# Contrast-Based Color Image Segmentation

Hsin-Chia Chen, Wei-Jung Chien, and Sheng-Jyh Wang

***Abstract*—In this letter, we propose a color image segmentation algorithm based on contrast information. Given a color image, we use contrast information, instead of the commonly used derivative information, to detect edges. To fit for human's visual perception, the CIE $L^*a^*b^*$ color space is used and the $\Delta E_{ab}$ color difference is adopted as the measure of color contrast. A subjective experiment is made to demonstrate the weak correlation between the perceived color contrast and the levels of $(L^*, a^*, b^*)$. This experiment implies the feasibility of using a single-threshold scheme to suppress perceptually faint boundaries. A complete segmentation scheme is proposed and the simulation results demonstrate the superiority of this approach in providing reasonable and reliable color image segmentation.**

***Index Terms*—CIE $L^*a^*b^*$ color space, color difference, color image segmentation, contrast.**

## I. Introduction

In recent years, plenty of efforts have been focusing on the segmentation of color images. In general, current image segmentation algorithms can be roughly classified into three major categories: 1) image domain-based techniques; 2) feature space-based techniques; and 3) physics-based techniques [1]. For image domain-based techniques [2]–[6], the similarity of neighboring pixels or the discontinuity of local information is used as the gauge for segmentation. Adjacent pixels with small intensity/color variations are merged together, while pixels with large enough variations are split apart. For feature space-based techniques [7]–[9], the data distribution of the entire image plays a crucial role. Clustering or grouping techniques are usually applied over the data distribution to allocate image data into groups. For physics-based techniques, the adopted mathematical tools are basically the same as the former two kinds of techniques, while an underlying physical model is used to account for the reflection properties of colored matter [1].

In this letter, we propose a new algorithm, which is an image domain-based technique. In this algorithm, we use contrast information, instead of the commonly used derivative information, as the gauge for color segmentation. So far, various forms of contrast have already been used for image enhancement [10], [11] and edge detection [3]. In [10], the contrast was defined as the ratio of high-frequency content and low-frequency content to fit human contrast sensitivity in spatial frequency, while in [11] a so-called simultaneous contrast was defined as the ratio of an object's luminance against its surrounding luminance. On the other hand, in [3], the contrast was defined as the square of 1st derivative to represent the strength of edges. Here, we adopt a new form of contrast, which is defined as the data difference across an edge. This contrast definition can be easily united with the widely used CIE $\Delta E_{ab}$ measure, which is defined over the CIE $L^*a^*b^*$ uniform color space and is closely related to human's visual perception [12]. As will be demonstrated at the end of this letter, the use of this contrast definition may provide reliable and reasonable segmentation results.

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## II. Directional Contrast Estimation

As mentioned above, the gauge of segmentation is usually based on data variation in a local area. Similarity-based algorithms group together pixels with small data variation, while discontinuity-based algorithms detect places with large data variation. To measure data variation, the derivative information is commonly used. Nevertheless, direct uses of derivative values may not faithfully reflect the way human perceives object boundaries. Fig. 1(a) shows an intensity profile extracted from a real image. Basically, each edge on this profile comprises three major factors: 1) edge height, 2) edge slope, and 3) noise irritation. Among these three factors, edge height is more related to the way human perceives edges than the other two [4]. However, all these three factors influence the measurement of the 1st derivative around an edge. For example, the values of its 1st differentiation are plotted in Fig. 1(b). In the middle of Fig. 1(a), there appear two apparent edges: a sharp edge around $x = 40$ and a smooth edge around $x = 50$. Even though these two edges have similar edge height, their 1st derivatives are quite different. Furthermore, the noise fluctuation around $x = 80$ generates a 1st derivative value that is as large as the 1st derivative value around $x = 50$. These two examples imply that a direct use of the 1st derivative information could be very risky if we aim for accurate segmentation.

In this letter, we name the edge height as edge contrast. It is defined as the intensity or color difference between the high-curvature points on the two sides of the boundary, as shown in Fig. 2. To detect these high-curvature points, we use a 2nd derivative operator to estimate the curvature of the profile. This 2nd derivative is designed as

$$B(x) = \delta(x) - N(x; 0, \sigma). \tag{1}$$

Here, $\delta(x)$ denotes the impulse function

$$\delta(x) = \begin{cases} 1, & x = 0 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

while $N(x; 0, \sigma)$ denotes a Gaussian function with zero mean and standard deviation $\sigma$.

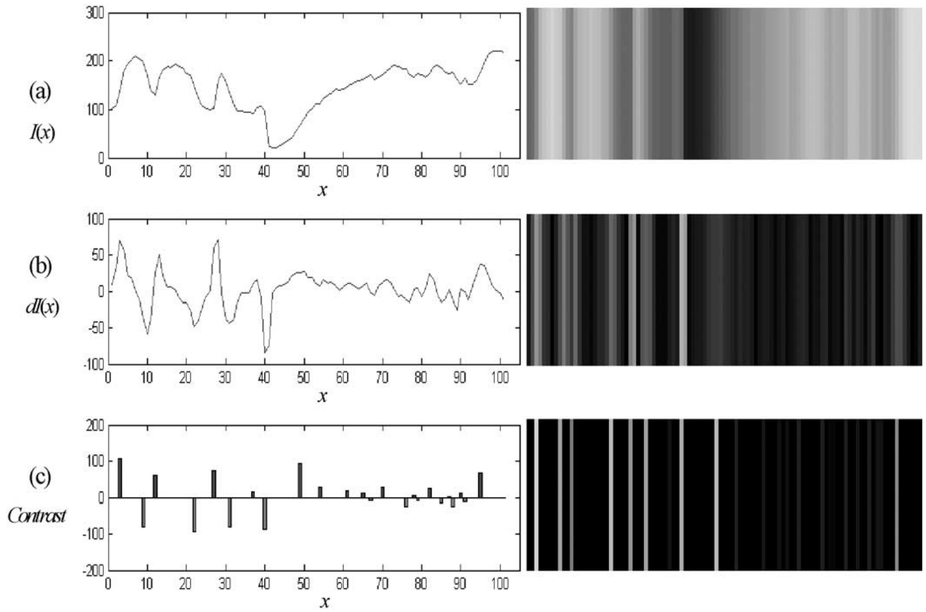


Fig. 1. (a) Intensity profile extracted from a real image. (b) The estimated 1st derivative information. (c) The estimated contrast information with $\sigma = 2.0$.

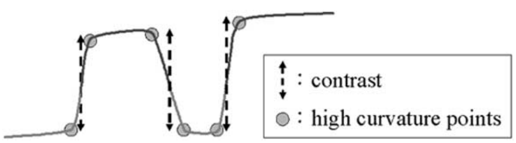


Fig. 2. Definition of contrast.

By convoluting a profile $I(x)$ with this operator, we have

$$\varphi(x) = I(x) \otimes B(x) = I(x) - I(x) \otimes N(x; 0, \sigma). \quad (3)$$

Basically, $\varphi(x)$ can be imagined as the 2nd derivative of the profile $I(x)$. Moreover, the local extremes of $\varphi(x)$ correspond to the high-curvature points of $I(x)$. Fig. 1(c) shows the contrast information extracted from Fig. 1(a) using (3) with $\sigma = 2.0$, which is determined empirically. It is obvious that Fig. 1(c) offers much more reliable information than Fig. 1(b).

Since the 2nd derivative is orientation-dependent, the contrast information at an image pixel has to be measured along various orientations. In the proposed algorithm, we detect boundaries by checking the relations between each pixel and its eight neighbors. Hence, four directional operators are used at each pixel to measure the curvature information at that pixel. These four directions are 0°, 45°, 90° and 135°, respectively. All these four directional contrast data are then grouped together in subsequent processes.

## III. Color Contrast in the CIE Lab Color Space

In color image segmentation, a proper choice of color space is also a crucial issue. In the selection of color space, we choose the CIE $L^*a^*b^*$ color space to work on due to its three major properties: 1) separation of achromatic information from chromatic information, 2) uniform color space, and 3) similar to human visual perception [12]. Here, $L^*$ represents the luminance component, while $a^*$ and $b^*$ represent color components. The formulae for converting an RGB image into the $(L^*, a^*, b^*)$ coordinates can be found in many color-related articles, like [12] and [13].

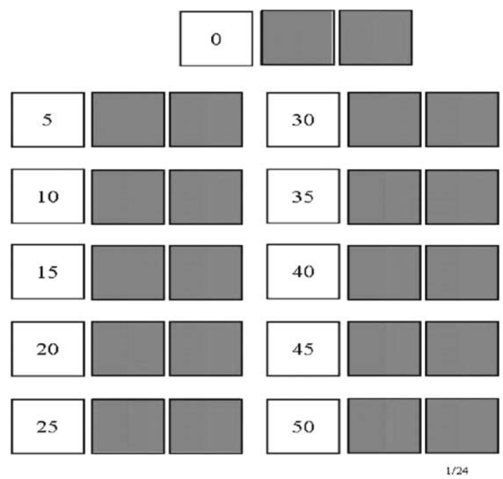


Fig. 3. Example of the test pattern in the subjective experiment.

In the CIE $L^*a^*b^*$ color space, the Euclidean distance between $(L_1^*, a_1^*, b_1^*)$ and $(L_2^*, a_2^*, b_2^*)$, defined as

$$\Delta E_{ab} = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2} \quad (4)$$

is approximately equivalent to the perceptual difference between these two colors [4], [12]. By incorporating this color difference formula into our contrast definition, we define the color contrast across an edge as

$$\text{color contrast} \equiv \sqrt{\text{contrast}_{L^*}^2 + \text{contrast}_{a^*}^2 + \text{contrast}_{b^*}^2}. \quad (5)$$

To further explore the correlation between color contrast and the luminance level or color level, we made a subjective experiment. In our experiment, 10 observers are involved and the patterns are displayed over a calibrated ViewSonic PT775 monitor for comparisons. Here, the values of luminance/color contrast are coarsely quantized into eleven steps, 0, 5, 10, 15, …, 50. In

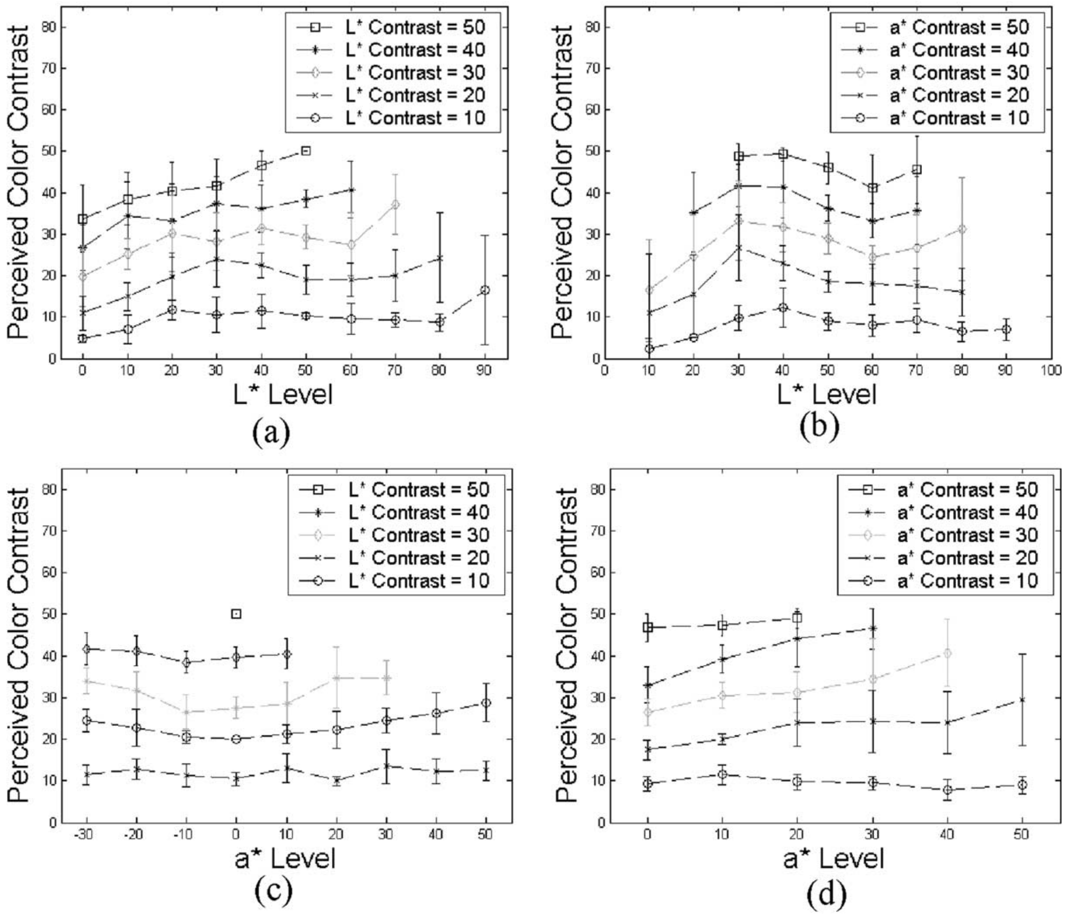


Fig. 4. Subjective experiment results for color contrast perception. (a) Perceived color contrast versus luminance level for 5 different $L^*$ contrasts. (b) Perceived color contrast versus luminance level for 5 different $a^*$ contrasts. (c) Perceived color contrast versus color level for 5 different $L^*$ contrasts. (d) Perceived color contrast versus color level for 5 different $a^*$ contrasts.

the experiment, a set of eleven step images with different contrast values but the same level value is used as reference. Each time, a step image with randomly specified contrast and level values is generated and is placed on the right side of each reference pattern for comparison, as shown in Fig. 3. The observers are asked to choose one or two reference patterns whose perceptual contrast is most similar to the randomly generated step image. In total, 131 testing images are examined and the averaged results are shown in Fig. 4(a)–(d). It could be seen that our color contrast definition is roughly equivalent to the perceived color contrast and is weakly correlated with luminance/color levels. This implies that a single global threshold may work reasonably well over the whole image to suppress perceptually faint edges.

## IV. Color Segmentation Algorithm

### *A. Segmentation Algorithm*

Based on directional contrast information and a single-threshold scheme over estimated color contrast, the flowchart of the proposed algorithm is illustrated in Fig. 5.

The color space conversion is applied to the color image first. Then four directional operators are applied to each component of $(L^*, a^*, b^*)$ to extract directional contrast.

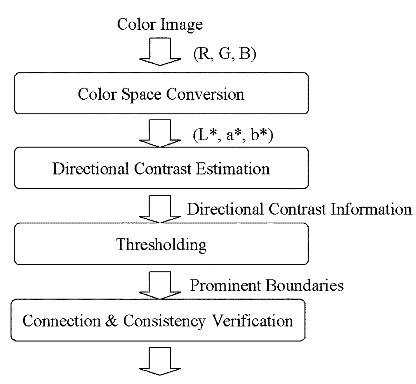


Fig. 5. Flow chart of the proposed algorithm.

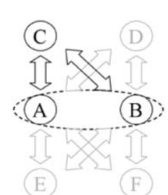


Fig. 6. Illustration of consistency verification.

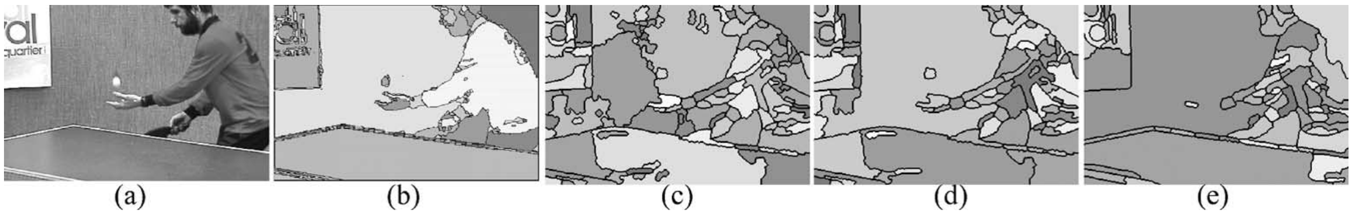


Fig. 7. (a) Original image. (b) Segmentation result of the proposed algorithm, represented in pseudo-color, with $\sigma = 1.4$ and threshold $= 23$. (c), (d), (e) Segmentation results of Deng and Manjunath's algorithm [6], represented in pseudo-color, with different threshold values.

A single threshold is then applied over the estimated color contrast to detect boundaries. These directional data are then merged together via the connection and verification process. In the connection and verification process, these horizontal boundaries and vertical boundaries are checked first. Any two neighboring pixels without a boundary between them are connected together. Then, these 45° and 135° boundaries are checked to remove logically inconsistent connections.

Here we use Fig. 6 to illustrate the meaning of logically consistent connection. Take the triplet of Pixel-A, Pixel-B and Pixel-C as an example. Let " $\sim$ " denote there is no boundary between two neighboring pixels; "$\nsim$ " denote there is a boundary between two neighboring pixels; and "$\cap$ " denote the logical AND. We have that

***If*** $A \sim B$ ***is true,***
***then either*** $(A \sim C) \cup (B \sim C)$ ***or*** $(A \nsim C) \cup (B \nsim C)$ ***has to be true.***
***Otherwise, the connection between Pixel-A and Pixel-B is logically inconsistent.***

In this verification step, all logically inconsistent connections are disconnected. Surviving connections are then merged together to produce the final segmentation result.

### *B. Segmentation Results*

Fig. 7(a) shows a color image. The segmented result of the proposed algorithm is shown in Fig. 7(b), represented in pseudo colors with $\sigma = 1.4$ and contrast-threshold $= 23$. Even though these two parameters are determined empirically, the parameter setting process is quite simple. Usually, a larger $\sigma$ is used to better suppress noise, while a smaller $\sigma$ value is used to distinguish tiny details. Similarly, a larger color-threshold is used to extract objects of larger intensity variations, while a small color-threshold is used to distinguish object details. In comparison, the parameter setting process is usually troublesome in many segmentation algorithms. Take Deng and Manjunath's algorithm [6] as an example, as we choose a small quantization threshold, many tiny details are revealed but the uniform background is split into several regions, as shown in Fig. 7(c). On the contrary, as we increase the value of quantization threshold, the background is merged together, but many tiny objects, like the palm in Fig. 7(e), are mistakenly merged. These two algorithms were performed on a PC with Intel Pentium III 800 Mhz and 256 MB memory. Given a $512 \times 512$ color image, the CPU time for Deng and Manjunath's algorithm is around 1 to 2 min, and for our proposed algorithm is around 10 to 20 s, without performing code optimization.

## V. CONCLUSION

In this letter, we propose the use of contrast information for color image segmentation. We found that the contrast information is quite useful and reliable in detecting boundaries. To estimate the color contrast in a 2-D image, we use four directional operators to extract directional color contrast information. A single-threshold scheme is then applied over the estimated color contrast to detect directional boundaries. Finally, these directional boundaries are merged together via a connection and verification process to form 2-D boundaries. The simulation results demonstrate that this new algorithm is capable of providing reasonable and reliable results.

## REFERENCES

[1] L. Lucchese and S. K. Mitra, "Color image segmentation: A state-of-the-artx survey," in *Proc. Indian National Science Academy (INSA-A)*, vol. 67, A, New Delhi, India, Mar. 2001, pp. 207–221.
[2] J. Canny, "Computational approach to edge detection," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. PAMI-8, pp. 679–698, Nov. 1986.
[3] A. Cumani, "Edge detection in multispectral images," *CVGIP: Graph. Models Image Process.*, vol. 53, no. 1, pp. 40–51, 1991.
[4] M. A. Ruzon and C. Tomasi, "Edge, junction, and corner detection using color distributions," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 23, pp. 1281–1295, Nov. 2001.
[5] W. Y. Ma and B. S. Manjunath, "Edge flow: A technique for boundary detection and image segmentation," *IEEE Trans. Image Processing*, vol. 9, pp. 1375–1388, Aug. 2000.
[6] Y. Deng and B. S. Manjunath, "Unsupervised segmentation of color-texture regions in images and video," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 23, pp. 800–810, Aug. 2001.
[7] J. Shi and J. Malik, "Normalized cuts and image segmentation," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 22, pp. 888–905, Aug. 2000.
[8] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 24, pp. 603–619, May 2002.
[9] C. Carson, S. Belongie, H. Greenspan, and J. Malik, "Blobworld image segmentation using expectation-maximization and its application to image querying," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 24, pp. 1026–1038, Aug. 2002.
[10] J. Tang, E. Peli, and S. Acton, "Image enhancement using a contrast measure in the compressed domain," *IEEE Signal Processing Lett.*, vol. 10, pp. 289–292, Oct. 2003.
[11] W. M. Morrow, R. B. Paranjape, R. M. Rangayyan, and J. E. L. Desautels, "Region-Based contrast enhancement of mammograms," *IEEE Trans. Med. Imag.*, vol. 11, no. 3, pp. 392–406, Sep. 1992.
[12] G. Wyszecki and W. Stiles, *Color Science: Concepts and Methods, Quantitative Data and Formulae*, 2nd ed. New York: Wiley, 1982.
[13] (1999) SRGB—Default RGB Color Space. International Electro technical Commission (IEC) 61966-2-1. [Online]. Available: http://www.iec.ch