A Study on Efficient Watershed Algorithm by Using Improved SUSAN Algorithm

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Abstract

In this paper, we propose an efficient method not only for producing accurate region segmentation, solving the over-segmentation problem of watershed algorithm but also for reducing post-processing time by reducing computation loads. Through this proposed method, region segmentation of neighboring objects and discrimination of similar intensities were effectively obtained.

Input image of watershed algorithm has used the derivative-based detectors such as Sobel and Canny. But proposed method uses the pixels-similarity-based detector, that is, SUSAN. By adopting this proposed method, we can reduce the noise problem and solve the problem of over-segmentation and not lose the edge information of objects. We also propose Zero-Crossing SUSAN. With Zero-Crossing SUSAN, the edge localization, times and computation loads can be improved over those obtained from existing SUSAN

1. Introduction

Generally, there are four types of image segmentation methods. The threshold methods are based on the postulate that all pixels whose value lie within a certain range belong to one class; the edge-based methods segment regions by detecting a sharp transition in intensity between regions; the region-based methods segment regions on the basis of similarities of pixels and regions; and the hybrid methods combine the advantages of the edge- and region-based methods

Watershed algorithm, classified as a hybrid method, is use when edge information produces insufficient results for image segmentation. But this method causes over-segmentation. Watershed algorithm uses a gradient image as an input image. Therefore, it is sensitive according to gradient values.

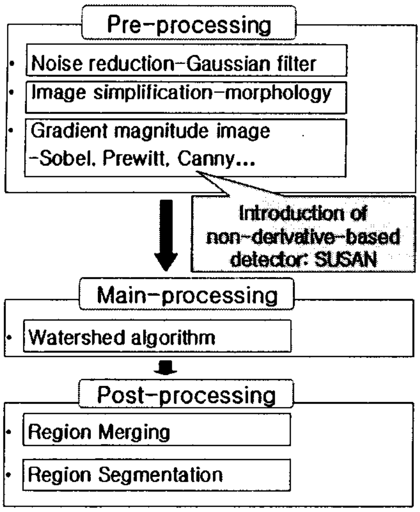
In this paper, we propose an efficient pre-processing method for watershed algorithm.

2. Related research

2.1 Watershed algorithm

Watershed algorithm was derived from the concept of geology, so an image is analyzed as a geographical surface[1] and completed by following the block diagram, in Figure 1.

In this paper, we propose an improved algorithm that can reduce over-segmentation efficiently.



[Figure 1] Block diagram of Watershed algorithm

To use Watershed algorithm more efficiently, we used the pre-processing step that uses the SUSAN(Smallest Univalue Segment Assimilating Nucleus)[10] algorithm instead of the derivative-based methods of Sobel, Prewitt and Canny as the step that obtains the gradient image.

The image used in watershed algorithm has been obtained from image the derivative-based image values. But differentiation produces many false negatives and false positives for edges and is, also, sensitive to noise; therefore, a noise reduction stage is needed in pre-processing.

By using SUSAN[10] as the input image to the Watershed, we were able to obtain more accurate responses which were robust to noise.
Therefore, incorrect local minima that result from noise of the input images were reduced while region boundaries preserved. More precise input values were also input to the Watershed algorithm.

2.2 proposed method

With SUSAN, over-segmentation can be more reduced than existing methods. But discrimination among adjacent objects is difficult because of much edge information and many thick edge lines

Edge detector such as LOG, which uses the second derivative, gives many zero-crossings. The output from the Zero-crossing detector is usually a binary image with single pixel-thick lines showing the positions of the zero crossing points.

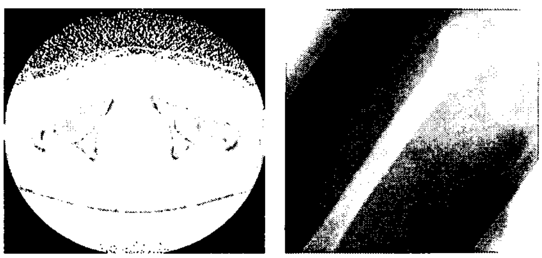
To reduce over-segmentation and find single pixel thickness line, we proposed SUSAN which adopts an idea of zero-crossing. We will call Proposed SUSAN as a Zero-Crossing SUSAN.

3. Watershed algorithm according to input images

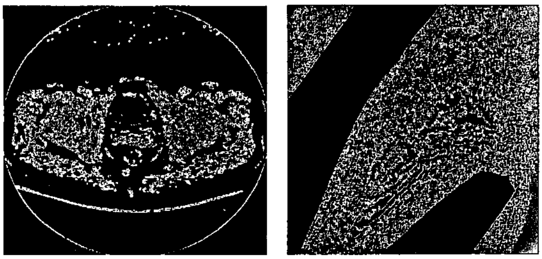
We analyzed Watershed algorithm according to input images to identify if an image was segmented such that it extracts objects accurately, and to identify the degree of over-segmentation and corresponding execution time of the algorithm.

Figure 2 shows the comparison of watershed algorithms among those that use the derivative-based image(Sobel, Canny) , SUSAN and Zero-Crossing SUSAN as the gradient image respectively. In case of CT image, we tested Watershed algorithms with same morphological conditions.

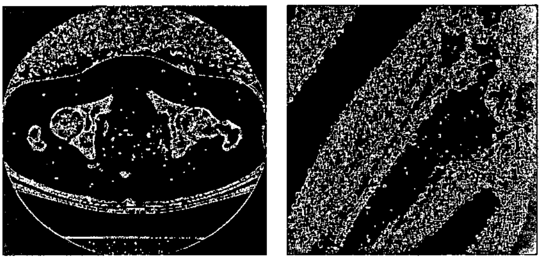
As a result, the image that used Sobel and Canny showed over-segmentation even in unnecessary regions because of similar image intensities near the hip joint. With SUSAN, results were better. But Watershed algorithm that used Zero-Crossing SUSAN gave the best results, showing much accurate region segmentation than those by the other three algorithms.



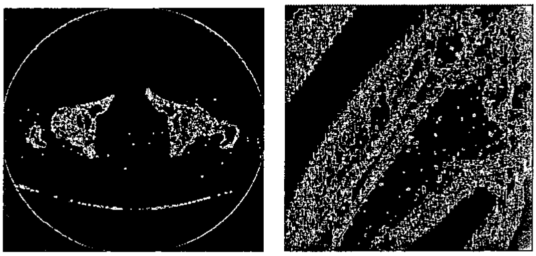
(a)



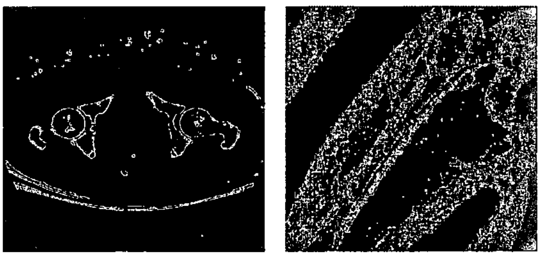
(b)



(c)



(d)



(e)

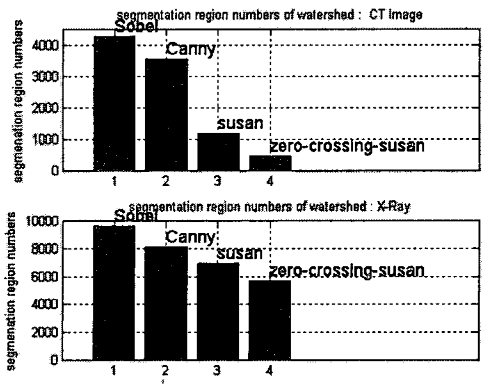
[Figure 2] Output of Watershed according to inputs (left: CT images, right: X-Ray images)
(a) Input image (b) Sobel (c) Canny
(d)SUSAN (e) Zero-Crossing SUSAN

4. Experimental results

Compared to the methods of Sobel, Canny and SUSAN, Zero-Crossing SUSAN was more suitable for pre-processing in the Watershed algorithm because it produced a more simple input.

Moreover, it presented more accurate segmentation than the derivative-based image methods even when the image intensities were similar.

By using the above two images of the hip joint, the number of segmentation regions resulting from the application of Watershed algorithm that used Sobel, Canny, and SUSAN as input images, respectively, is showed in Figure 3. Top of the figure shows the CT image results and the bottom part shows the X-Ray image results.



[Figure 3] Number of Watershed over-segmentation regions

The total execution times of the Watershed algorithm for the two type images (CT and X-Ray) are given in Table 1.

In the pre-processing step, we were excluded Execution times of image simplifications such as noise reduction and morphology. Execution times of Sobel, Canny, SUSAN and Zero-Crossing SUSAN were just presented.

As shown in this table, Zero-Crossing SUSAN was able to segment regions much faster than the other three methods.

In the post-processing, we merged the segmentation regions by using the HSWO(Hierarchical stepwise optimization)[3].

As was shown, the SUSAN-based input image produced better results than the derivative-based input image but the

Zero-Crossing SUSAN-based image produced even better results.

Execution time (millisecond)				
1) CT Image				
	Sobel	Canny	SUSAN	Zero-Crossing SUSAN
Pre-processing	67.297	250.335	107.782	110.296
Main-processing	1476.295	1468.207	1202.626	1172.791
Post-processing	11209.484	2262.488	581.155	389.056
total time	12753.076	3981.03	1891.563	1672.143
2) X-Ray Image				
Pre-processing	69.750	249.114	105.189	118.358
Main-processing	1594.402	1580.02	1562.682	1191.92
Post-processing	62066.845	68762.1	43197.73	2443.67
total time	63730.997	70591.2	44865.6	3753.94

[Table 1] Execution time of each portion of the Watershed algorithm

5. Conclusion

We proposed an efficient method that can reduce the execution times and excessive computational loads of Watershed algorithm due to over-segmentation.

We reduced the execution times of main- and post-processing as well as the computation loads by finding the object contours accurately in pre-processing and by preventing over-segmentation without under-segmenting. With these reductions, Watershed algorithm we were able to identify which algorithm was the most efficient when Watershed algorithm was used under the same conditions.

[Reference]

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