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Context-free Marker-controlled Watershed Transform for Over-segmentation Reduction

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Abstract

A modified watershed transform is proposed which is context-free marker-controlled and minima imposition-free to reduce the over-segmentation and to speedup the transform. In contrast to the conventional methods in which *a priori* knowledge, such as flat zones, zones of homogeneous texture, and morphological distance, is required for marker extraction, context-free marker extraction is proposed by using the attention operator based on the GST (generalized symmetry transform). By using the context-free marker, the proposed watershed transform exploit marker-constrained labeling to speedup the computation and to reduce the over-segmentation by eliminating the unnecessary geodesic reconstruction such as the minima imposition and thereby eliminating the necessity of the post-processing of region merging. The simulation results show that the proposed method can extract context-free markers inside the objects from the complex background that includes multiple objects and efficiently reduces over-segmentation and computation time.

1. Introduction

Image segmentation based on the homogeneity and connectivity of an image is widely used in such applications as computer visions, object recognitions, and MPEG-4, etc., in which images are processed in units of object, like in the object-oriented coding [1][2]. A number of algorithms and technologies are proposed for image segmentation; thresholding, edge-based segmentation, and region-based segmentation, etc. [1][2]. Recently, watershed algorithm, as an operator that segments image regions by closed contour with edges and region information on the gradient image, has been served as one of the major decision tools in mathematical morphology [3]. However, the direct segmentation of the gradient image by the watershed results in an extreme over-segmentation. The algorithm assigns a different region for each individual local minimum of the gradient. To reduce the over-segmentation, marker-controlled watershed in usually introduced and noise-reduction filter is used as a preprocessing, and region merging is required as a post-processing after the watershed transform [4][7].

The marker-controlled segmentation transforms the input image in such a way that the boundaries of the transformed image correspond to the object's boundaries [6]. And a very efficient morphological approach to segmentation relies on marker extraction followed by the watershed algorithm [5]. However, the choice of an appropriate marker detector relies on some *a priori* knowledge about the properties of the object. After the marker extraction, the geodesic reconstruction such as the minima imposition is needed.

A suitable marker image is determined by using the known facts about the object of the input image, or some transformation of the input image itself [6]. For instance, Vincent [8] used morphological maximum distance points as markers to segment the image containing coffee beans. Daniel *et al.* [9] extract markers under the assumption that the objects have large edge magnitude to compress video images. Shaparenko *et al.* [10] extracted markers under the assumption that each region has different texture. And Soille *et al.* [3] used the skeleton similar to the objects to find the markers. Park *et al.* [11] extracts flat regions as markers on the assumption that the inner parts of the objects are flat. But, region merging is required as a post-processing to reduce the over-segmentation if the inner parts of the objects are not flat.

All these above marker-controlled segmentation methods mentioned above *a priori* information on the objects is required and geodesic reconstruction is required as a preprocessing that has large computational complexity. Thus, an efficient watershed transform is need to be studied in which *a priori* information on the objects and the less pre- and post-processings are required.

In this paper, context-free markers were extracted by using the attention operator based on the GST [12] that accentuates the symmetry of the object. And through using the watershed transformation exploiting marker-constrained labeling, the over-segmentation was reduced.

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Processing time is also reduced since the proposed context-free marker-controlled segmentation can eliminate minima imposition procedure, and the modified watershed transformation efficiently uses a first-in-first-out type data structure. Experiments are conducted on the images containing various figures and the real image containing objects.

2. The Proposed Context-free Marker-controlled Segmentation

In this paper, we proposed a context-free marker-controlled watershed transform. Fig. 1 shows the flow chart of the proposed algorithm. In the proposed context-free marker-controlled segmentation, a gray image is input and simplified. Then context-free marker is extracted by using the GST. And a segmented image is obtained by applying the modified watershed transformation.

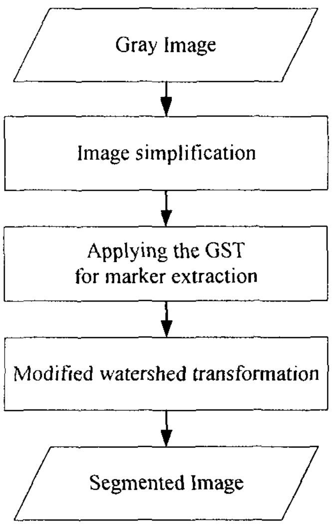


Fig. 1. The flow chart of the proposed context-free marker-controlled segmentation.

2.1. Image Simplification

In image segmentation, smoothing of texture component in inner region is needed to simplify images for easy segmentation without loss of edges. The simplified image was computed by using open-close-by-reconstruction filter that is based on mathematical morphological operation for easy segmentation [7].

2.2. Context-free marker extraction using the GST

Generally, objects are highly symmetric, so the positions of the objects can be determined by using the GST in which symmetry magnitude is enlarged at the inside of the object without *a priori* information of the object. Reisfeld *et al.* [12] generalized the symmetry transformation implied in shape analysis and proposed the GST that accentuates the symmetry of an object by using the magnitude and direction of intensity gradient. In the GST, a phase weight function $P(i,j)$ was defined as

$$P(i,j) = [1-\cos(\theta_j + \theta_i - 2\alpha_{ij})] \times [1-\cos(\theta_j - \theta_i)] \,. \tag{1}$$

where, α_{ij} is the angle counterclockwise between the line from pixel p_i to p_j and the horizontal axis. θ_i and θ_j are the direction of intensity gradient of each pixel. And, the distance weight function $D_\sigma(i,j)$ was defined as

$$D_\sigma(i,j) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{\|p_i - p_j\|}{2\sigma}\right). \tag{2}$$

where, σ is the size of the region where symmetry transformation is applied. The symmetry contribution $C(i,j)$ of the two pixels was defined as

$$C(i,j) = D_\sigma(i,j) P(i,j) \log(1+r_i) \log(1+r_j) \,. \tag{3}$$

where, r_i and r_j are the magnitude of the intensity gradient of each pixel. Thus, symmetry contribution is large when the directions of intensity gradient between two pixels are symmetric, and the distance between two pixels is short and when the magnitude of the intensity gradient between two pixels is large. And the set of symmetry pixels $\Gamma(p)$ was defined as

$$\Gamma(p) = \left\{ (i,j) \middle| \frac{p_i + p_j}{2} = p \right\}. \tag{4}$$

The symmetry magnitude of each point p is defined as

$$M_\sigma(p) = \sum_{(i,j)\in\Gamma(p)} C(i,j) \,. \tag{5}$$

The positions of the objects namely, the inner points of objects have large symmetry magnitude since objects usually have large symmetry. Thus these extreme points are used in this paper as the markers for watershed transform. And, the marker image f_m is defined as

$$f_m(x) = \begin{cases} 0, & \text{if } x \text{ belongs to a marker,} \\ MAX & \text{otherwise.} \end{cases} \tag{6}$$

And the input image of the modified watershed transformation is obtained by compounding the gradient image gotten through GST processing and marker image as follows;

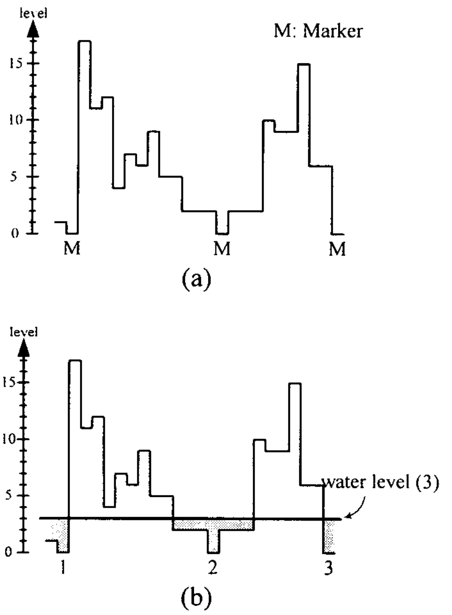
$$f_i = (f_g + 1) \wedge f_m \tag{7}$$

where, f_g is the gradient image, and $\wedge$ is pixel-wise minimum operator. The input image of modified watershed transformation, f_i, is obtained by pixel-wise minimum operation between the marker image and the gradient image increased by 1 to have minimum value at marker point. And the segmented image was obtained by applying modified watershed transformation to it.

2.3. The modified watershed transform

The modified watershed transformation proposed in this paper introduces a marker-constrained labeling and modified immersion process to reduce the over-segmentation and computational time. The marker-controlled segmentation eliminates minima imposition procedure. Marker-constrained labeling assigns the different label to each marker region of the minimal water level but the same label to the local minima above the water level. During the immersion process, if a new local minimum region meets another new local minimum region, then these regions are merged automatically. And if a new minimum region meets marker region, then its label is changed into the label of the marker region. The processing time was reduced by the efficient use of a first-in-first-out type data structure for this region changing. And if one marker region meets another marker region then watersheds are created.

Fig. 2 shows a example of the proposed method applied in 1-D signal. Fig. 2(a) is input 1-D signal with marker represented as minimum value of "0". From Fig. 2(b) to Fig. 2(e), the images show that water is immersed from "0" to the maximum gray level. And Fig. 2(f) shows the final segmented result. The image of Fig. 2(b) for the water level 3 shows that marker regions in Fig. 2(a) have different labels each other. The image of Fig. 2(c) for the water level 6 shows that the new local regions have the same label N. The image of Fig. 2(d) for the next water level shows that these two regions are merged automatically. For the case of Fig. 2(e) in which a new minimum region meets marker region, its label N is changed into the label of the marker region. The region transformation is performed efficiently using a queue. If one marker region meets another marker region, then watersheds are created like in Fig. 2(f).



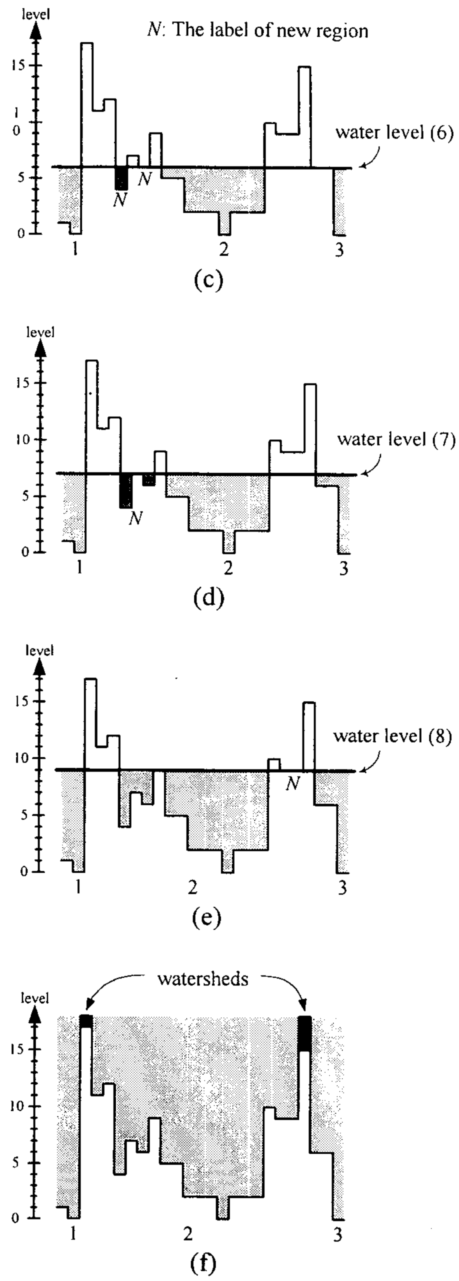
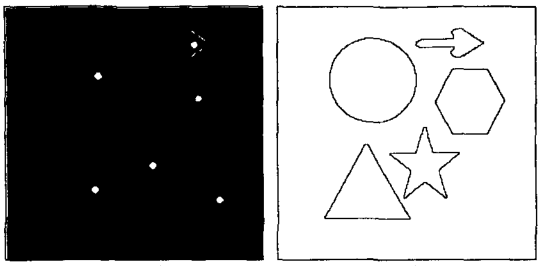


Fig. 2. 1-D signal example of the modified watershed transform: (a) Input 1-D signal, (b) water level 3, (c) water level 6, (d) water level 7, (e) water level 9, and (f) the result of the modified watershed transform.

3. Experiments, Results, and Discussions

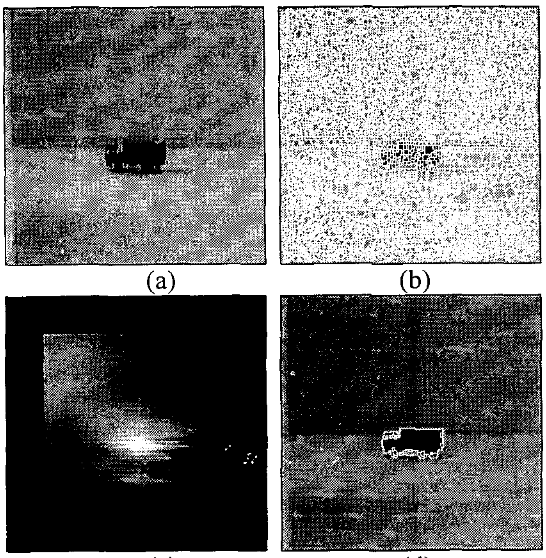
To evaluate the proposed algorithm, it is applied to the synthetic and the real images. First, the image including various figures is segmented to evaluate the modified watershed transform itself. Fig. 3 shows that proper segmentation is possible, and computing time is reduced highly by eliminating the unnecessary geodesic reconstruction.



(a) (b)

Fig. 3. The result of the modified watershed transform: (a) The manually marked image and (b) segmented image.

To segment the real image that includes a truck, first GST is applied and context-free markers are extracted, and finally modified watershed transformation is applied. The result of the proposed context-free marker-controlled watershed, Fig.4(d), shows far more reduction of the over-segmentation as compared to that of the conventional method in Fig. 4(b).



(a) (b) (c) (d)

Fig. 4. The result of the proposed marker-controlled segmentation: (a) Input image, (b) the result of the conventional watershed without markers, (c) the result of the GST, (d) the result of the proposed segmentation.

Table 1 is shows the processing time of the proposed watershed transform as compared to the conventional watershed transform [3] for 256×256 images used in the previous experiment except marker extraction procedure. Experiments are conducted at Pentium II 450 MHz PC.

Table 1. Processing time comparision.

[msec]

	Processing time		Total time
	Minima imposition	Watershed	
Conventional	3,159	169	3,328
Proposed	0	247	247

4. Conclusions

In this paper, a context-free marker-controlled and minima imposition-free watershed based image segmentation is proposed. It has two major advantages. First, the over-segmentation can be reduced efficiently for various objects since context-free markers are extracted efficiently by using an attention operator based on the GST. Second, the computation time can be highly reduced since the marker-controlled segmentation is made possible without the minima imposition by proposing the modified watershed transform exploiting marker-constrained labeling. Above advantages are verified through the experiments. The attention operator based on the GST can extract proper markers without using *a priori* information of the object.

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