

Face Segmentation Using Skin Color Map in Videophone Applications

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Abstract— This paper addresses our proposed method to automatically segment out the person's face from a given image that consists of a head-and-shoulders view of the person and a complex background scene. The method involves a fast, reliable and effective algorithm that exploits the spatial distribution characteristics of human skin color. A universal skin-color map is derived and used on the chrominance component of the input image to detect pixels with skin color appearance. Then, based on the spatial distribution of the detected skin-color pixels and their corresponding luminance values, the algorithm employs a set of novel regularization processes to reinforce regions of skin-color pixels that are more likely to belong to the facial regions and eliminate those that are not. The performance of the face segmentation algorithm is illustrated by some simulation results carried out on various head-and-shoulders test images.

The use of face segmentation for video coding in application such as videotelephony is then presented. We explain how the face segmentation results can be used to improve the perceptual quality of videophone sequence encoded by the H.261-compliant coder.

Keywords— Image Segmentation, Facial Image Analysis, Face Location, Color Image Processing, Videophone Communication, Video Coding, H.261, Quantization.

I. INTRODUCTION

THE task of finding a person's face in a picture seems to be effortless for human to perform. However it is far from simple for machine of current technology to do the same. In fact, development of such machine or system has been widely and actively studied in the field of image understanding for the past few decades with applications such as machine vision and face recognition in mind. Moreover, in recent years, the research activities in this area have intensified as a result of its applications being extended towards video representation and coding purposes.

The main objective of this research is to design a system that can find a person's face from a given image data. This problem is commonly referred to as face location, face extraction or face segmentation. Regardless of which terminology, they all share the same objective. However, note that the problem usually deals with finding the position and contour of a person's face since its location is unknown, but given the knowledge of its existence. If not, then there is also a need to discriminate between "images containing faces" and "images not containing faces". This is known as face detection. Nevertheless, this paper focuses on face segmentation.

The significance of this problem can be illustrated by its vast applications as face segmentation holds an important key to future advances in human-to-human and human-

to-machine communications. The segmentation of facial region provides a content-based representation of the image where it can be used for image encoding, manipulation, enhancement, indexing, modeling, pattern recognition and object tracking purposes. Some major applications include:

- *Coding area of interest with better quality.* The subjective quality of a very-low-bit-rate encoded videophone sequence can be improved by coding the facial image region that is of interest to viewers at higher quality [1] [2].
- *Content-based representation and MPEG-4.* Face segmentation is a useful tool for the MPEG-4 content-based functionality. It provides content-based representation of the image, which can subsequently be used for coding, editing or other interactivity purposes.
- *3D human face model fitting.* The delimitation of the person's face is the fundamental requirement of 3D human face model fitting used in model-based coding [3], computer animation and morphing.
- *Image enhancement.* Face segmentation information can be used in a post-processing task for enhancing images, such as the automatic adjustment of tint in the facial region.
- *Face recognition.* Finding the person's face is the first important step in the human face recognition, classification and identification systems.
- *Face tracking.* Face location can be used to design a video camera system that tracks a person's face in a room. It can be used as part of an intelligent vision system or simply in video surveillance.

Although the research on face segmentation has been pursued at a feverish pace, there are still many problems yet to be fully and convincingly solved as the level of difficulty of the problem depends highly on the complexity level of the image content and its application. Many existing methods only work well on simple input images with benign background and frontal view of the person's face. While to cope with more complicated images and conditions, many more assumptions will then have to be made. Many of the approaches proposed over the years involved the combination of shape, motion and statistical analysis [4] [5] [6] [7] [8] [9] [10] [11] [12] [13]. In recent times, however, a new approach of using color information has been introduced.

In this paper, we will discuss the color analysis approach to face segmentation. The discussion includes the derivation of a universal model of human skin color, the use of appropriate color space and the limitations of color segmentation. We then present a practical solution to the face segmentation problem. This includes how to derive

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a robust skin-color reference map, and how to overcome the limitations of color segmentation. In addition to face segmentation, one of its applications on video coding will be presented in further detail. It will explain how the face segmentation results can be exploited by an existing video coder so that it encodes the area of interest (i.e. facial region) with higher fidelity and hence produces images with better-rendered facial features.

This paper is organized as follows. After this introductory part, the color analysis approach to face segmentation is presented in Section II. Then, in Section III, we present our contributions to this field of research, which includes our proposed skin-color reference map and methodology to face segmentation. The simulation results of our proposed algorithm along with some discussions are provided in Section IV. This is followed by a section on a video coding technique that uses the face segmentation results. Then the conclusions and further research directions are presented in Section VI.

II. COLOR ANALYSIS

The use of color information was introduced to the face locating problem in recent years, and it has gained increasing attention since then. Some recent publications that have reported this study include [14], [15], [16], [17], [18], [19], [20], [21], [22] and [23] (in order of publication date). They have all shown, in one way or another, that color is a powerful descriptor that has practical use in the extraction of face location.

The color information is typically used for region rather than edge segmentation. We classify the region segmentation into two general approaches as illustrated in Fig. 1. One approach is to employ color as a feature for partitioning an image into a set of homogeneous regions. For instance, the color component of the image can be used in the region growing technique as demonstrated in [24], or as a basis for a simple thresholding technique as shown in [23]. The other approach, however, makes use of color as a feature for identifying a specific object in an image. In this case, the skin color can be used to identify the human face. This is feasible because human faces have a special color distribution that differs significantly (although not entirely) from those of the background objects. Hence this approach requires a color map that models the skin color distribution characteristics.

The skin-color map can be derived in two ways on account of not all faces have identical color feature. One approach is to pre-define or manually obtain the map such that it suits only an individual color feature. For example, here we obtain the skin color feature of the subject in a standard head-and-shoulders test image called *Foreman*. Although this is a color image in YCrCb format, its gray-scale version is shown in Fig. 2. The figure also shows a white contour highlighting the facial region. The histograms of the color information (i.e. Cr and Cb values) bounded within this contour are obtained as shown in Fig. 3. The diagrams show that the chrominance values in the facial region are narrowly distributed, which implies

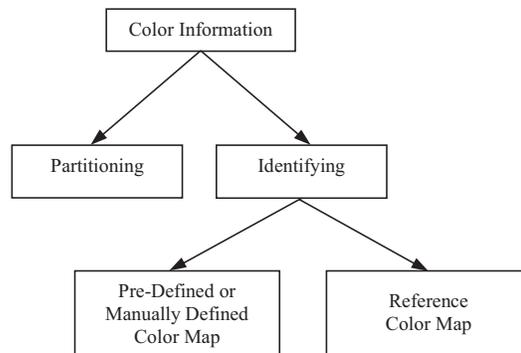


Fig. 1. The use of color information for region segmentation.



Fig. 2. *Foreman* image with a white contour highlighting the facial region.

that the skin color is fairly uniform. Therefore this individual color feature can simply be defined by the presence of Cr values within, say, 136 and 156, and Cb values within 110 and 123. Using these ranges of values, we managed to locate the subject's face in another frame of *Foreman* and also in a different scene (a standard test image called *Carphone*), as can be seen in Fig. 4. This approach was suggested in the past by Li and Forchheimer in [14], however, detail procedure on the modeling of individual color feature and their choice of color space were not disclosed.

In another approach, the skin-color map can be designed by adopting histogramming technique on a given set of training data and subsequently used as a reference for any human face. Such method was successfully adopted by us [21] [25], Sobottka and Pitas [18], and Cornall and Pang [22].

Among the two approaches, the first is likely to produce better segmentation result in terms of reliability and accuracy by virtue of using a precise map. However, it is realized at the expense of having a face segmentation process that is either too restrictive because it uses a pre-defined map, or requires human interaction to manually define the necessary map. Therefore, the second approach is more practical and appealing as it attempts to cater for all per-

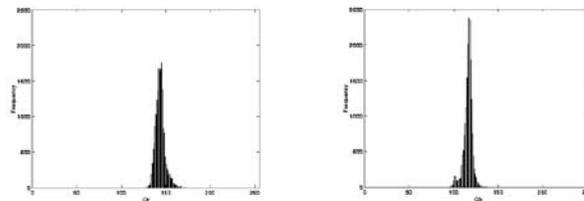


Fig. 3. The histograms of Cr and Cb components in the facial region.



Fig. 4. *Foreman* and *Carphone* images, and their color segmentation results obtained by using the same pre-defined skin-color map.

sonal color features in an automatic manner, albeit less precise. This, however, raises a very important issue regarding the coverage of all human races with one reference map. In addition, the general use of skin-color model for region segmentation prompts two other questions, namely, which color space to use, and how to distinguish other parts of the body and background objects with skin color appearance from the actual facial region.

A. Color Space

An image can be presented in a number of different color space models, such as:

- *RGB*. This stands for the three primary colors: red, green and blue. It is a hardware-oriented model and well known for its color monitor display purpose.
- *HSV*. An abbreviation of *Hue-Saturation-Value*. *Hue* is a color attribute that describes a pure color, while *saturation* defines the relative purity or the amount of white light mixed with a *hue*, and *value* refers to the brightness of the image. This model is commonly used for image analysis.
- *YCrCb*. This is yet another hardware-oriented model. However, unlike the RGB space, here the luminance is separated from the chrominance data. The Y value represents the luminance (or brightness) component while the Cr and Cb values, also known as the color difference signals, represent the chrominance component of the image.

These are some, and certainly not all, of the color space models available in image processing. Therefore it is important to choose the appropriate color space for modeling human skin color. The factors that need to be considered are *application* and *effectiveness*. The intended purpose of the face segmentation will usually determine which color space to use, at the same time, it is essential that an effective and robust skin-color model can be derived from the given color space. For instance, in this paper we propose the use of the YCrCb color space, and the reason is twofold. First, an effective use of the chrominance information for modeling human skin color can be achieved in this color space. Second, this format is typically used in video coding, and therefore the use of the same, instead of

another, for segmentation will avoid the extra computation required in conversion. On the other hand, both Sobottka and Pitas [18], and Saxe and Foulds [19] have opted for the HSV color space as it is compatible to the human color perception, and the *hue* and *saturation* components have been reported to also be sufficient discriminating color information for modeling skin color. However, this color space is not suitable for video coding. Hunke and Waibel [15], and Graf *et al.* [26] used a normalized RGB color space. The normalization was employed to minimize the dependence on the luminance values.

On this note, it is interesting to point out that unlike the YCrCb and HSV color spaces whereby the brightness component is decoupled from the color information of the image, the RGB color space is not. Therefore, Graf *et al.* have suggested pre-processing calibration in order to cope with unknown lighting condition. From this point of view, the skin-color model derived from the RGB color space will be inferior to those obtained from the YCrCb or HSV color spaces. Based on the same reasoning, we hypothesize that a skin-color model can remain effective regardless of the variation of skin color (e.g. black, white or yellow) if the derivation of the model is independent of the brightness information of the image. This will be discussed in the later sections.

B. Limitations of Color Segmentation

A simple region segmentation based on the skin-color map can provide accurate and reliable results if there is a good contrast between skin color and those of the background objects. However, if the color characteristic of the background is similar to that of the skin, then pinpointing the exact face location is more difficult as there will be more falsely detected background regions with skin color appearance. Note that in the context of face segmentation, other parts of the body are also considered as background objects. There are a number of methods to discriminate between the face and the background objects, and they include the use of other cues such as motion and shape.

Provided the temporal information is available and *a priori* knowledge of a stationary background and no camera motion, motion analysis can be incorporated into the face localization system to identify non-moving skin-color regions as background objects. Alternatively, shape analysis involving ellipse-fitting can also be employed to identify the facial region from among the detected skin-color regions. It is a common observation that the appearance of a human face resembles an oval shape and therefore it can be approximated by an ellipse [2]. In this paper, however, we propose a set of regularization processes that are based on the spatial distribution and the corresponding luminance values of the detected skin-color pixels. This approach overcomes the restriction of motion analysis and avoids the extensive computation of the ellipse-fitting method. The details will be discussed in the next section along with our proposed method to face segmentation.

In addition to poor color contrast, there are other limitations of color segmentation when input image is taken in

some particular lighting conditions. The color process will encounter some difficulty when input image has either:

- a ‘bright spot’ on the subject’s face due to reflection of intense lighting, or
- a dark shadow on the face as a result of the use of strong directional lighting that has partially blackened the facial region, or
- captured with the use of color filters.

Note that these types of images (particularly in case 1 and 2) are posing great technical challenges not only to the color segmentation approach but also to a wide range of other face segmentation approaches, especially those approaches that utilize edge image, intensity image or facial feature points extraction.

However, we have found that the color analysis approach is immune to moderate illumination changes and shading resulting from slightly unbalance light source, as these conditions do not alter the chrominance characteristics of the skin-color model.

III. FACE SEGMENTATION ALGORITHM

In this section, we present our methodology to perform face segmentation. Our proposed approach is automatic in the sense that it uses an unsupervised segmentation algorithm, and hence no manual adjustment of any design parameter is needed in order to suit any particular input image. Moreover, the algorithm can be implemented in real-time and its underlying assumptions are minimal. In fact, the only principal assumption is that the person’s face must be present in the given image since we are locating and not detecting whether there is a face. Thus, the input information required by the algorithm is a single color image that consists of a head-and-shoulders view of the person and a background scene, and the facial region can be as small as only a 32×32 pixels window (or 1%) of a CIF-size (352×288) input image. The format of the input image is to follow the YCrCb color space, based on the reason given in the previous section. The spatial sampling frequency ratio of Y, Cr and Cb is 4:1:1. So, for a CIF-size image, Y has 288 lines and 352 pixels per line while both Cr and Cb have 144 lines and 176 pixels per line each.

The algorithm consists of five operating stages, as outlined in Fig. 5. It begins by employing a low-level process like color segmentation in the first stage, and then it uses higher-level operations that involve some heuristic knowledge about the local connectivity of the skin-color pixels in the later stages. Thus each stage makes full use of the result yielded by its preceding stage in order to refine the output result. Consequently, all the stages must be carried out progressively according to the given sequence.

A detail description of each stage is presented below. For illustration purpose, we will use a studio-based head-and-shoulders image called *Miss America* to present the intermediate results obtained from each stage of the algorithm. This input image is shown in Fig. 6.

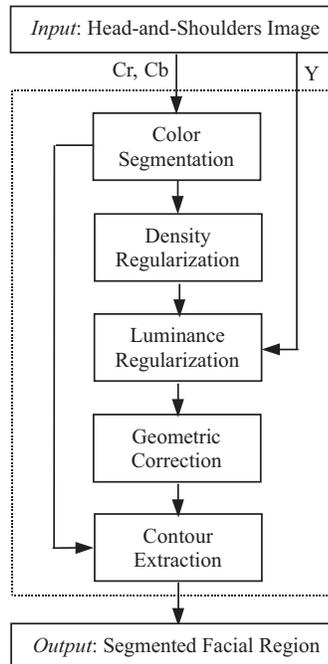


Fig. 5. Outline of face segmentation algorithm.



Fig. 6. The input image of *Miss America*.

A. Stage One - Color Segmentation

The first stage of the algorithm involves the use of color information in a fast, low-level region segmentation process. The aim is to classify pixels of the input image into skin-color and non-skin-color. To do so, we have devised a skin-color reference map in YCrCb color space.

We have found that skin-color region can be identified by the presence of a certain set of chrominance (i.e. Cr and Cb) values that is narrowly and consistently distributed in the YCrCb color space. The location of these chrominance values has been found and can be illustrated using the CIE chromaticity diagram as shown in Fig. 7. We denote R_{Cr} and R_{Cb} as the respective ranges of Cr and Cb values that correspond to skin color, which subsequently define our skin-color reference map. The ranges that we found to be the most suitable for all the input images that we have tested are $R_{Cr} = [133, 173]$ and $R_{Cb} = [77, 127]$. This map has been proven, in our experiments, to be very robust against different types of skin color. Our conjecture is that the different skin color that we perceived from video image cannot be differentiated from the chrominance information of that image region. So, a map that is derived from Cr and Cb chrominance values will remain effective regardless of skin color variation (see Section IV for the

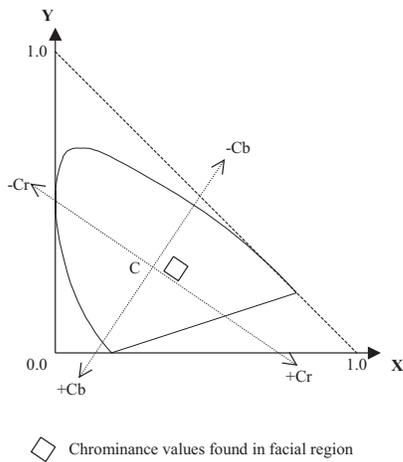


Fig. 7. Skin-color region in CIE chromaticity diagram.



Fig. 8. Bitmap produced by stage one.

experimental results). Moreover, our intuitive justification for the manifestation of similar Cr and Cb distributions of skin color of all races is that the apparent difference in skin color that viewers perceived is mainly due to the darkness or fairness of the skin; these features are characterized by the difference in the brightness of the color, and the brightness of the color is governed by Y but not Cr and Cb.

With this skin-color reference map, the color segmentation can now begin. Since we are utilizing only the color information, the segmentation requires only the chrominance component of the input image. Consider an input image of $M \times N$ pixels and therefore the dimension of Cr and Cb is $M/2 \times N/2$. The output of the color segmentation, and hence stage one of the algorithm, is a bitmap of $M/2 \times N/2$ size, described as

$$O_1(x, y) = \begin{cases} 1, & \text{if } [Cr(x, y) \in R_{Cr}] \cap [Cb(x, y) \in R_{Cb}] \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $x = 0, \dots, M/2 - 1$ and $y = 0, \dots, N/2 - 1$. The output pixel at point (x, y) is classified as skin-color and set to 1 if both the Cr and Cb values at that point fall inside their respective ranges, R_{Cr} and R_{Cb} . Otherwise, the pixel is classified as non-skin-color and set to 0. To illustrate this, we perform color segmentation on the input image of *Miss America*, and the bitmap produced can be seen in Fig. 8. The output value of 1 is shown in black while the value of 0 is shown in white (this convention will be used throughout this paper).

Among all the stages, this first stage is the most vital one. Based on our model of the human skin color, the

color segmentation has to remove as many pixels as possible that are unlikely to belong to the facial region while catering for a wide variety of skin color. However, if it falsely removes too many pixels that belong to the facial region, then the error will propagate down the remaining stages of the algorithm, and consequently causing a failure to the entire algorithm.

Nevertheless, the result of color segmentation is the detection of pixels in facial area and may also include other areas where the chrominance values coincide with those of the skin color (as it is the case in Fig. 8). Hence the successive operating stages of the algorithm are used to remove these unwanted areas.

B. Stage Two - Density Regularization

This stage considers the bitmap produced by the previous stage to contain the facial region that is corrupted by noise. The noise may appear as small holes on the facial region due to undetected facial features such as eyes and mouth, or it may also appear as objects with skin color appearance in the background scene. Therefore this stage performs simple morphological operations such as *dilation* to fill in any small hole in the facial area and *erosion* to remove any small object in the background area. The intention is not necessarily to remove entirely, but to reduce the amount and size of the noise.

To distinguish between these two areas, we first need to identify regions of the bitmap that have higher probability of being the facial region. The probability measure that we used is derived from our observation that the facial color is very uniform, and therefore the skin-color pixels belonging to the facial region will appear in a large cluster, while the skin-color pixels belonging to the background may appear as large clusters or small isolated objects. Thus, we study the density distribution of the skin-color pixels detected in stage one. An $M/8 \times N/8$ array of density values called density map, $D(x, y)$, is computed as

$$D(x, y) = \sum_{i=0}^3 \sum_{j=0}^3 O_1(4x + i, 4y + j) \quad (2)$$

where $x = 0, \dots, M/8 - 1$ and $y = 0, \dots, N/8 - 1$. It first partitions the output bitmap, $O_1(x, y)$, of stage one into non-overlapping groups of 4×4 pixels, then it counts the number of skin-color pixels within each group and assigns this value to the corresponding point of the density map.

According to the density value, we classify each point into three types, namely zero ($D = 0$), intermediate ($0 < D < 16$) and full ($D = 16$). A group of points with zero density value will represent a non-facial region, while a group of full-density points will signify a cluster of skin-color pixels and a high probability of belonging to a facial region. Any point of intermediate density value will indicate the presence of noise. The density map of *Miss America* with the three density classifications is depicted in Fig. 9. The point of zero density is shown in white, intermediate density in gray and full density in black.

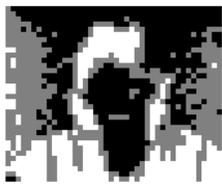


Fig. 9. The density map after classification.



Fig. 10. Bitmap produced by stage two.

Once the density map is derived, we can then begin the process that we termed as density regularization. This involves the following three steps:

1. Discard all points at the edge of the density map, i.e. set $D(0, y) = D(\frac{M}{8}-1, y) = D(x, 0) = D(x, \frac{N}{8}-1) = 0$ for all $x = 0, \dots, M/8 - 1$ and $y = 0, \dots, N/8 - 1$.
2. Erode any full-density point (i.e. set to 0) if it is surrounded by less than 5 other full-density points in its local 3×3 neighborhood.
3. Dilate any point of either zero- or intermediate-density (i.e. set to 16) if there are more than 2 full-density points in its local 3×3 neighborhood.

After this process, the density map is converted to the output bitmap of stage two as

$$O_2(x, y) = \begin{cases} 1, & \text{if } D(x, y) = 16 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

for all $x = 0, \dots, M/8 - 1$ and $y = 0, \dots, N/8 - 1$.

The result of stage two for the *Miss America* image is displayed in Fig. 10. Note that this bitmap is now four times lower in spatial resolution than that of the output bitmap in stage one.

C. Stage Three - Luminance Regularization

We have found that, in a typical videophone image, the brightness is non-uniform throughout the facial region, while the background region tends to have a more even distribution of brightness. Hence based on this characteristic, background region that was previously detected due to its skin color appearance can be further eliminated.

The analysis employed in this stage involves the spatial distribution characteristic of the luminance values since they define the brightness of the image. We use standard deviation as the statistical measure of the distribution. Note that the size of the previously obtained bitmap $O_2(x, y)$ is $M/8 \times N/8$, hence each point corresponds to a group of 8×8 luminance values, denoted by W , in the original input image. For every skin-color pixels in $O_2(x, y)$, we calculate the standard deviation, denoted as $\sigma(x, y)$, of

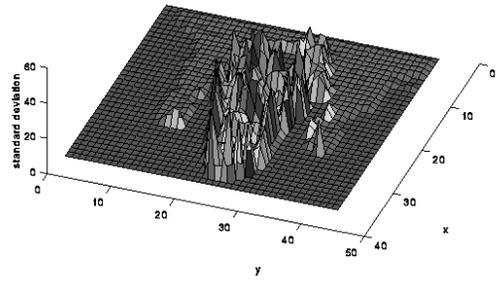


Fig. 11. Standard deviation values of the detected pixels in $O_2(x, y)$.



Fig. 12. Bitmap produced by stage three.

its corresponding group of luminance values, using

$$\sigma(x, y) = \sqrt{\mathbb{E}[W^2] - (\mathbb{E}[W])^2}. \quad (4)$$

Fig. 11 depicts the standard deviation values calculated for the *Miss America* image.

If the standard deviation is below a value of 2 then the corresponding 8×8 pixels region is considered as too uniform, and therefore, unlikely to be part of the facial region. As a result, the output bitmap of stage three, denoted as $O_3(x, y)$, is derived as

$$O_3(x, y) = \begin{cases} 1, & \text{if } O_2(x, y) = 1 \text{ and } \sigma(x, y) \geq 2 \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

for all $x = 0, \dots, M/8 - 1$ and $y = 0, \dots, N/8 - 1$. The output bitmap of this stage for the *Miss America* image is presented in Fig. 12. The figure shows that a significant portion of the unwanted background region was eliminated at this stage.

D. Stage Four - Geometric Correction

We performed a horizontal and vertical scanning process to identify the presence of any odd structure in the previously obtained bitmap, $O_3(x, y)$, and subsequently removed it. This is to ensure that a correct geometric shape of the facial region is obtained. However, prior to the scanning process, we will attempt to further remove any more noise by using a similar technique as initially introduced in stage two. Therefore, a pixel in $O_3(x, y)$ with the value of 1 will remain as detected pixel if there are more than 3 other pixels, in its local 3×3 neighborhood, with the same value. At the same time, a pixel in $O_3(x, y)$ with the value of 0 will be reconverted to the value of 1 (i.e. as a potential pixel of the facial region) if it is surrounded by more than 5 pixels, in its local 3×3 neighborhood, with



Fig. 13. Bitmap produced by stage four.



Fig. 14. Bitmap produced by stage five.

the value of 1. These simple procedures will ensure that noise appearing on the facial region are filled in and that isolated noise object on the background are removed.

We then commence the horizontal scanning process on the “filtered” bitmap. We search for any short continuous run of pixels that are assigned with the value of 1. For a CIF-size image, the threshold for a group of connected pixels to belong to the facial region is 4. Therefore, any group of less than 4 horizontally connected pixels with the value of 1 will be eliminated and assigned to 0. Similar process is then performed in the vertical direction. The rationale behind this method is that, based on our observation, any such short horizontal or vertical run of pixels with the value of 1 is unlikely to be part of a reasonable size and well detected facial region. As a result, the output bitmap of this stage should contain the facial region with minimal or no noise, as demonstrated in Fig. 13.

E. Stage Five - Contour Extraction

In this final stage, we convert the $M/8 \times N/8$ output bitmap of stage four back to the dimension of $M/2 \times N/2$. To achieve the increase in spatial resolution, we utilize the edge information that is already made available by the color segmentation in stage one. Therefore all the boundary points in the previous bitmap will be mapped into the corresponding group of 4×4 pixels with the value of each pixel as defined in the output bitmap of stage one. The representative output bitmap of this final stage of the algorithm is shown in Fig. 14.

IV. SEGMENTATION RESULTS

The proposed skin-color reference map is intended to work on a wide range of skin color including people of European, Asian and African decent. Therefore, to show that it works on subject with skin color other than white (i.e. as it is the case with *Miss America* image), we have used the same map to perform the color segmentation process on subjects with black and yellow skin color. The results obtained were very good, as it can be seen in Fig. 15. The



Fig. 15. The results produced by the color segmentation process in stage one and the final output of the face segmentation algorithm.

skin-color pixels were correctly identified, in both input images, with only a small amount of noise appearing, as expected, in the facial regions and background scenes, which can be removed by the remaining stages of the algorithm.

We have further tested the skin-color map with 30 samples of images. Skin colors were classified into 3 classes: white, yellow and black. 10 samples, each of which contained the facial region of different subject and captured in different lighting condition, were taken from each class to form the test set. We have constructed three normalized histograms for each sample in the separate Y, Cr and Cb components. The normalization process was used to account for the variation of facial region size in each sample. We have then taken the average results from the 10 samples of each class. These average normalized histogram results are presented in Fig. 16. Since all samples were taken from different and unknown lighting conditions, the histograms of Y component for all three classes cannot be used to verify whether the variations of luminance values in these image samples were caused by the different skin color or by the different lighting condition. However the use of such samples illustrated that the variation in illumination does not seem to affect the skin color distribution in the Cr and Cb components. On the other hand, the histograms of Cr and Cb components for all three classes clearly showed that the chrominance values are indeed narrowly distributed, and more importantly, the distributions are consistent across different classes. This demonstrated that an effective skin-color reference map could be achieved based on the Cr and Cb components of the input image.

The face segmentation algorithm with this universal skin-color reference map was tested on many head-and-shoulders images. Here we emphasize that the face segmentation process was designed to be completely automatic, and therefore the same design parameters and rules (including the reference skin-color map and the heuristic) as described in the previous section were applied to all the test images. The test set now contained 20 images from each class of skin color. Therefore, a total of 60 images of different subjects, background complexities and lighting

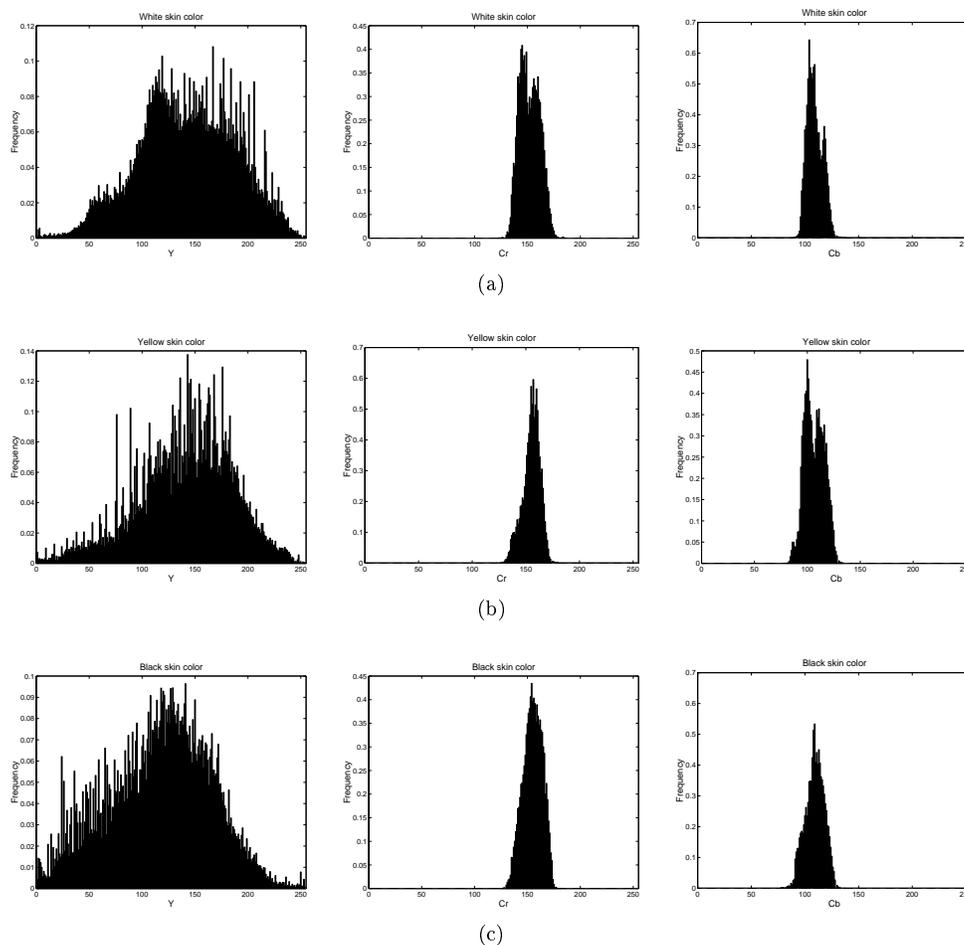


Fig. 16. The histograms of Y, Cr and Cb values of different facial skin colors, (a) white, (b) yellow, and (c) black.

conditions from the three classes were used. Using this test set, a success rate of 82% was achieved. The algorithm has performed successful segmentation of 49 out of 60 faces. Out of the 11 unsuccessful cases, 7 cases have incorrect localization, 2 partial localization and 2 cases with both incorrect and partial localization.

The representative results shown in Fig. 17 illustrated the successful face segmentation achieved by the algorithm on two images with different background complexities. The edges of the facial regions were accurately obtained with no noise appearing on either the facial region or the background. Moreover, the results were obtained in real-time as it took a SUN SPARC 20 computer less than $1\mu s$ to perform all computations required on a CIF-size input image.

In all 7 incorrect localization cases, the segmentation results did contain the complete facial regions but they also included some background regions. In 4 out of 7, the subject's hair, which is considered as background region, was falsely identified as facial region. Partial localization occurred in 2 cases and resulted in the localization of incomplete facial region. These were caused by thick facial hair, i.e. mustache and beard. The 2 cases with both incorrect and partial localization have facial regions partially localized and the results also contained some background



Fig. 17. The segmented facial regions and the remaining background scenes.

regions.

Note that in all cases the facial regions were always located, whether they be completely or partially.

V. CODING

Here we describe a video coding technique, termed as Foreground/Background (FB) coding scheme, that uses the face segmentation results to code the area of interest with

better quality. In application such as videotelephony, the face of the speaker is typically the most important image region for the viewer. Therefore, the face segmentation algorithm is used to separate the facial area from its background scene to become the foreground region. Here, we propose to use the classical block-based video coding system, and to be consistent with many of the video coding standards [27] [28] [29] [30], the foreground and background regions will only need to be identified at the macroblock (MB) level.

In the FB encoding process, we allocate fewer bits for encoding the background MBs by using higher quantization level. In doing so, we free up more bits that can then be used for encoding the foreground MBs. This bit transfer leads to a better quality encoded area of interest at the expense of having lower quality background image. This is based on the premise that the background is usually of less significance to the viewer's perception, so the overall subjective quality of the image is perceptively improved and more pleasing to the viewer.

This concept was initially proposed by us in [1], where we presented the introduction of FB coding scheme and also its implementation as an additional encoding option for the H.263 codec [30]. In this paper, however, we will use the H.261 codec.

A. H.261FB

We have integrated the FB coding scheme into the well-known H.261 video coding system [29]. Hereafter, we termed this approach as the H.261FB. The H.261FB coder utilizes the information obtained from the face segmentation algorithm as described in Section III to enable bit transfer between the foreground and background MBs. This redistribution of bit allocation is simply attained by controlling the quantization level in a discriminatory manner. In addition, a new rate control strategy is devised in order to regulate the bitstream produced by this discriminatory quantization process.

This approach will still produce a bitstream that conforms to the H.261 standard. The reason is that the new quantization process does not involve any modification to the bitstream syntax; it merely assigns two different values to two different regions. As for the rate control, there is no standardized technique. Hence the manufacturers of the encoder have the freedom to devise their own strategy. Moreover, we do not need to transmit the segmentation information to the decoder, as it is used in the encoder only. Therefore the integration is supported by the syntax, and a full H.261 decoder compatibility is maintained.

B. Discriminatory Quantization Process

Two quantizers, instead of one, are used in the H.261FB approach. We assigned Q_f and Q_b to be the quantizers for the foreground (FG) and background (BG) MBs respectively. Among the two, Q_f is a finer quantizer while Q_b is the coarser one. The H.261FB uses the *MQUANT* header to switch between these two quantizers as shown in (6). The *MQUANT* header is a fixed length codeword of 5 bits

that indicates the quantization level to be used for the current MB. Hence this 5-bit codeword represents a range of quantization level from 1 to 31.

$$MQUANT = \begin{cases} Q_f, & \text{if current MB belongs to FG,} \\ Q_b, & \text{if current MB belongs to BG.} \end{cases} \quad (6)$$

It is, however, not necessary for the encoder to send this header for every MB. The transmission of *MQUANT* header is only required in one of the following cases:

1. When the current MB is in a different region to the previously encoded MB, i.e. a change from foreground to background MB or vice versa.
2. When the rate control algorithm updates the quantization level in order to maintain a constant bit rate.

Naturally, this approach has to sustain a slight increase in the transmission of *MQUANT* header. However, the benefit easily outweighs this overhead cost as it will be demonstrated in the simulation results.

C. Rate Control Function

A new rate control strategy is needed to adjust not one but now two quantizers periodically in order to regulate the bit rate. To do so, the quantizer can be adjusted as follows. The quantization parameter (or level) assigned to the quantizer can be defined as a simple function of buffer contents. Mathematically, the quantization parameter, QP , can be expressed as

$$QP = \frac{BufferContents}{Q_{division}} + Q_{offset}, \quad (7)$$

where $Q_{division}$ is the quantization division factor of the buffer and Q_{offset} is the offset factor. The *BufferContents* variable indicates how much data (in unit of bits) is currently stored in the buffer.

According to the RM8 coder [31] (a reference implementation of the H.261 coder, developed by the standardization study group), Q_{offset} is set to 1 to avoid zero quantization, while $Q_{division}$ is equal to the target *Bitrate* divided by a constant value of 320, i.e.

$$Q_{division} = \frac{Bitrate}{320} = \frac{64000 \times p}{320} = 200p, \quad (8)$$

where $Bitrate = p \times 64$ kbits/s, $p = 1, \dots, 30$. Hence for the RM8 coder, the next quantization parameter is determined by the function described as

$$QP = \min \left\{ \left\lceil \frac{BufferContents}{200p} + 1 \right\rceil, 31 \right\}, \quad (9)$$

The value of QP is clipped at 31 because the *MQUANT* header is a fixed length codeword of 5 bits. As the *BufferContents* increases, QP also increases in order to offset any rise in bit rate. The value of QP will remain at the maximum of 31 until the buffer is full, which takes place when the *BufferContents* variable reaches the maximum capacity of the buffer. When *BufferContents* variable exceeds the buffer size, buffer overflow is said to occur. In such event,

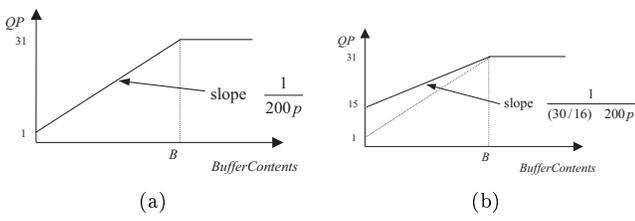


Fig. 18. (a) Rate control function used in the RM8 coder and (b) proposed rate control function for the background MBs in the H.261FB coder.

the macroblock is skipped (i.e. not transmitted), and as a result, quantization is no longer needed.

In the H.261FB approach, two similar rate control functions as mentioned above are used - one for the foreground region and another for the background. Each function will have different values of $Q_{division}$ and Q_{offset} . For instance, we can set Q_{offset} to a higher value such that the function forces the quantizer to always adopt a coarser quantization parameter. Therefore the amount of bit transfer between foreground and background macroblocks is mainly determined by the value of Q_{offset} being assigned to their respective rate control functions. On the other hand, the offset factor, $Q_{division}$, governs how the bits are distributed within the same region.

Here we choose (9), the function defined in RM8, for the foreground region (see Fig. 18(a)). As for the background region, we shift Q_{offset} to 15 and set $Q_{division}$ to $(30/16) \times 200p$ (see Fig. 18(b)). This constrains the quantizer to a minimum value of 15 while the clipping of the quantization level to its maximum value will occur at the same level of buffer occupancy, B , as in the case of RM8.

D. Coding Results

The FB coding scheme is demonstrated on the CIF *Foreman* video sequence. First, we used our proposed face segmentation algorithm to separate each frame of the input sequence into foreground and background MBs. The results for the first frame of the sequence are shown in Fig. 19(a) and 19(b).

We then encoded the sequence with both the RM8 and H.261FB coders. Note that, other than the use of the discriminatory quantization process and the new rate control function as described in previous section, the rest of the implementation of the H.261FB coder is same as the RM8.

To evaluate the discriminatory quantization process, we performed intraframe coding on the first frame. In order to provide a fair comparison of image quality, the quantization parameters were manually obtained so that both approaches consume similar amount of bits. Therefore the quantizer for the RM8 coder was fixed at 22 throughout the entire encoding processing. For the H.261FB coder, the foreground quantizer, Q_f , and the background quantizer, Q_b , were set at 11 and 31 respectively. Overall, the RM8 coder spent an average of 105.81 bits per macroblock. Furthermore, we have identified that it spent an average of

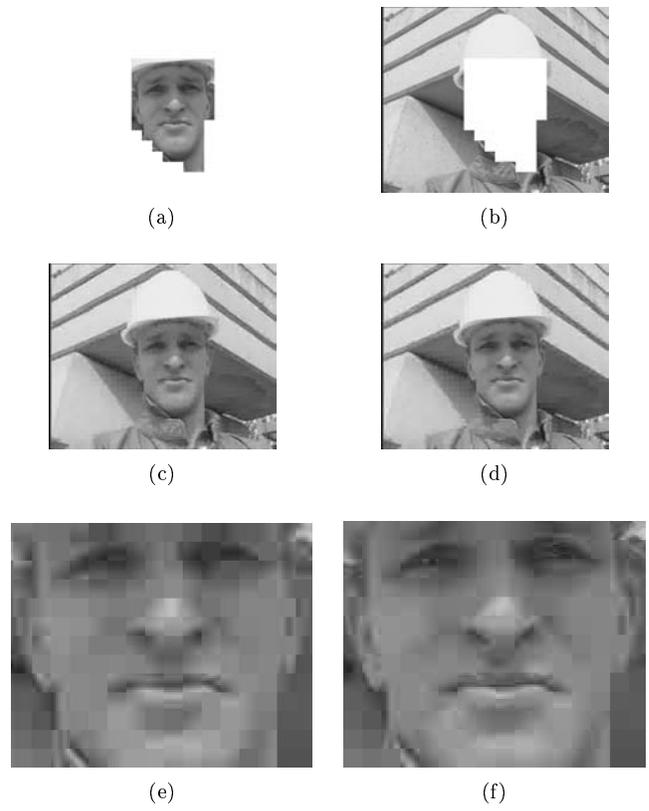


Fig. 19. (a) Foreground MBs, (b) background MBs, (c) coded by RM8, (d) coded by H.261FB, (e) magnified image of (c), and (f) magnified image of (d).

89.01 bits per MB in the foreground region and 109.54 bits per MB in the background region. The quality of the encoded image is shown in Fig. 19(c). This is compared with the H.261FB-encoded image shown in Fig. 19(d) whereby the coder spent an average of 134.72 bits per foreground MB and 90.70 bits per background MB, while its overall average bit per MB was 98.70. This overall amount of bits used is about 7.11 bits per MB fewer than that of the RM8, and yet the figures clearly show that the area of interest is much improved in the H.261FB-encoded image as a result of the bit transfer from background to foreground region, while its degradation in the background region was hardly noticeable. The improvement can be further illustrated by magnifying the face region of the images as shown in Fig. 19(e) and 19(f).

To demonstrate the performance of our proposed rate control functions for the FB coding scheme, both the RM8 and H.261FB coders were used to encode 100 frames of the *Foreman* sequence at a target bit rate of 192 kbits/s and frame rate of 10 f/s. A plot displaying the bit rates achieved by both coders is provided in Fig. 20. The simulation revealed that the subjective quality of the H.261FB-coded images was much better than the RM8-coded images, and yet their bit rates were slightly lower. We illustrate the improvement by showing a representative frame 72 of the encoded images in Fig. 21. It can be clearly observed that the H.261FB-coded image in Fig. 21(b) has a better

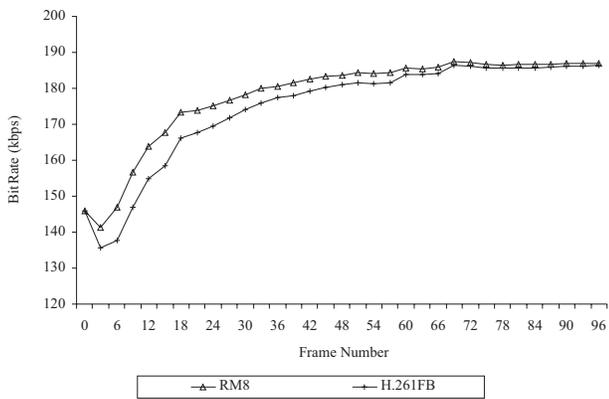


Fig. 20. Bit rates achieved by RM8 and H.261FB coders at a target bit rate of 192 kbits/s.



Fig. 21. Frame 72 of the coded results in Figure 20, (a) RM8 and (b) H.261FB.

perceived quality and rendition of facial features than the RM8-coded image shown in Fig. 21(a).

VI. CONCLUDING REMARKS

The color analysis approach to face segmentation was discussed. In this approach, the face location can be identified by performing region segmentation with the use of a skin-color map. This is feasible because human faces have a special color distribution characteristic that differs significantly from those of the background objects. We have found that pixels belonging to the facial region, of the image in YCrCb color space, exhibit similar chrominance values. Furthermore, a consistent range of chrominance values was also discovered from many different facial images, which include people of European, Asian and African descent. This led us to the derivation of a skin-color map that models the facial color of all human races.

With this universal skin-color map, we classified pixels of the input image into skin-color and non-skin-color. Consequently, a bitmap is produced, containing the facial region that is corrupted by noise. The noise may appear as small holes on the facial region due to undetected facial features, or it may also appear as objects with skin-color appearance in the background scene. To cope with this noise and, at the same time, refine the facial region detection, we have proposed a set of novel region-based regularization processes that are based on the spatial distribution study

of the detected skin-color pixels and their corresponding luminance values. All the operations are unsupervised and low in computational complexity.

Our proposed face segmentation methodology was implemented and tested on many input images, each of which contains the head-and-shoulders view of a person and a complex background scene. A set of representative results from our simulations was shown in the paper. The results demonstrated that our algorithm can accurately segment out the facial regions from a diverse range of images that includes subjects with different skin colors and the presence of various background complexities. Furthermore, the face segmentation was done automatically and in real-time.

The use of face segmentation for video coding in application such as videotelephony was then presented. We described a foreground/background video coding scheme that uses the face segmentation results to improve the perceptual quality of the encoded image with better rendition of the facial features. This technique involves bit transfer between the facial region and the background. The redistribution of bit allocation is controlled by a discriminatory quantization process. Then the bitstream generated from this process is regularized by a new rate control strategy. We have integrated this approach into the H.261 framework with success. Improved image quality was obtained as shown by the simulation results in the paper.

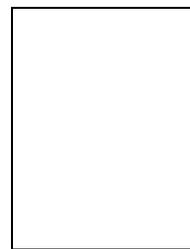
Our future research will involve the use of temporal information to assist in face localization and also for tracking. While for coding, a further study of the rate control strategy, the use of segmentation-assisted motion estimation and the proposal of coding the foreground and background regions at different frame rates will be investigated.

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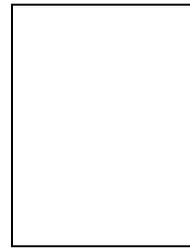
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FIGURE CAPTIONS

- Fig. 1. The use of color information for region segmentation.
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- Fig. 3. The histograms of Cr and Cb components in the facial region.
- Fig. 4. *Foreman* and *Carphone* images, and their color segmentation results obtained by using the same pre-defined skin-color map.
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