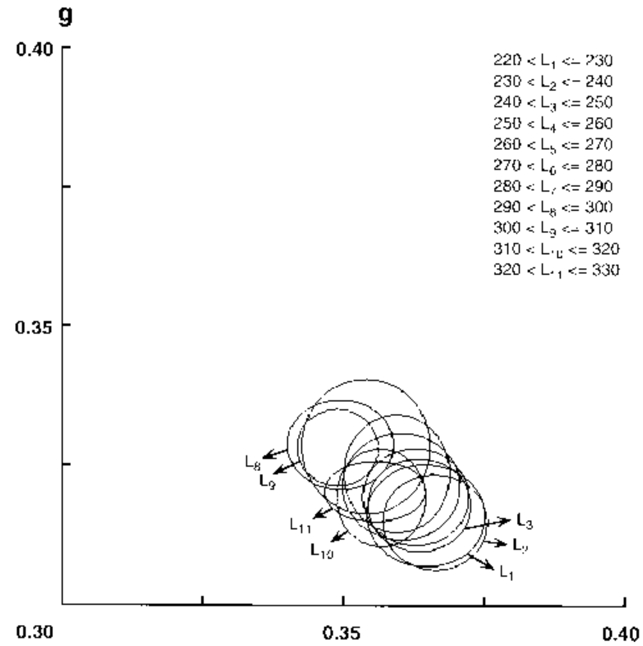


Figure 6. Ellipsoid distributions of chromaticities of lip-color pixels in lightness intervals at confidence level 90%.

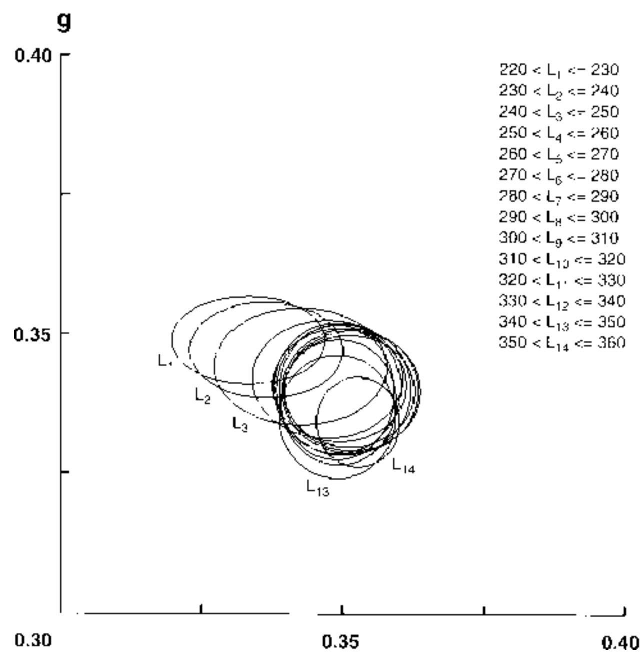
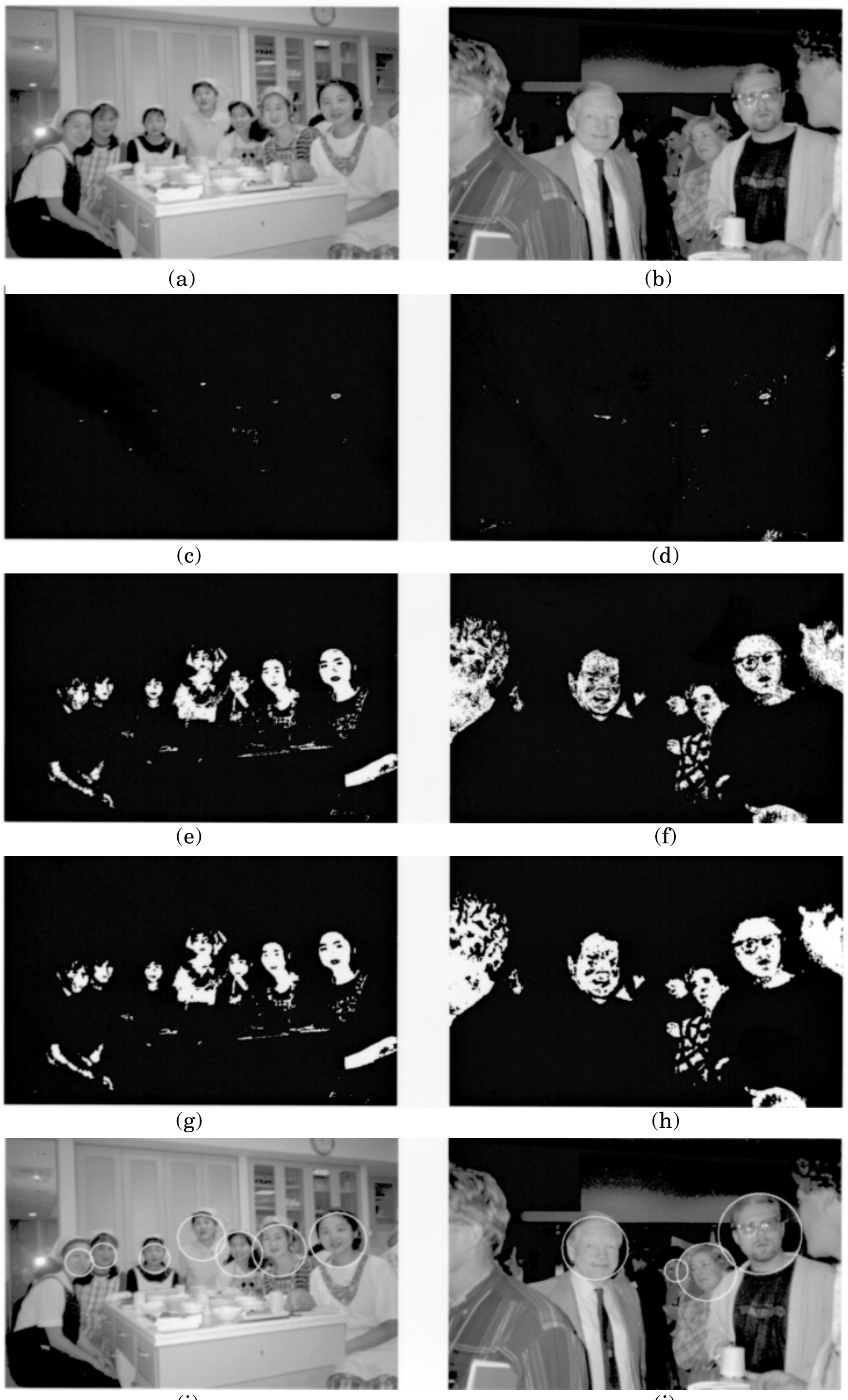


Figure 7. Ellipsoid distributions of chromaticities of skin-color pixels in lightness intervals at confidence level 90%.

only with face objects with area size greater than or equal to 400 pixels. Note that the assumption of this study was the orientation of images are known a priori. The algorithm can detect the face objects from color images with specific orientation: landscape or portrait, but not for both.

Figure 8 shows examples of experimental results of face extraction. Figures 8(a) and 8(b) are the original images. White pixels in the images in Figs. 8(c) and 8(d) and in Figs. 8(e) and 8(f) are the lip-color pixels that were extracted based on the ellipsoid distributions of lip- and skin-color chromaticities shown in Figs. 6 and 7, respectively. In addition, Figs. 8(g) and 8(h) show the segmented regions after segmenting and labeling the lip- and skin-color



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 8. Example of face extraction: (a) and (b) original images, (c) and (d) extracted lip-color pixels, (e) and (f) extracted skin-color pixels, (g) and (h) segmented skin-color and lip-color regions, and (i) and (j) extracted face images.

Figure 9. Experimental results of face extraction from 104 learning and test images. *(Continued on next page.)*

Figure 9. Experimental results of face extraction from 104 learning and test images. *(Continued from previous page.)*

TABLE II. Extraction Results Using the Previous and Current Algorithms

	Number of face objects	
	Previous algorithm	Current algorithm
Detected	196	202
Undefined	30(10)*	12(9)*
Undetected	6	18
Total	232	232
Error detection	27	8

* Numbers in parentheses are the undefined face regions detected as face objects.

regions. The skin-color region that has a lip-color region inside its region or at its boundary is the face candidate. The face objects were extracted from the face candidates in Figs. 8(g) and 8(h) by evaluating their seven pattern variable values and then implementing the valid range pattern variable values of face class as the references for the recognition. Circles in Figs. 8(i) and 8(j) show the locations of the detected face objects.

The experimental results of face extraction are shown in Fig. 9. Images from Nos. 1 to 24 are the training images, and the rest are the test images. In the current study, the training experiment on 79 face objects in 24 learning images gave 75 detected faces, 1 undetected face, 3 undefined face regions, and 2 error detections of nonface regions. Testing experiments on 153 face objects in 80 testing images gave 127 detected faces, 17 undetected faces, 9 undefined face regions, and 6 error detections of nonface regions. Three faces in undefined face regions in the training images and six faces in nine undefined face regions in the testing images could be extracted as face object class. Examples of undefined face regions can be seen in images 14, 18, and 20 in Fig. 9. This occurred because the face regions merged with the objects with skin color.

The face extraction experiments using the previous algorithm[25] on these 104 learning and test images gave 196 detected faces, 6 undetected faces, 30 undefined face regions, and 27 error detections of nonface regions. Ten face objects in thirty undefined face regions could be extracted as face objects by the previous algorithm. Three face objects not detected by the previous algorithm from six faces could be detected by the current algorithm; 15 face objects not detected by the current algorithm from 18 faces could be detected by the previous algorithm. The experimental results of face extraction using the previous and current algorithms are summarized in Table II.

If the undefined face regions are also considered, the percentage of face extraction using the previous algorithm was 88.8% and using the current algorithm was 90.9%. Without considering the undefined face regions, the previous and current algorithms gave 97.0 and 91.8% face extraction, respectively. The previous algorithm performed better than the current algorithm for extracting face objects that do not merge with other skin-color objects in the original images. Nevertheless, the previous algorithm also resulted in greater error detection of nonface regions detected as face objects than the current algorithm did. The current algorithm reduced the number of undefined regions. In addition, the current algorithm could detect face objects in undefined face regions better than the previous algorithm. Several conditions that might cause the failure of face extraction using the current algorithm are

- Face object merges with other lip- or skin-color objects.
- Face object is too small.
- Chromaticities of lip- or skin-color pixels on the face object are significantly different from the reference database of lip- and skin-color pixels.
- Face object has full beard or mustache.
- Orientation of face object.

Some examples of these conditions that resulted in undetected face objects can be seen in Fig. 9.

Conclusion

We have proposed a new and automatic technique for extracting faces based on a simple idea. The face objects of interest in color images of people usually have lip regions as subset regions. The face extraction was done by applying the criteria of range values of pattern variables on the face candidates.

Good color quality of images is important to some extent. The color quality of images, in particular in their face objects, might affect the performance of the technique. This algorithm needs a proper database of chromaticities of skin and lip-color pixels. Because the lip and skin colors in images recorded on color film depend on the illumination type used in taking the picture, a technique for recognizing the light source type of color negative film is needed before applying this face extraction algorithm when working with images exposed by different illumination types. Hence, the proper database of chromaticities of lip- and skin-color pixels can be chosen according to the illumination type. The technique for recognizing the light source type given in Ref. 25 can be applied as an alternative for this purpose. Before face extraction, the appropriate extraction of skin- and lip-color pixels and segmentation of skin- and lip-color regions is critically important for reducing the number of clutter regions and noise pixels and reserving the lip regions in face objects. Restricting face extraction only to face candidate regions reduces the execution time for the classification process. The algorithm for evaluating pattern variable values shown in Fig. 5 reduces execution time for classifying, as well.

The proposed technique is simple, automatic, and significant for locating or detecting face objects in color images. Some practical applications are color treatment or color manipulation on faces, special effects manipulation of faces, and automating the control over color reproduction of face regions from color negative film in printing machines. By modifying this technique properly, in particular, the databases of lip- and skin-color chromaticities in lightness intervals, it may be applied for extracting face objects in color images recorded by other imaging media. In addition, the proposed technique could be put into practice as an alternative preprocessing algorithm before implementing the operations of facial feature extraction and face recognition techniques.

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