WAR Journal of Multidisciplinary Bulletin
(WARJMB)
ISSN (Online): 1595-6709
ISSN (Print): 1595-6636
Received: 02-09-2025 Revised: 26-09-2025 Accepted: 05-10-2025 Published: 18-10-2025

Research Article

BOUNDARY BLUR DEGREE ESTIMATION BASED ON IMAGE CONTOUR DETECTION ALGORITHMS

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OPEN ACCESS

Published in
VOl- 1 Issue: 4
DOI:10.5281/zenodo.18075538
PP: 59-65

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Abstract

The boundary blur degree estimation of ROI in the image can be effectively used not only to estimate the quality of the image but also to extract the useful information within the ROI. In this paper, we estimated the boundary blur degree by comparing two image segmentation results; one is segmented by using SLIC (Simple Linear Iterative Clustering) superpixel, another is by Level-Set algorithm. In detail, first, we segmented the original image using the Level-Set algorithm, which is used as a basis for comparison. And then, the original image is divided into superpixels by SLIC algorithm, and based on the segmentation energy between the superpixels, the ROI is extracted by using segments with high segmentation energy among all segments. As a result of the normalized comparison of these two segmented regions, we estimated the boundary blur degree. The experiment results show that our segmentation method has a high segmentation accuracy for an image with the boundary blur, 99%, and the ROI boundary blur can be estimated by proposed method.

Keywords: Image processing; Image segmentation; Computer Vision; Superpixel; Level-Set; Image blur degree

Introduction

Blur is a general image degradation caused by low quality cameras or intentional photographing for highlighting moving or salient objects [1].

The boundary blur information of ROI in an image can be used for image quality estimation, as well as, it has various information. For example, in medical image, the boundary blur information of ROI can reflect the stage of cancer or various diseases and can be applied to automatically focus on the field of vision distance measurement. Therefore, various methods for estimating the boundary blur degree in images have been developed worldwide and have been actively applied to image quality estimation and various applications. Y. Zou et al. proposed a robust image blur classifier to classify images into sharp, intentional blur, and unintentional blur. They used spatial pyramids to extract global features of the image, and then detected unintentional blur pixels by applying random forest [1]. In [2], the image-moment-based blur invariant features are calculated to eliminate the image motion blur and defocus blur that occur when there is a relative motion between the imaging camera and the detected object, and is used for accurate recognition of the object. In [3], a sharpness metric based on LBP and segmentation algorithm is proposed to identify the focused or defocused images, and used for image classification. In [4], the boundary from video surveillance was detected by improving the original Sobel operator certainly, and based on the blur degree of the

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recorded video, the image properties were obtained. In addition, several methods have been proposed by many researchers to estimate the boundary blur of an image, but in most cases, they have been used to remove the boundary blur information in an image. However, boundary blur can be used as a physical quantity that reflects a certain state of an object. For example, in the medical field, ROI blur in CT images may be used in the stage of a disease, and the boundary blur degree due to defocus in infrared image with optical systems can be effectively used for autofocusing and vision based distance measurement.

In this paper, two boundary detection algorithms were used to perform image segmentation to estimate the boundary blur degree of the ROI in the obtained image, and we estimated the blur degree of the ROI through comparison between the segmented results. For this, we first applied an image segmentation method using SLIC superpixels with relatively high accuracy of image segmentation, which uses segmenting and merging between superpixels to extract the boundary of the ROI and, based on it, apply a morphological algorithm to extract the final ROI. Then, a Level-Set algorithm with good global convergence was applied to the original image to obtain the ROI, and estimate the boundary blur degree of the ROI using the difference of the two image segmentation results.

2. Method

2.1 The ROI extraction by SLIC superpixel

To segment correctly ROI from image, we use the classic image segmentation technique. In detail, we segment the original image by SLIC superpixel. SLIC superpixel is a superpixel segmentation method proposed by Achanta et. in 2010 year. The features of SLIC superpixel segmentation method are follows, the computational cost is low, its number is controlled by user, the boundaries of each superpixel describes the contours of object as well in image and over-segmentation rate is low. Thus, this method is well-known as its performance is better than other methods [5]. Figure 1(b) shows superpixel segmentation result by SLIC superpixel method.

(A) (B)

Figure 1. SLIC superpixel segmentation of **image**. (a) original image. (b) image segmented by SLIC superpixel method The boundaries of each superpixel describe well the contour of ROI in the image (Fig 1). That is, the ROI boundary consists of the part of superpixels' boundary.

To extract the ROI by obtained superpixels, we use the image segmentation method based on graph by Fulkerson et. [6]. Thus, we form a graph $g=(\nu,\varepsilon)$, where the graph node ν is superpixel and the arc of graph ε is defined by similarity between neighboring superpixels. The similarity between superpixel *i* and *j*, $\varepsilon^{(i,j)}$, is calculated by Eq. (1).

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$$\varepsilon^{(i,j)} = \frac{E^{(i,j)}}{N^{(i,j)}} \quad (1)$$

where $E^{(i,j)}$ and $N^{(i,j)}$ is the segmentation energy between superpixel i and j and the number of neighboring superpixel, respectively. The segmentation energy between two superpixels, $E^{(i,j)}$, is calculated by Eq. (2).

$$E^{(i,j)} = \frac{\left| I^{(i)} - I^{(j)} \right|}{max(E)} \quad (2)$$

where $I^{(i)}$ and $I^{(j)}$ is the value of superpixel i and j, respectively, $max(E)$ means the maximum value among the difference between neighboring superpixels. So, $E^{(i,j)}$ is normalized within [0, 1]. Thus, when any two neighboring superpixels are similar in contrast, the segmentation energy is towards 0, and inversely when two neighboring superpixels are different, the it is towards 1. And segmentation energy between non-neighboring superpixels is 1.

Like this, after forming the graph by superpixels, we start merging between superpixels from the minimum segmentation energy($\varepsilon^{(i,j)}$), since it means two superpixels are very similar, so these can be merged into one region, that segmentation energy between two superpixels are low. Due to merging between two superpixels, the topological structure of graph is changed, at same time, segmentation energy between a merged superpixel and its neighboring superpixels, ε, is also changed. So ε is calculated by following Eq. (3).

$$\varepsilon^{(k,j')} = \frac{E^{(k,j')}}{N^{(k,i)} + N^{(k,j)}}, region_{j'} = region_i \cup region_j \quad (3)$$

where $\varepsilon^{(k,j')}$ is the segmentation energy between new superpixel and original, and $N^{(k,i)}$ and $N^{(k,j)}$ is the number of neighboring between original superpixel i & j and k, respectively. $E^{(k,j')}$ is the segmentation energy between new superpixel j' and original superpixel k, that is calculated by Eq. (3). By merging between similar superpixels, consequently, we can extract the pulmonary contour (Fig. 2(a)). Also considering topology structure of lung region, we can extract the lung region (Figure 2-b).

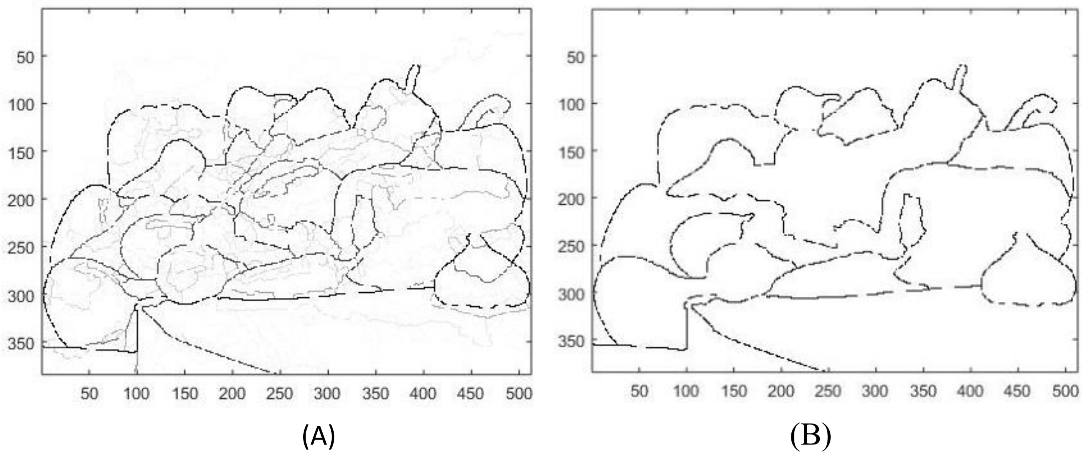

Figure2. Segmentation result and extracted lung region. (a) segmentation result (b) extracted lung region

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2.2 The ROI extraction by Level-Set algorithm

The Level-Set algorithm is an image segmentation algorithm that necessarily divides an image into two regions, known as the convergence of the operation.

To obtain the comparing region for ROI boundary blur degree estimation, we use the Level-Set algorithm by Li et. [7]. In their algorithm, an observed image can be modeled as

$$I = bJ + n \quad (4)$$

where J is the true image, b is the component that accounts for the intensity inhomogeneity, and n is additive noise. The component b is referred to as a *bias field* (or *shading image*). The true image J measures an intrinsic physical property of the objects being imaged, which is therefore assumed to be piecewise(approximately) constant. The bias field b is assumed to be slowly varying. The additive noise n can be assumed to be zero-mean Gaussian noise. In their algorithm, they assumed that the observed image contains some Gaussian noise, and set and minimized the energy function, and then, extracted the contour of object. So, the blur part can be well segmented that seems to be Gaussian noise. The below Figure 3 shows the segmentation result when proposed Level-Set algorithm in ref. [7] is applied in the candidate RIO. For blood vessel region, nodule region and trachea region, we segmented, respectively (Fig. 3).

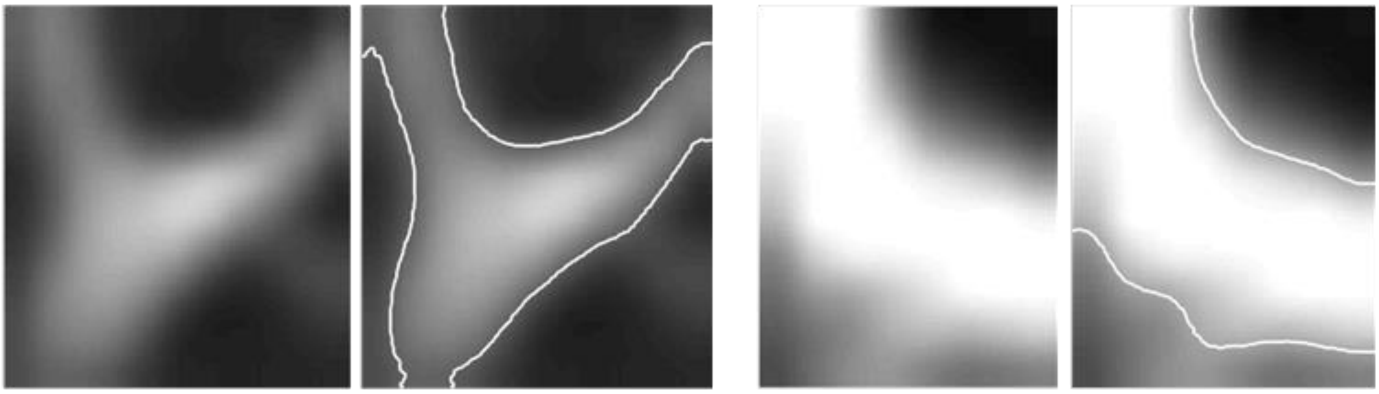

Figure 3. Contour detecting result by Level-Set algorithm for the medical image.

By Level-Set algorithm, the high contrast region from candidate ROI is correctly segmented, that was extracted in previous stage. In our study, we use this region as the ground truth region, and then estimate the blue degree of the RIO. Fig. 4 shows the principle for estimating the size of fuzzy region. In figure 4, the black region indicates the result of region segmentation from Level-Set algorithm. And all region including gray region is obtained by superpixels merging using a threshold.

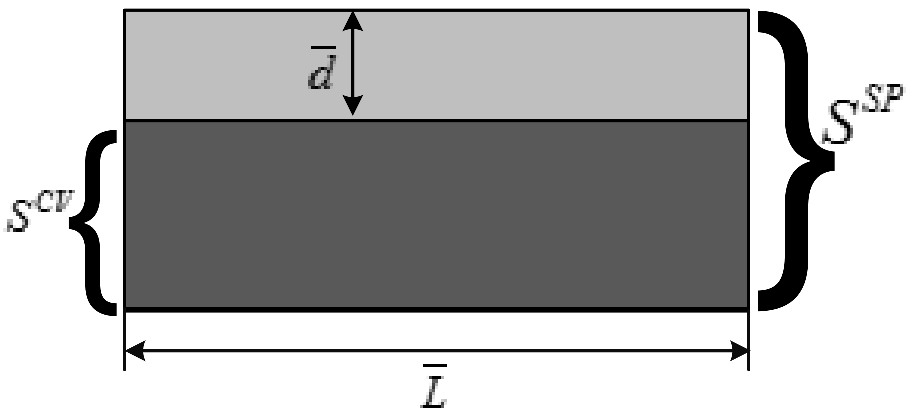

Figure 4. The diagram for calculating the size of fuzzy region

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Thus, the thickness average of fuzzy region is approximately calculated by Eq. (5).

$$\bar{d} = \frac{S^{SP} - S^{LS}}{\left(L^{SP} + L^{LS}\right)/2} \qquad (5)$$

Here, S^{SP} and L^{SP} are the size and the length of the boundary of the ROI obtained using SLIC superpixels, and S^{LS} and L^{LS} are the size and the length of the boundary of the ROI obtained by applying the Level-Set algorithm. Finally, the average thickness, which represents the size of the blurry region, eventually reflects the blur degree of the ROI.

3. Experimental results and Discussion

We used artificial images that were already known the ROI within the image to estimate the image segmentation accuracy and blur degree. Thus, we applied the proposed method to the blurred image, and again we analyzed the effectiveness of our method by evaluating the blur degree using Eq. (5) by applying the proposed method to the blurred image. Since a used image is known to be of the size of the ROI, the blur degree calculated from the experimental results can quantitatively reflect the blur degree of the original image.

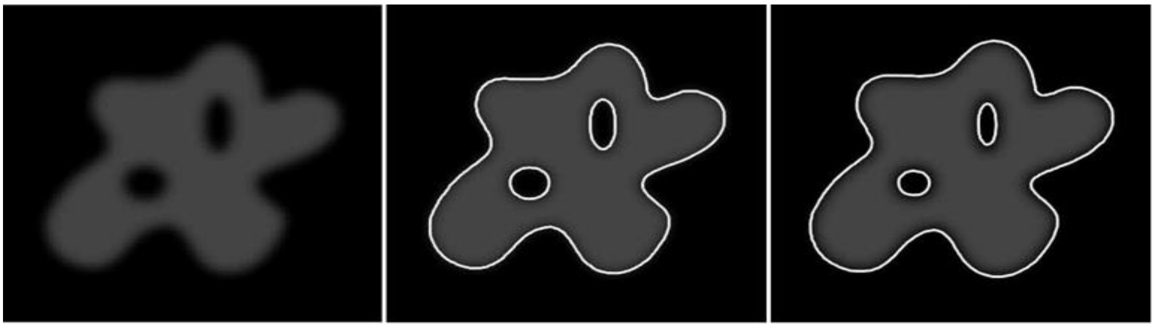
Fig. 5 gives the results of ROI segmentation by the Level-Set algorithm and the proposed algorithm for the blurred artificial image.

(a) (b) (c)

Figure 5. Segmentation results for blurred-free images.

(a) original image (b) segmentation image by Level-Set algorithm (c)segmentation image using SLIC superpixels

The Fig. 6 shows the results of ROI segmentation for the case of applying artificial blur to an image of known domain size of ROI and applying the Level-Set algorithm and the proposed algorithm.



(a) (b) (c)

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Figure 6. Segmentation results for images with artificial blur a) original image b) segmentation image by level set algorithm c) segmentation image using SLIC superpixel

The accuracy of image segmentation by each algorithm was evaluated by the following method.

$$recall = \frac{N_{true\_result}}{N_{GT}} \quad (6)$$

$$precision = \frac{N_{true\_result}}{N_{result}} \quad (7)$$

$$F = 2 \cdot \frac{recall \cdot precision}{recall + precision} \quad (8)$$

N_{GT} is the number of foreground pixels, N_{true_result} is the number of correct foreground pixels by the algorithm, and N_{result} is the number of foreground pixels segmented by the algorithm. Eq. (8) is used as an index to comprehensively reflect the segmentation accuracy of the algorithm.

Table 1 shows the results of the segmentation accuracy calculated by Eq. (6) -Eq. (8) in the blur-free image. As shown in Table 1, it can be seen that the accuracy of the Level-Set algorithm is high in the blur-free image.

Table 1. Accuracy of image segmentation

Segmentation algorithm	N_{GT}	N_{result}	N_{true_result}	$recall$	$precision$	F
CV algorithm	29 635	29 546	29 546	0.997	1	0.998 5
Proposed algorithm	29 635	29 937	29 635	1	0.989 9	0.994 9

Table 2 shows the results of the segmentation accuracy calculation for the blur case. And the results show that the segmentation accuracy by proposed algorithm is higher than by the Level-Set algorithm.

Table 2. Accuracy of image segmentation

Segmentation algorithm	N_{GT}	N_{result}	N_{true_result}	$recall$	$precision$	F
CV algorithm	29 635	28 372	28 372	0.957 4	1	0.978 2
Proposed algorithm	29 635	29 516	29 516	0.996 0	1	0.998 0

Table 3 shows the results of the blur degree calculated by Eq. (5) for the cases without and with artificial blur. And the results show that the proposed algorithm accurately reflects the blur degree at the ROI boundary in the real image.

Table 3. Results of blur degree Estimation of Object Contour

Type	Level-Set method	Proposed method	$\overline{d}$

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Without blur	29 546	29 937	0.08
With blur	28 372	29 516	0.23

Table 3 shows the results of the blur degree calculated by Eq. (5) for the cases without and with artificial turbidity. And the results show that the proposed algorithm accurately reflects the blur degree at the ROI boundary in the real image.

4. Conclusions

In this paper, the proposed method applied two image segmentation algorithms for images, respectively, and used normalized values for difference region as a blur index to be applied uniformly for different types of ROI regions. Indeed, ROI regions in an image may have cavities inside, and the image boundaries are complex, so that the absolute difference regions cannot reflect the blur of any type of ROI.

The proposed method can be applied to the assessment of the quality of images obtained from cameras or estimation of stage of sickness in medical images, autofocus control in night glasses image or to the field of measurement of distance.

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