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An Image Segmentation Method for Eliminating Illumination Influence

Shuqiang Guo and Liqun Wang

School of Information Engineering
Northeast Dianli University
Jilin, Jilin, 132012, China
guoshuqiang@gmail.com

Honghui Fan

School of Computer Engineering
Jiangsu University of Technology
Changzhou, Jiangsu, 213001, China
fanghonghui@hotmail.com

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Abstract. *Image segmentation plays an important role in the fields of multimedia, image processing and computer vision. However, image segmentation is a difficult problem in the process of image understanding and analysis. Erroneous segmentation results often occur, especially if an interfering light source is involved, because of the influence of shadow and light intensity. This paper presents a novel method based on color constancy to eliminate the influence of light intensity and position. The experimental results show that this method is more effective than conventional image segmentation methods such as the Otu method, the K-Means method, and others.*
Keywords: Color constancy; Image segmentation; ISODATA clustering; Machine vision

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1. **Introduction.** The image quality captured by digital cameras, video cameras and other electronic equipment is affected by the intrinsic parameters of the camera, the surface characteristics of the object and the lighting conditions. Any changes in any of these three factors will influence the final color signal of the image. In general, if the effect of differences in the lens photo sensitive coefficient is ignored, the lighting conditions will be the main external factor that impacts image color. Different lighting conditions can cause the same object surface to appear to have completely different colors; color is an extremely unstable visual feature. Fortunately, the human visual system is capable of perceiving colors with constancy; it can eliminate the effect of light on color and obtain a true reading of the color of the object surface [1]. In order to improve the stability of computer vision systems, computer scholars have introduced the color constancy theory and presented calculations of color constancy. The purpose of computational color constancy is to eliminate the effect of illumination on the color of images so as to obtain the color properties of the object surface. In this paper, a color image segmentation method, in combination with color constancy and ISODATA clustering, is put forward.

Image segmentation is a key step in the progression from image processing to image analysis. Segmentation is the basis for expressing the image, and it has an important influence on the measurement of image features. Image segmentation, feature extraction and parameter measurement based on image segmentation can transform the original image into more abstract and more compact forms. Segmentation makes it possible to analyze and understand the image. Image segmentation has attracted the attention of scholars and researchers since the 1970's. To date, thousands of segmentation algorithms have been developed; so many, in fact, that several classification methods have been put forward to categorize these algorithms. Traditional image segmentation methods can generally be divided into the following four classes: (1) threshold-based method [2, 3]; (2) edge-based method [4]; (3) region-based method [5, 6]; and (4) specific theory-based method [7, 8, 9].

However, in most cases these image segmentation methods are applied in conditions in which the lighting is uniform, or in which the lighting condition is ignored altogether. Recently, many image segmentation methods that consider lighting conditions have appeared. Li-sheng Jin proposed an image segmentation method that is highly robust in its treatment of shadows and strong illumination conditions [10]. Another image segmentation method, which analyzes the correlation of neighboring image pixels and merges similar areas, is proposed by Li Ma [11]. However, these methods are easily affected by texture and may lead to incorrect segmentation, because they use the difference in gray levels to determine the similarity of the regions they are merging.

In addition, in recent years, much has been achieved in the area of color constancy. Finlayson Graham D analyzes color constancy for the RGB values of color images [12], and Bauml Karl-Heinz puts forward a method of removing shadows in images using the color constancy feature of color images [13]. Gijsenij has researched color constancy to identify the most important characteristics of color in images using natural image statistics [14]. The focus of the aforementioned studies is the theoretical study of color constancy. The applications of color constancy theories in image processing are few in number.

In this paper, a novel image segmentation method based on ISODATA clustering and color constancy is proposed. Using this method, we can remove the effect of illumination on image segmentation, and the color image can be segmented more accurately, even if the image is taken in non-uniform illumination conditions.

2. **Computational Model of Color Constancy.**

Color constancy is the ability to perceive the colors of objects, without reference to the color of the light source. This ability is generally considered to be possible for the human visual system, although the exact details of how it works in human vision remain uncertain. Experiments show that the human visual system is capable of easily identifying and restoring the color of the target image in the brain, even if the target's color is changed by the color and brightness of the light source. This ability of the human visual system is called color constancy [15].

According to color constancy theory, light shines on the surface of an object and reflects into the eye or digital camera, and then the image is formatted. Therefore, when the light is reflected by the object surface, the RGB value of the image can be calculated by the following equation [16]:

$$p_k = \tau \int_{\lambda} E(\lambda)S(\lambda)F_k(\lambda)d\lambda, \qquad k = \{R, G, B\} \tag{1}$$

In Eq.(1), λ is the wavelength of the incident light source; $E(\lambda)$ is the color of the light source; $S(\lambda)$ is the reflectance characteristic function of the object surface; $F(\lambda)$ is the photographic characteristic function of the digital camera; and τ is the gain coefficient of the camera. If the photographic characteristic approximates to the δ function, then the photographic characteristic function $F(\lambda)$ can be calculated by:

$$F_k(\lambda) = \delta(\lambda - \lambda_k), \qquad k = \{R, G, B\} \tag{2}$$

Therefore, Eq.(1) can be simplified as:

$$p_k = \tau E(\lambda_k) S(\lambda_k), \qquad k = \{R, G, B\} \tag{3}$$

As shown in Eq.(2), the RGB value in three color channels equals the product of the light source characteristic function $E(\lambda)$ and the reflectance characteristic function of the object surface $S(\lambda)$. Because τ and the reflectance characteristics function $S(\lambda)$ are constants in the same surface of object, the RGB value of each channel in the same surface correlates only with the light source characteristic function.

We posit that the color characteristic of the light source can be used instead of the blackbody radiation. According to Planck's law of blackbody radiation, the radiation energy of blackbody radiation can be calculated by:

$$E(\lambda) = C_1 \lambda^{-5} \left[\exp\left(\frac{C_2}{T\lambda} \right) - 1 \right] \tag{4}$$

where C_1 and C_2 are constants, T is the blackbody temperature, and the unit is K. According to Finlayson's research results [10], when the visible wavelength range is between 360nm and 830nm, and the blackbody temperature T is below 10000K, then $\exp(\frac{C_2}{T\lambda}) \gg 1$. In this case, Eq. (4) can be approximated as:

$$E(\lambda) \approx C_1 \lambda^{-5} \exp\left(\frac{C_2}{T\lambda} \right) \tag{5}$$

According to Eq.(4), the energy ratio of the wavelengths of λ_1 and λ_2 can be given as:

$$\frac{E(\lambda_1)}{E(\lambda_2)} \approx \left(\frac{\lambda_2}{\lambda_1} \right)^5 \exp\left[\frac{-C_2}{T} \left(\frac{1}{\lambda_1} - \frac{1}{\lambda_2} \right) \right] \tag{6}$$

If both sides of equation are taken as the bottom e of the logarithm, then Eq.(6) can be transformed as:

$$\ln \frac{E(\lambda_1)}{E(\lambda_2)} = \ln \left(\frac{\lambda_2}{\lambda_1} \right)^5 - \frac{C_2}{T} \left(\frac{1}{\lambda_1} - \frac{1}{\lambda_2} \right) \tag{7}$$

When the wavelength of RGB is expressed as λ_R, λ_G and λ_B respectively, then Eq.(7) can be transformed as :

$$\begin{bmatrix} \ln \dfrac{E(\lambda_R)}{E(\lambda_G)} \\ \\ \ln \dfrac{E(\lambda_B)}{E(\lambda_G)} \end{bmatrix} = \begin{bmatrix} \ln \left(\dfrac{\lambda_G}{\lambda_R} \right)^5 \\ \\ \ln \left(\dfrac{\lambda_G}{\lambda_B} \right)^5 \end{bmatrix} - \frac{C_2}{T} \begin{bmatrix} \dfrac{1}{\lambda_R} - \dfrac{1}{\lambda_G} \\ \\ \dfrac{1}{\lambda_B} - \dfrac{1}{\lambda_G} \end{bmatrix} \tag{8}$$

The left side of the equation is the natural logarithm ratio of the RGB energy in three channels. According to Eq.(3) and Eq.(8), the following equation can be obtained:

$$\begin{bmatrix} \ln \dfrac{p_R}{p_G} \\ \\ \ln \dfrac{p_B}{p_G} \end{bmatrix} = \begin{bmatrix} \ln \dfrac{S(\lambda_R)}{S(\lambda_G)} \left(\dfrac{\lambda_G}{\lambda_R} \right)^5 \\ \\ \ln \dfrac{S(\lambda_B)}{S(\lambda_G)} \left(\dfrac{\lambda_G}{\lambda_B} \right)^5 \end{bmatrix} - \frac{C_2}{T} \begin{bmatrix} \dfrac{1}{\lambda_R} - \dfrac{1}{\lambda_G} \\ \\ \dfrac{1}{\lambda_B} - \dfrac{1}{\lambda_G} \end{bmatrix} \tag{9}$$

where p_R, p_B and p_G are the RGB values in the three channels. Therefore, the natural logarithmic ratio of the RGB values on the same surface of the object is a straight line, the slope of which is the inverse of the blackbody temperature T.

3. Segmentation Method Based on Color Constancy.

3.1. **Overview.** In this paper, the processing flow of image segmentation is shown in Figure 1. First, the similarity measurement is calculated using the aforementioned color constancy in the RGB channels. Second, the image is segmented based on ISODATA clustering analysis, which is an iterative, self-organizing clustering method. Finally, the processed image is output.

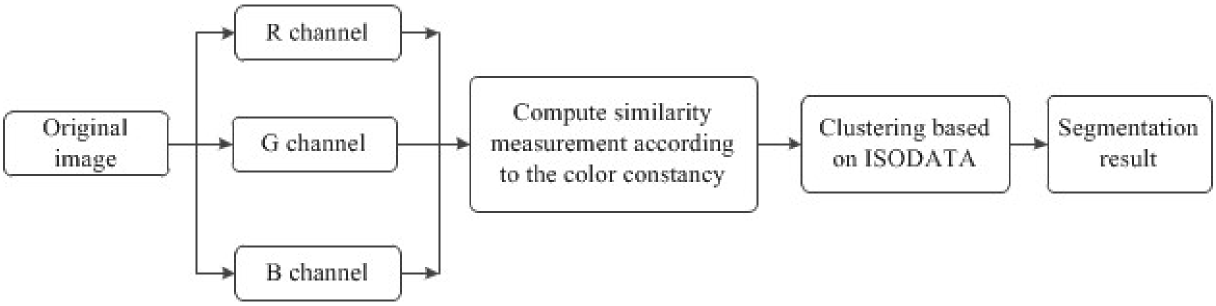


FIGURE 1. Processing Procedure of Segmentation Method Based on Color Constancy

3.2. **Similarity Measurement Calculation based on Color Constancy.** In order to make the RGB value of an image accurately reflect the blackbody radiation energy in Eq. (9), gamma correction must be applied to the RGB value of each channel. The values p_1 and p_2 are calculated after gamma correction, and then the difference vector B between two pixels can be given as:

$$B(p_1, p_2) = \begin{bmatrix} \ln \frac{p_{1\_R}}{p_{1\_G}} \\ \\ \ln \frac{p_{1\_B}}{p_{1\_G}} \end{bmatrix} - \begin{bmatrix} \ln \frac{p_{2\_R}}{p_{2\_G}} \\ \\ \ln \frac{p_{2\_B}}{p_{2\_G}} \end{bmatrix} \tag{10}$$

The second item on the right side of Eq.(1) is expressed by the following equation:

$$d = \begin{bmatrix} \frac{1}{\lambda_R} - \frac{1}{\lambda_G} \\ \\ \frac{1}{\lambda_B} - \frac{1}{\lambda_G} \end{bmatrix} \tag{11}$$

The similarity measurement of the two pixels p_1 and p_2 is given as:

$$J(p_1, p_2) = \frac{|B(p_1, p_2) \cdot d|}{|B(p_1, p_2)|\,|d|} \tag{12}$$

As shown in Eq. (1) , the value of $J(p_1, p_2)$ ranges from 0 to 1. When the two pixels are on the same surface in a situation of non-uniform illumination, the value of $J(p_1, p_2)$ tends toward 1. On the other hand, if the two pixels are on different surfaces of the object, the value of $J(p_1, p_2)$ tends toward 0. Using this feature, the value of $J(p_1, p_2)$ can be regarded as the similarity measurement that can be used to segment the image using ISODATA clustering.

3.3. **Image Segmentation using ISODATA.** In this method, the color of the image is the basis of the clustering analysis. However, if the RGB color space is a non-uniform color space, then the geometric distance of the RGB space is not proportional to the color difference. Therefore, in order to more accurately describe the color difference, the CIELAB color space is applied to calculate the color difference. The transformational relationship between the RGB color space and the CIELAB color space is given as:

$$x = X(p), \quad p = P(x) \tag{13}$$

where x is the RGB value of the image in the RGB color space, X is the transfer function from the CIELAB color space to the RGB color space function. p is a value in the CIELAB color space, and P is the transfer function from the RGB color space to the CIELAB color space.

The distance function D for clustering is calculated by the following equation:

$$D(x_1, x_2) = A(x_1, x_2)\Delta E^*(x_1, x_2) \tag{14}$$

where A is the weight function, and its calculation formula is as follows:

$$A(x_1, x_2) = 1 - \alpha J(P(x_1), P(x_2)) \tag{15}$$

where α is an adjustable parameter. In this paper, parameter α takes the empirical value $\alpha = 0.4$, and ΔE^* is the color difference in the CIELAB space, and which can be obtained by the following equation:

$$\Delta E^*(x_1, x_2) = \sqrt{\sum_k (x_{1k} - x_{2k})^2}, \qquad k = \{L^*, a^*, b^*\} \tag{16}$$

The similarity measurement between any two points in the image can be calculated by Eq.(12). According to the similarity measurement, the image can be segmented by ISODATA clustering. The procedure of clustering is as follows [17]:

(1) Letting $k = k_{\text{init}}$, randomly sample k cluster initial centers $Z = \{z_1, z_2, \ldots, z_k\}$ from S.

(2) Assign each point to its closest cluster center. For $1 \le i \le k$, let $S_i \subseteq S$ be the subset of points that are closer to z_i than to any other cluster center of Z. That is, for any $x \in S$,

$$x \in S_j \ \text{ if } \ D(x, z_j) < D(x, z_i), \forall i \neq j. \tag{17}$$

(3) Remove cluster centers with fewer than $n_{\min}$ points. (The associated points of S are not deleted, but are ignored for the remainder of the iteration.) Adjust the value of k and relabel the remaining clusters $S_1, \ldots, S_k$ accordingly.

(4) Move each cluster center to the centroid of the associated set of points. That is,

$$z_j \leftarrow \frac{1}{n_j} \sum_{x \in S_j} x, \quad \text{for} \ \ 1 < j < k. \tag{18}$$

If any clusters were deleted in Step 3, then the algorithm returns to Step 2.

(5) Let Δj be the average distance of points of S_j to the associated cluster center z_j , and let Δ be the overall average of these distances.

$$\Delta_j \leftarrow \frac{1}{n_j} \sum_{x \in S_j} D(x, z_j), for 1 < j < k. \tag{19}$$

(6) If this is the last iteration, then set $L_{\min} = 0$ and go to Step 9. Also, if $2k > k_{\text{init}}$ and it is either an even numbered iteration or $k \ge 2k_{\text{init}}$, then go to Step 9.

(7) For each cluster S_j , compute a vector $v_j = (v_1, \ldots, v_d)$ whose ith coordinate is the standard deviation of the ith coordinates of the vectors directed from z_j to every point of S_j . That is,

$$v_{ji} \leftarrow \left(\frac{1}{n_j} \sum_{x \in S_j} \{A(x, c_i)(x_i - c_{ij})\}^2 \right)^{1/2} \quad \text{for } 1 \leq j \leq k \text{ and } 1 \leq i \leq d \tag{20}$$

Let $v_{j,\max}$ denote the largest coordinate of v_j.

(8) For each cluster S_j, if $v_{j,\max} > \sigma_{\max}$ and either

$$((\Delta j > \Delta \text{ and } (n_j > 2(n_{\min} + 1)))) \text{ or } k \leq \frac{k_{\text{init}}}{2} \tag{21}$$

then increment k and split S_j into two clusters by replacing its center with two cluster centers centered around z_j and separated by an amount and direction that depends on $v_{j,\max}$. If any clusters are split in this step, then go to Step 2.

(9) Compute the pairwise intercluster distances between all distinct pairs of cluster centers

$$d_{ij} \leftarrow D(z_i, z_j), \text{ for } 1 \leq i \leq j \leq k. \tag{22}$$

(10) Sort the intercluster distances of Step 9 in increasing order, and select a subset of at most $P_{\max}$ of the closest such pairs of clusters, such that each pair has an intercluster distance of at most Lmin. For each such pair (i, j), if neither S_i nor S_j has been involved in a merger in this iteration, replace the two clusters S_i and S_j with a merged cluster $S_i \cup S_j$, whose associated cluster center is their weighted average

$$z_{ij} \leftarrow \frac{1}{n_i + n_j}(n_i z_i + n_j z_j) \text{ for } 1 \leq i \leq j \leq k. \tag{23}$$

Relabel the remaining clusters and decrease k accordingly.

(11) If the number of iterations is not the final iteration, then return to Step 2.

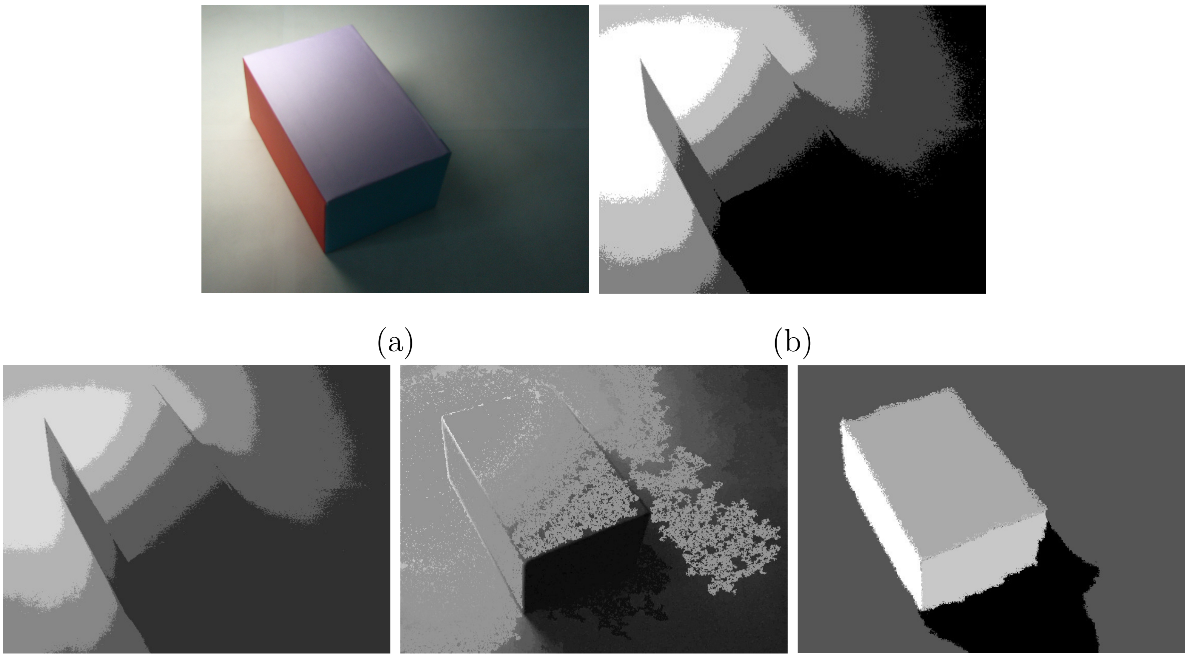
On the basis of the above ISODATA algorithm, the image segmentation results are obtained. According to Eq.(12), and Eq.(13), both the color difference and color constancy are considered in this ISODATA clustering algorithm, and the clustering result can effectively remove the influence of illumination on image segmentation.

4. **Experimental Results and Analysis.** In order to validate the effectiveness of this method, an experiment is performed. In this experiment, an image taken by a digital camera is segmented using the traditional edge-based segmentation method and also using the aforementioned segmentation method based on color constancy. The image is taken with a Panasonic Lumix camera, the object is in front of a white background, the image size is 640 × 470 pixels, the camera focal length is 35mm, and the parameters of the ISODATA clustering are shown in Table 1.

As shown in Figure 2 and Figure 3, Figure 2(a) and Figure 3(a) show the original image taken in the aforementioned conditions. The performance criterion, which is called the Segmentation Accuracy (SA), is computed by:

$$SA = \sum_i \frac{N_{R_i}}{N'_{R_i}} P(R_i) \tag{24}$$

where N'_{R_i} is the number of pixels in the ideal segmented region R_i, as shown in Figure 4; N_i is the number of pixels of the experimental results in the ideal segmented region; and $P(R_i)$ is the probability of R_i in the ideal segmentation results. The greater the SA of the image segmentation results, the more effective the segmentation method.



(a) (b)

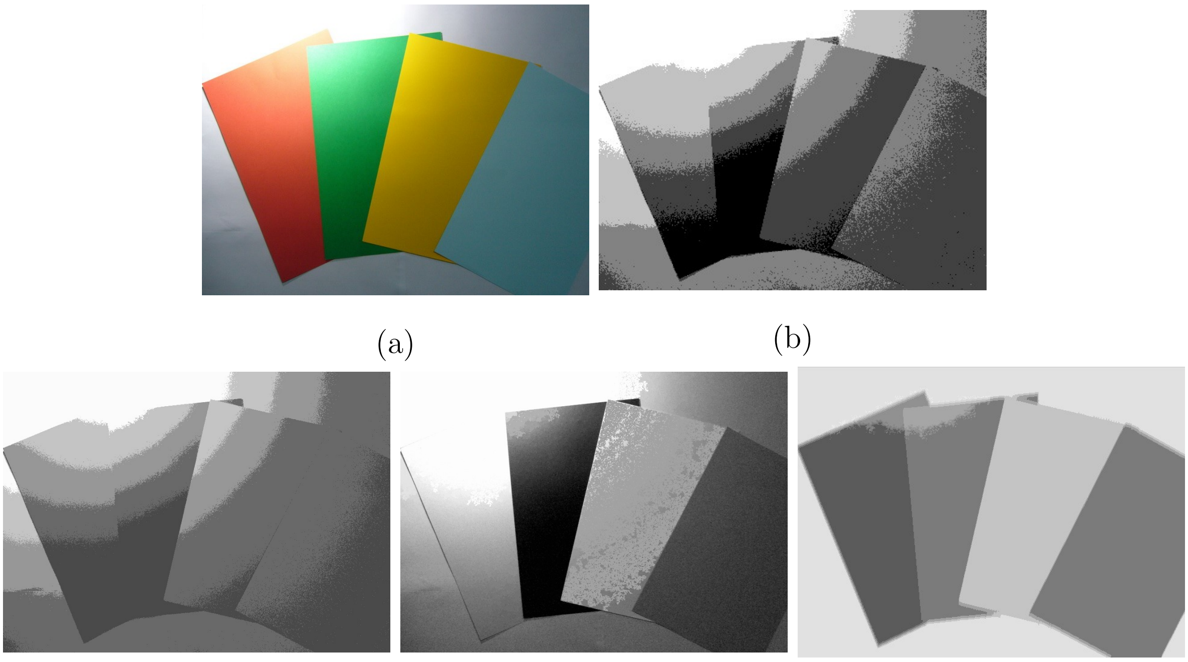
(c) (d) (e)

Figure 2. Segmentation Results on Cuboid Image: (a) Original image; (b) Segmentation Result based on Otu; (c) Segmentation Result based on K-Means; (d) Segmentation Result based on Mean-Shift; (f) Segmentation Result based on Color Constancy

Table 1. ISODATA Parameters of Experiment

ISODATA Parameters	**Value**
Starting number of clusters	20
Desired number of clusters	6
Maximum number of clusters	50
Minimum number of pixels per cluster	100
Exclusion Distance	3.5
The threshold of standard deviation	3×10^{-5}
Maximum number if iterations	50

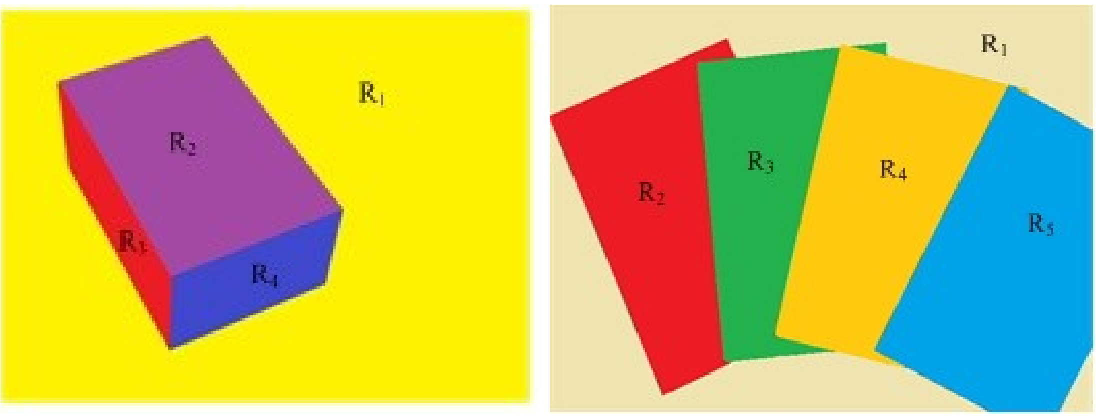
Figure 2(b), (c) and (d) are the segmentation results of the Otsu, K-Means and Mean-shift segmentation methods, respectively, and Figure 2(f) is the image segmentation result using the aforementioned color constancy and ISODATA clustering methods. The segmentation accuracy results of the various segmentation methods are listed in Table 2. According to Table 2, the segmentation method based on color constancy and ISODATA clustering is the most effective for eliminating the influence of illumination. The traditional segmentation methods can lead to over segmentation, because of the effect of the illumination condition, as shown in Figure 2(b), (c) and (d). In other words, one surface of the cuboid is divided into several areas in Figure 2(b), (c) and (d), and the top edge of the cuboid is not separated from the background. Compared with traditional segmentation methods, Figure 2(f) shows that the same surface of the cuboid is divided into the



(a) (b)

(c) (d) (e)

FIGURE 3. Segmentation Results on Papers Image: (a) Original image; (b) Segmentation Result based on Otu; (c) Segmentation Result based on K-Means; (d) Segmentation Result based on Mean-Shift; (f) Segmentation Result based on Color Constancy



(a) (b)

FIGURE 4. Ideal segmentation result: (a) Ideal segmentation result on Cuboid Image; (b) Ideal segmentation result on Papers image

same areas using the integrated color constancy and ISODATA clustering methods. The segmentation result of Figure 3 is similar to that of Figure 2. These results prove that the image segmentation method proposed in this paper is effective in eliminating the effect of non-uniform illumination.

Figure 5 shows the image segmentation experiment in a natural scene. In Figure 5(a), there are four boxes in the image, and there is bright sunshine in the left side of the image. The four boxes are a purple cylindrical box, a silver rectangular box, and a green and a red round rectangular box. Because of the non-uniform irradiation of the strong sunlight,

TABLE 2. Segmentation Accuracy of Segmentation Methods

	Segmentation Methods	SA
Cuboid Image	Otsu method	34.21%
	K-Means method	31.74%
	Mean-shift method	67.39%
	Color constancy method	87.41%
Papers image	Otsu method	44.74%
	K-Means method	39.33%
	Mean-shift method	81.58%
	Color constancy method	93.74%

(a) (b)

FIGURE 5. Segmentation result in natural scene: (a) original image; (b) segmentation result

the color of each box face is slightly different. Figure 5(b) provides the segmentation results using the color constancy method proposed in this paper. As shown in Figure 5(b), although the color of the silver box differs slightly on each face, the top face and the side face can be segmented clearly. According to the segmentation results of the purple cylindrical box, the top face is segmented in one region. However, because the side face does not meet the conditions of the proposed method, the same color of the side face is divided into three different regions, and the over-segmentation phenomenon occurs. The segmentation effect on the round rectangular boxes occurs between the rectangular box and the cylindrical box.

5. **Conclusion.** In this paper, a novel image segmentation method based on ISODATA clustering and color constancy is presented. The experimental results show that compared with traditional image segmentation methods based on boundary and region analysis, the proposed method can successfully divide an image in conditions of non-uniform illumination, and it can inhibit the generating of false contours.

This experiment is carried out in ideal conditions using a standard light source and a regular cube object. In the future, we will consider the problem of image segmentation in non-ideal conditions, such as multiple light sources and complex object shapes.

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