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A Study on a Proposed Superpixel Algorithm by Increasing Color Contrast of the Original Image Using Edge Information

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Abstract: This study proposes a superpixel algorithm which divides boundary of an object by increasing color contrast of original image using edge information. A bilateral filter was used to remove texture of an object's surface from original image. Then edge is detected by difference of value blurring using a Gaussian filter. The color contrast of original image is improved and the Simple Linear Iterative Clustering (SLIC) algorithm is applied. In the existing algorithms, boundaries are not clear due to small variations of color values, resulting in segmentation into same object and a non-uniform size and shape, depending on texture. However, in the proposed algorithm, edges with edge features are detected to improve color contrast of edge positions which are divided along boundaries and reduce result of unnecessary division according to texture. The proposed Superpixel algorithm can improve the response rate by increasing necessary division by texture and dividing more precisely according to boundary.

Key words: Superpixel, bilateral filter, edge detection, image analysis, image segmentation, variations

INTRODUCTION

Image analysis divides size, shape, contour, color, pattern and texture of an object into numerical values and divides data with similar features into non-overlapping regions (Shi and Malik, 2000; Malyszko and Wierzchon, 2007; Li *et al*., 2012; Levinshtein *et al*., 2009; Comaniciu and Meer, 2002; Wang and Wang, 2012; Zhang *et al*., 2017). Image segmentation is used in various fields of image processing because it can reduce complexity of algorithm by dividing it into pixels having similar features and patterns. Image segmentation is largely based on region-based and graph-based methods (Felzenszwalb and Huttenlocher, 2004). The region-based method is a method of finding an optimal partition by repeating process of assigning similar data to a randomly set center point and resetting center point. In the graph-based method, each pixel is regarded as a node and a graph having a weight of difference value between neighbor pixels is used. It is a way to divide a graph, so, that it has minimum weight value. Conventional methods sometimes show division results that ignore boundaries to maintain a certain size and shape. This split result divides the color and distance into weights. Since, color weights are low and distance weights are high, the result of dividing is shown by ignoring the boundary. To overcome this problem, we propose a superpixel algorithm with increased color contrast using edge information (Cho *et al*., 2014; Lin *et al*., 2016; Tomasi and Manduchi, 1998).

Literature review

Bilateral filter: The bilateral filter is a nonlinear filter that blurs image while preserving edge (Eq. 1). The bilateral filter is filtered by Weighted average (W_p) using range deviation and spatial deviation between center pixel (f_r) and surrounding pixels (g_s). The space deviation indicates change in color of center pixel and surrounding pixels and range deviation means distance between center pixel and surrounding pixels. The result is that as distance from center pixel decreases, value of weighted average decreases inversely. If surrounding values are similar to each other, a blurring effect is given. Therefore, it has property of preserving edge. In Eq. 2, I(X) denotes original image located at pixel coordinate X and $I^{filtered}$ denotes image to which bilateral filter is applied:

$$W_p = \sum_{X \in \Omega} f_r\left(\left\|I(X_i)\text{-}I(X)\right\|\right) g_s\left(\left\|X_i\text{-}X\right\|\right) \quad (1)$$

$$I^{filtered}(X) = \frac{1}{W_p}\sum_{X_i \in \Omega} I(X_i) f_r\left(\left\|I(X_i)\text{-}I(X)\right\|\right) g_s\left(\left\|X_i\text{-}X\right\|\right) \quad (2)$$

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Fig. 1: Bilateral filter: a) Original image; b) Zoom-in original image and c) Zoom-in bilateral filter image

Figure 1 compares results before and after applying a bilateral filter. With an edge, results of blurred images can be preserved. Blurring can be widely used in pre-treatment imaging where characteristic texture is removed, leaving a resulting image.

Superpixel: A superpixel classifies pixels with similar features into one set. It was developed to approach, analyze and process images on a set basis (Yoo *et al*., 2013; Han *et al*., 2012; Lee *et al*., 2013). Using a superpixel as a pre-processing process can reduce complexity of an algorithm because it is analyzed and processed as a set of pixels with similar features. Therefore, it is used in various fields as a pre-processing process in image processing. The representative algorithms of superpixel are GS04 and SLIC algorithms.

GS04 (Graph-based segmentation): The GS04 algorithm is a graph-based segmentation method that sets all pixels of an image to one node of a graph. The graph divides superpixels using difference between interior of superpixel $MInt(C_1, C_2)$ and the difference between two superpixels $Dif(C_1, C_2)$. C-means superpixel, $Dif(C_1, C_2)$ is the smallest edge weight value connecting two superpixels and represents the minimum difference between Eq. 3 and 4:

$$MInt(C_1,C_2) = \min\left(Int(C_1)+r(C_1),\ Int(C_2)+r(C_2)\right) \quad (3)$$

$$r(C) = \frac{k}{|C|}(k \propto imageSize \quad (4)$$

$MInt(C_1, C_2)$ has a Minimum Spanning Tree (MST) value that connects the peak of a superpixel with an edge. This implies an internal aggregation:

$$D(C_1,C_2) = \begin{cases} \text{True, if } Dif(C_1, C_2) > MInt(C_1, C_2) \\ \text{False, otherwise} \end{cases} \quad (5)$$

Equation 5 shows that if the difference between two superpixels is larger than that of each superpixel, they are divided into separate superpixels and if they are smaller, they are merged into the same superpixel. The above method is slow because size k of the graph is proportional to the size of image and sizes and shapes are irregular because only two superpixels are compared.

Simple Linear Iterative Clustering (SLIC): The SLIC algorithm (Achanta *et al*., 2012) is an algorithm that divides an image into groups of pixels of the same color and position that have a uniform shape and size. Although, the SLIC adopts clustering method, it does not search the whole image but improves the speed by limiting the search distance and preserves the edge by examining similarity between pixels. The steps to using the SLIC algorithm are as follows: place a seed which is the initial center point of the divided region at a constant interval over the entire image. (It should not be arranged on an edge or in an area of noise where peripheral pixels change color abruptly).

All pixels that are not set to a seed are assigned to a seed located at the shortest distance, using Euclidean distance. Calculate color differences (d_{lab}) and distances (d_{xy}) to determine the similarity (D_s) between a seed and assigned pixels:

$$d_{lab} = \sqrt{(l_k-l_i)^2+(a_k-a_i)^2(b_k-b_i)^2} \quad (6)$$

$$d_{xy} = \sqrt{(x_k-x_i)^2+(y_k-y_i)^2} \quad (7)$$

Find the center of gravity of the pixels assigned to a seed and reset the seed to the lowest center of gravity:

$$D_s = d_{lab}+\frac{m}{S}d_{xy} \quad (8)$$

Repeat steps 3 and 4 until the seed does not change. The above method has the property of maintaining a constant size and shape by Eq. 8. If these feature boundaries are ambiguous, it is possible to perform erroneous image segmentation. Figure 2 shows the results of the two superpixel algorithms.

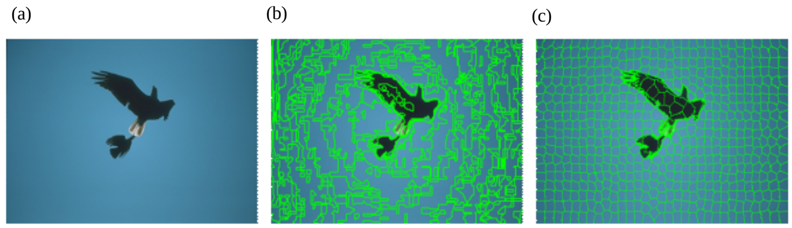

Fig. 2: Superpixel: a) Original image; b) GS04 result image and c) SLIC result image

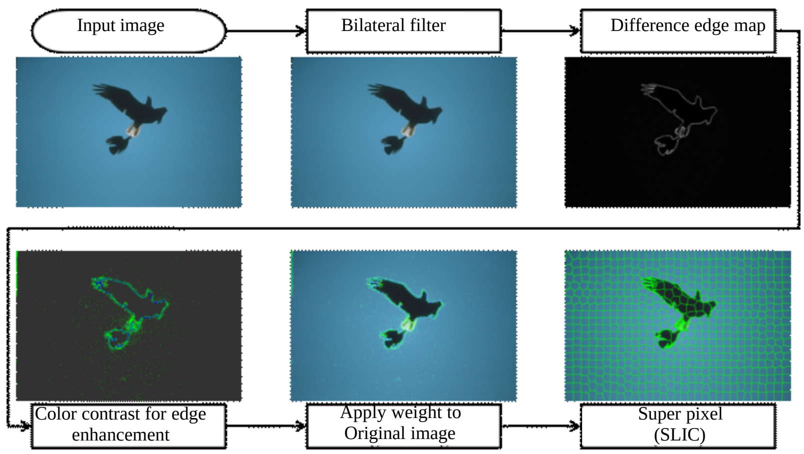

Fig. 3: Flow chart

MATERIALS AND METHODS

In order to minimize the SLIC problems above, a color contrast analysis, clearly showing boundaries is needed. An edge is detected by the DEM method to distinguish color change. The color values of surrounding pixels in the original image are analyzed and the weight is calculated using the position information of the detected edges. Applying the weight to the original image and applying the SLIC algorithm to the image improved color contrast. The proposed algorithm proceeds as shown in Fig. 3.

Difference Edge Map (DEM): In the DEM detection process a bilateral filter is used to remove texture that may appear in the original image. Applying a Gaussian filter gives an overall large blurring effect with a small blurring effect at the parts where color change occurs rapidly. The results are shown in Fig. 4. The image before and after applying the Gaussian filter is converted into gray-scale and an edge is obtained by identifying pixel differences. The results are shown in Fig. 5. The DEM obtained by the above method uses a bilateral filter to detect edges that change rapidly due to the nature of the Gaussian filter without causing edges due to textures:

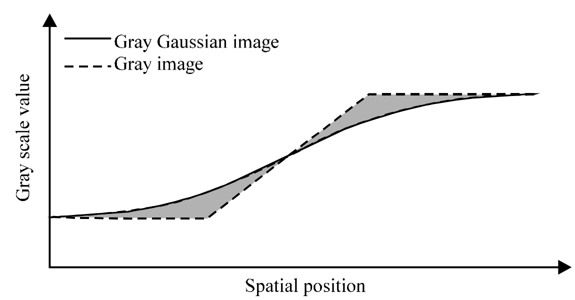

Fig. 4: DEM Graph

$$\mathrm{DEM}(x, y) = \left|\mathrm{GrayI}^{\mathrm{filter}}(x, y)\text{-}\mathrm{GrayGI}^{\mathrm{filter}}(x, y)\right| \quad (9)$$

Where:

$\mathrm{GrayI}^{\mathrm{filtered}}(x, y)$ = Bilateral filter applied to the original image

G = An applied Gaussian filter and Gray is the gray-scale conversion of each image

An image was removed using a bilateral filter and converted to gray-scale. Image blurring was then produced as a result of applying a Gaussian filter to the image to detect the edge section. The

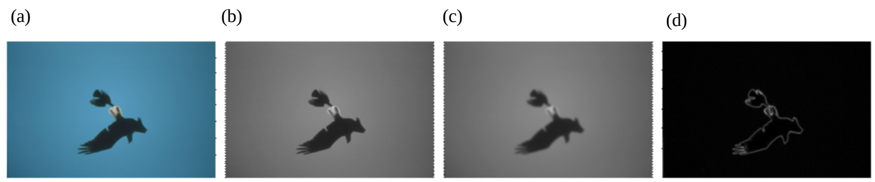

Fig. 5: DEM Image: a) Original image; b) Gray-scale image with bilateral filter applied to original image; c) Gray-scale image with bilateral filter and Gaussian filter applied to original image and d) DEM result image

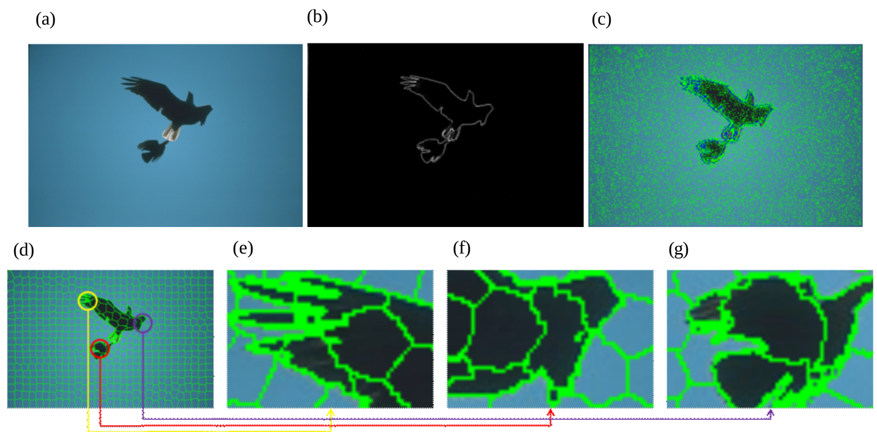

Fig. 6: Applying SLIC after pre-processing image: a) Original image; b) DEM image; c) Processing edge information image; d) SLIC result image; e) Zoom-in proposed method result image 1; f) Zoom-in proposed method result image 2 and g) Zoom-in proposed method result image 3

difference between b and c can be used to detect edges with bilateral filtering and Gaussian filter features d.

Color contrast for edge enhancement: The values of surrounding pixels in the original image are analyzed based on positions of the DEM obtained above. Surrounding pixels are divided into two groups of colors with the largest population of surrounding pixels using Eq. 10:

$$GA_S = \begin{cases} GA_1, \text{ if } \left|I(DEM_x, DEM_y)-GA_1\right| \\ < \left|I(DEM_x, DEM_y)-GA_2\right| \\ GA_2, \text{ otherwise} \end{cases} \quad (10)$$

$I(DEM_x, DEM_y)$ is the pixel value of the original image at the DEM position and GA_1 and GA_2 are the average colors of the two groups divided at the $I(DEM_x, DEM_y)$ position. The group that is the most similar to the original color of the DEM location is GA_s and the group that is not similar is the GA_{Ns}. In order to assimilate the color value of the original image corresponding to the valid GA_s DEM result, the color of the original image at the DEM position is weighted ω using the degree of GA_s and the pixel deviation. ω is determined by Eq. 11:

$$\omega = \left(GA_S - I\left(DEM_x, DEM_y\right)\right) \times \left(1 - \frac{\left|GA_S - GA_{NS}\right|}{255}\right) \quad (11)$$

If the pixel deviation is small, the ω obtained by the formula is a part where the boundary is ambiguous and the boundary is clarified by giving a larger value of ω. If the pixel deviation is large, a small value is given to preserve the boundary:

$$O_{xy}' = O_{xy} + \omega \quad (12)$$

The color contrast ω is applied, so, as to be similar to GA_S according to the pixel value of the DEM position original image. As a result, it is shown that there is a small color value variation range in the edge part and when the boundary is ambiguous, the error in the super pixel division process is reduced. The results are shown in Fig. 6. a is the original image and b is the DEM result image. c is a visual representation of a, the result of color contrast applied to the image. d is the result of applying color contrast to a and segmenting using the SLIC algorithm. Figure 6e-g are results of enlarging (Fig. 6d-f) are distinguished from the wing and the background and g is divided into the color of the tail.

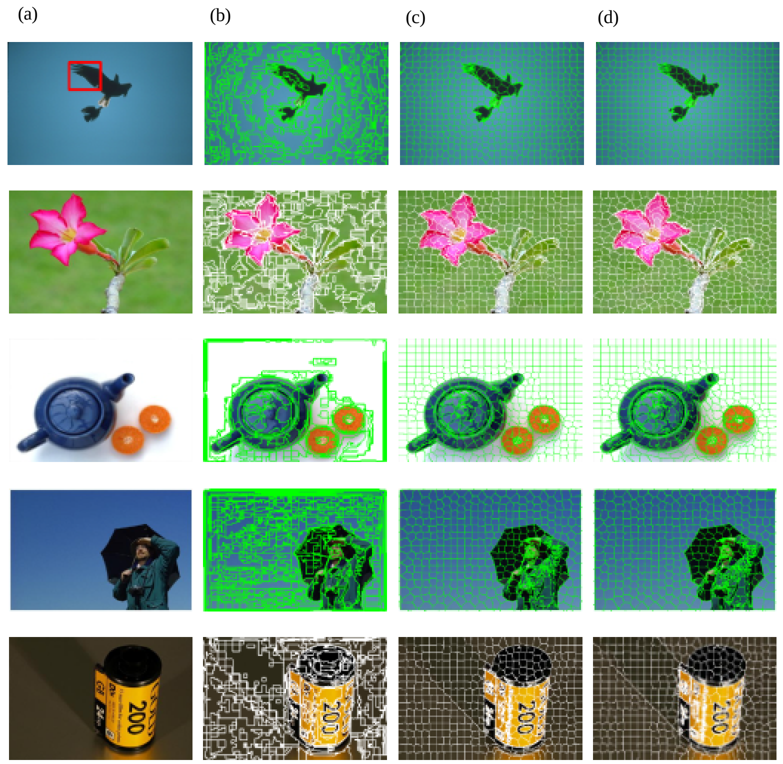

Fig. 7: Experimental result: a) Original image; b) GS04 result image; c) SLIC result image and d) Proposed method image

RESULTS AND DISCUSSION

Figure 7 shows the experimental images. Images in column a are the original images, columns b-d are the GS04 result images, the SLIC result images and the proposed algorithm result images, respectively. The GS04 images are not easy to analyze and process because the size and shape of the segmentation results are not constant. SLIC result images which are relatively uniform in size compared to the GS04 images have boundaries that are very unstable due to the texture. The proposed algorithm shows the results of images with uniform size and shape. In order to objectively evaluate the segmentation performance of the image, we can calculate the precision and the recall using Eq. 13 and 14. When the recall is increased, the false detection increases. Conversely, if the condition is strengthened to reduce false detection, the detection rate is lowered. In general, the detection rate and accuracy are inversely related to each other and he harmonic mean (F-measure) is calculated by Eq. 15 to express the performance as a single number:

$$\text{Recall} = R = \frac{T_P}{T_P + F_N} \tag{13}$$

$$\text{Precision} = P = \frac{T_P}{T_P + F_P} \tag{14}$$

Table 1: Boundary recall value of the result image

Variables	GS04	SLIC	Proposed method
Bird	0.400779	0.260082	0.291590
Flower	0.309575	0.239592	0.270832
Tea set	0.311376	0.275826	0.301252
Man	0.300499	0.275491	0.283974
Film	0.352962	0.286494	0.302650

Table 2: Precision value of the result image

Variables	GS04	SLIC	Proposed method
Bird	0.0583087	0.115828	0.123935
Flower	0.149107	0.211440	0.216957
Tea set	0.407216	0.524699	0.539242
Man	0.153458	0.384901	0.387885
Film	0.303479	0.448898	0.455136

$$\text{F} - \text{measure} = \text{F} = 2\times\frac{\text{P}\times\text{R}}{\text{P}+\text{R}} \tag{15}$$

Table 1 and 2 show the results of calculating the boundary recall values and precision values of images in Fig. 7. Table 3 shows the results of calculating the F-measure of the result images in Fig. 7, using the ground truths calculated in Table 1 and 2. Figure 7b shows that the number of divisions is the largest and the accuracy is low due to the large number of segment boundaries out of the ground truth. On the other hand, the detection rate is high because there are many portions applied to the ground truth. Since, the accuracy is too low

Table 3: F-measure value of the result image

Variables	GS04	SLIC	Proposed method
Bird	0.0627351	0.121387	0.130112
Flower	0.155774	0.213512	0.220580
Tea set	0.397124	0.488319	0.506221
Man	0.159919	0.372680	0.376509
Film	0.307033	0.428827	0.436958

compared to other algorithms, the value of the F-measure is low. In the case of c and d columns, the overall ratio is similar but the accuracy and detection rates of the proposed algorithm are slightly higher.

Table 3 shows the results of calculating the F-measure of the result image of Fig. 5 with the ground truth using the equations in Table 1 and 2. Figure 5b shows that the number of divisions is the largest and the accuracy is low due to the large number of segment boundaries out of the ground truth. On the other hand, the detection rate is high because there are many portions applied to the ground truth. However, since, the accuracy is too low compared to other algorithms, the value of F-measure is low. In the case of c and d columns, the overall ratio is similar but the accuracy and detection rate of the proposed algorithm are slightly higher.

CONCLUSION

The algorithm proposed in this study improves the segmentation result by ignoring boundaries with less color change width. This is done by dividing more or maintaining a certain size and shape, due to the texture in existing algorithms. In the proposed algorithm, edges with edge features are detected first. Then, the color contrast is increased through the color analysis based on the detected edge position information. As a result, it improves the false division result in the existing algorithms. The proposed algorithm can in the future be used in the field of object recognition or object tracking by pre-processing image processing.

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