International Journal of Advanced Smart Convergence Vol.7 No.4 108-113 (2018)
http://dx.doi.org/10.7236/IJASC.2018.7.4.108

IJASC 18-4-13

Region-Based Gradient and Its Application to Image Segmentation

Hyoung Seok Kim

Department of Applied Software Engineering, Dong-eui University, Korea
hskim@deu.ac.kr

Abstract

In this study, we introduce a new image gradient computation based on understanding of image generation. Most images consist of groups of pixels with similar color information because the images are generally obtained by taking a picture of the real world. The general gradient operator for an image compares only the neighboring pixels and cannot obtain information about a wide area, and there is a risk of falling into a local minimum problem. Therefore, it is necessary to attempt to introduce the gradient operator of the interval concept. We present a bow-tie gradient by color values of pixels on bow-tie region of a given pixel. To confirm the superiority of our study, we applied our bow-tie gradient to image segmentation algorithms for various images.

Keywords: *Bow-tie Gradient, Image Segmentation, Level Set Method.*

1. Introduction

Computer graphics is a field of research in the area of creating images based on information. From a broad point of view, computer graphics relate to the following four research areas: geometric modeling, visualization, image processing, and computer vision. Image processing is the process of modifying an image in order to create a new image from a given image, whereas computer vision is a research field that extracts information from a given image [1]. Practical applications such as license plate recognition and iris recognition belong to these fields. An important function required in such applications is how to play the role of the human eye, which is also a core technology that is indispensable for autonomous vehicles and robots that are currently receiving much attention.

One of the common features of these research areas is to deal with images. Among the many applications that are needed is a key technology that automatically extracts regions of interest from an image. For example, to recognize an object, you first need to search for it in the view of computer vision. To do this, you need a technique that automatically locates the region of interest in the image and extracts the meaningful parts of the object. This process is called image segmentation. In this study, we propose a key tool for image segmentation.

Manuscript Received: Oct. 8, 2018 / Revised: Oct. 15, 2018 / Accepted: Oct. 21, 2018
Corresponding Author: hskim@deu.ac.kr
Tel: +82-51-890-1989, Fax: +82-0505-182-6906
Department of Applied Software Engineering, Dong-eui University, Korea

Image segmentation is the most basic and important task in image processing and computer vision. Image segmentation is the division of an image into meaningful areas in relation to a particular application. Figure 1 shows the case of extracting a monkey from the background, and Figure 2 shows a case where objects of a complex shape are separated one by one and displayed in different colors.

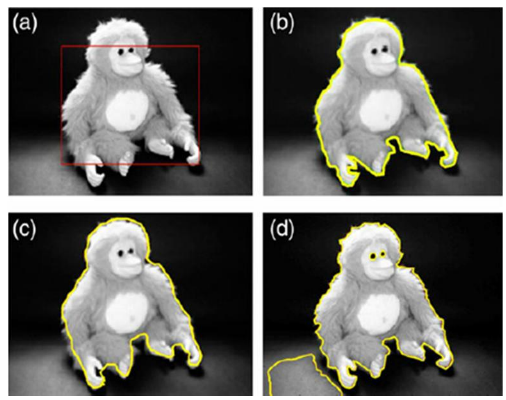

Figure 1. Separation of objects from background

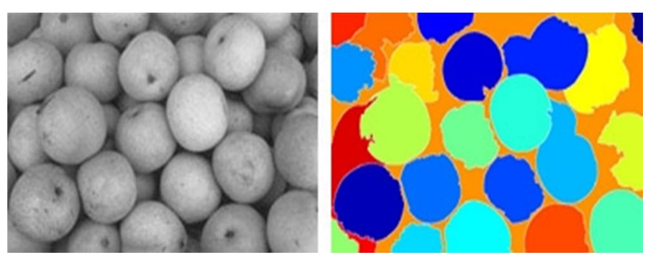

Figure 2. Detection of Multiple objects

As seen in all applications, the basic technique required for image segmentation is to effectively find changes between adjacent pixels, and it is important to find a solution to "what is the criteria for" good looking"? Gradient in mathematics plays a role of a fundamental solution to this problem, and means a measure of color change between neighboring pixels. In general, we want to use the basic expression defined in mathematics, but we cannot apply it because the space defined is different. The gradient of mathematics is defined in continuous space, whereas the image is treated in discrete space. In this study, we introduce a new conceptual gradient that matches the discrete space. In other words, it is a bow-tie gradient defined by using values of pixels in a bow-tie region.

2. Bow-tie Gradient Operator

One of the most important operations in image processing is to recognize changes in image values of adjacent pixels. In general, an image is obtained by taking a scene, which consists of a structural region containing the entire skeleton and a texture region containing detail within the region. In order to effectively handle various functions, it is necessary to divide the structure into a structural region and a texture region. In the structure-texture decomposition process, the input image is decomposed into a structural image and a texture image, which include non-repetitive edges and smooth shading, and the texture image includes vibration patterns and noise [2]. The goal of texture filtering is to find as much of the structural image as possible during texture removal. The most important part of this calculation process is the pixel slope operation which distinguishes structure and texture. In order to facilitate this work, this paper introduces a new gradient operator.

The gradient operator is generally defined as follows for a continuous surface.

$$\begin{aligned} \nabla I &= \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right) \\ \frac{\partial I}{\partial x} &= \lim_{\triangle x \to 0} \frac{I(x+\triangle x, y) - I(x,y)}{\triangle x} \\ \frac{\partial I}{\partial y} &= \lim_{\triangle y \to 0} \frac{I(x, y+\triangle y) - I(x,y)}{\triangle y} \end{aligned} \tag{1}$$

In a one-dimensional discrete signal, the general gradient operator for pixel p is a forward differentiation defined as:

$$(\nabla I)_p \equiv I_{p+1} - I_p. \tag{2}$$

This value measures the difference between two adjacent signal values, i.e. the difference between adjacent pixel values. This general gradient operator compares only the neighboring pixels and cannot obtain information about a wide area, and there is a risk of falling into a local minimum problem. Therefore, it is necessary to attempt to introduce the gradient operator of the interval concept.

The interval gradient operator for pixel p is defined by the difference between the left-interval and right-interval Gaussian filtering functions:

$$(\nabla_{\Omega} I)_p \equiv g_\sigma^r(I_p) - g_\sigma^l(I_p). \tag{3}$$

The two Gaussian filtering functions are defined as follows:

$$\begin{aligned} g_\sigma^l(I_p) &= \frac{1}{k_l} \sum_{n \in \Omega(p)} w_\sigma(p-n) I_n, \\ g_\sigma^r(I_p) &= \frac{1}{k_r} \sum_{n \in \Omega(p)} w_\sigma(n-(p+1)) I_n. \end{aligned} \tag{4}$$

The weight is an interval exponential function with interval size, and is defined by the following equation

$$w_\sigma(x) = \begin{cases} \exp\left(-\frac{x^2}{2\sigma^2}\right), & x \geq 0 \\ 0 & otherwise \end{cases}. \tag{5}$$

$$k_l = \sum_{n \in \Omega(p)} w_\sigma(p-n), \quad k_r = \sum_{n \in \Omega(p)} w_\sigma(n-n-1). \tag{6}$$

Since the section slope operator defined in this way applies the weight of pixel values only for a given direction, it has a disadvantage that it does not accurately contain image information around a pixel to be searched. To solve this problem, we introduce the butterfly-tie shape gradient operator. The bow-tie gradient operator of a pixel p is defined as half the difference between the total intensity of the right group and the total intensity of the left group as follows:

$$(\nabla_B I)_p = \frac{BG^r(p) - BG^l(p)}{2}\ . \tag{7}$$

$$\begin{aligned} BG^l(p) &= \frac{1}{k_l}\sum_{n \in \Omega(p)} w_\sigma(p-n)cgi(n), \\ BG^r(p) &= \frac{1}{k_r}\sum_{n \in \Omega(p)} w_\sigma(n-(p+1))cgi(n). \end{aligned} \tag{8}$$

Figure 3 shows two groups of bow-tie regions of red pixels. Nine blue pixels are the pixels used to calculate the right group intensity, and nine green pixels are the pixels used to calculate the intensity of the left group. The nine pixels in the right group are composed of three columns, and three right pixel values can be obtained by applying a Gaussian filter having a sigma value corresponding to the number of pixels to each column. Applying Gaussian weighting to the value of the right pixel yields the right group intensity.

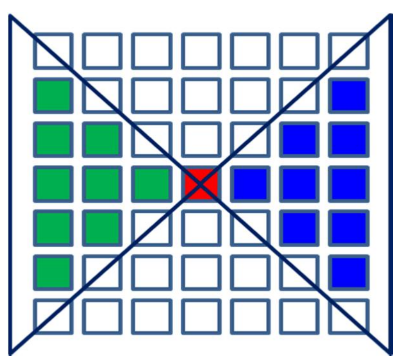

Figure 3. Bow-tie region

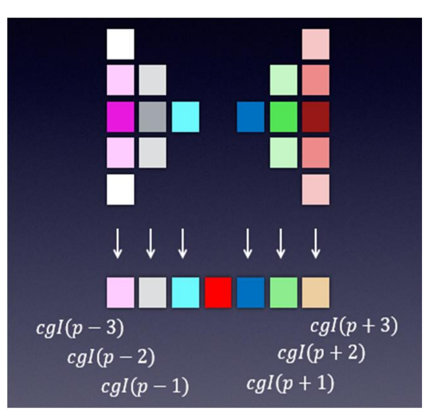

Figure 4. Brightness computation in bow-tie regions

3. Experimental Results

In this study, bow-tie shaped gradient is applied to the Distance Regularized Level Set Evolution algorithm proposed by Chunmin Li [3]. The DRLSE algorithm is a type of level set method. If the user specifies a rectangle containing the region of interest, the algorithm will automatically find the relatively large pixel of the tilt operator and automatically look for the region of interest.

Now we want to show our experimental results. The images in the middle row of Figure 5 are the original images, and the left images are the image segmentation results obtained by applying the forward slope. The images on the right are the image segmentation results obtained by applying the bow-tie gradient operator proposed in this study. It can be seen that the forward gradient operator method is more effective in the region where the distinction from the background is more effective, while it is undesirable in the region where the distinction is not clear. In the orange example, we can see that our method is better. If the background and foreground are not clear, we can see that our method is more effective.

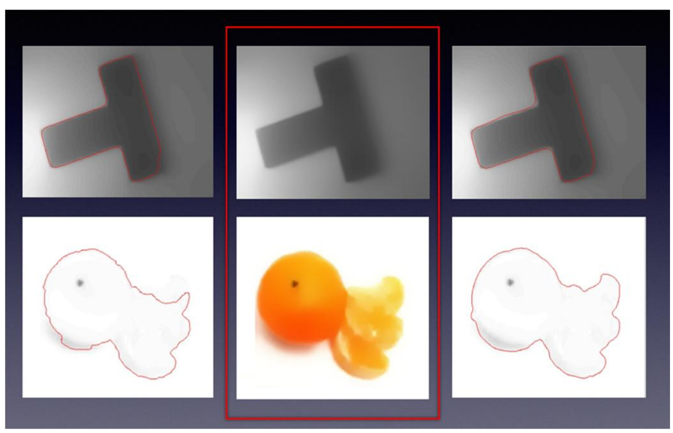

Figure 5. Experimental results 1.

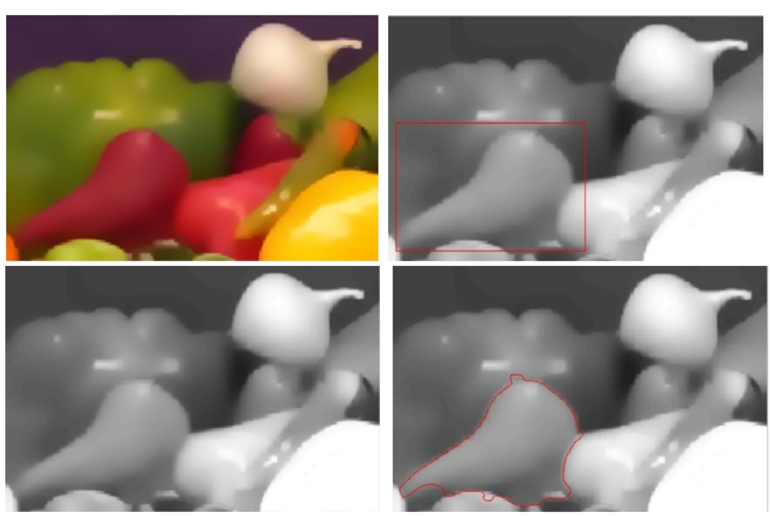

Figure 6. Experimental results 2.

The first image in Figure 6 is the input image, and the second image shows a rectangle that marks the red vegetation in the lower left corner as the region of interest. The image segmentation result obtained by applying the forward gradient operator obtained the result that the desired object could not be found like the third image. On the other hand, the fourth image shows that our method can capture the desired region more accurately.

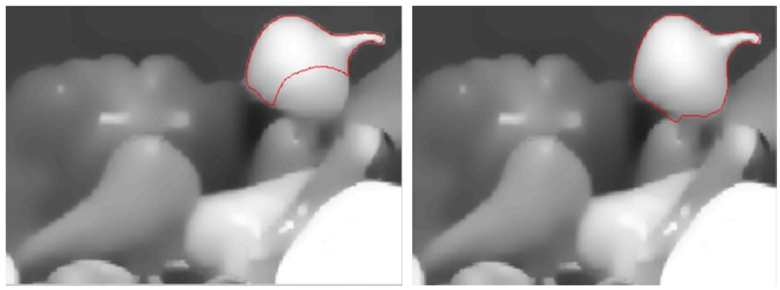

Figure 7. Experimental results 3.

To find the onion on the top right for the same source image, you can see that the result from the bow-tie gradient operator is better than the forward gradient, as shown in the right image in Figure 7.

4. Conclusion

The conclusion of this study is as follows. In this paper, we introduce a new gradient operator which is essential for image processing such as image segmentation. The bow-tie shape gradient operator is effective for ignoring or eliminating textures and is more effective when the image is blurred than the conventional method. Although much is still lacking, it is necessary to analyze the hermeneutical characteristics of the bow-tie gradient operator and to perform more experiments on various images in order to obtain better results.

References

[1] Szeliski, R., *Computer Vision: Algorithms and Applications,* Springer, New-York, 2011.

[2] Hyunjoon Lee, Junho Jeon, Junho Kim, Seungyong Lee, “Structure-Texture Decomposition of Images with Interval Gradient”, *Computer Graphics Forum,* Vol 36, Issue 6, pp 262-274, 2017.

[3] Li, C., Xu, C., Cui, C., Fox, M., “Distance Regularized Level Set Evolution and Its Application to Image Segmentation”, *IEEE Trans. On Image Processing*, Vol. 19, No. 12, pp 3243-3254, 2010.

[4] Cho H., Lee H, Kang H., Lee S., “Bilateral texture filtering”, *ACM Trans. Graphics*, Vol 33, No. 4, Article No. 128, 2014.

[5] Kass M., Solomon J., “Smoothed local histogram filters”, *ACM Trans. Graphics*, Vol 29, No. 4, 100 :1-100 :10, 2010.

[6] Weiss B., “Fast median and bilateral filtering”, *ACM Trans. Graphics*, Vol 25, No. 3, 519-526, 2006.

[7] Min D., Choi S., Lu J., Ham B., Sohn K., Do M. N., “Fast global image smoothing based on weighted least squares”, IEEE Trans. Image Processing, Vol. 23, No. 12, 5638-5653, 2014.