Improved Watershed Image Segmentation Using the Morphological Multi-Scale Gradient

Jugdergarav Gelegdorj*, Hyung-Suk Chu**, Chong-Koo An***

Abstract

In this paper, we present an improved multi-scale gradient algorithm. The proposed algorithm works the effectively handling of both step and blurred edges. In the proposed algorithm, the image sharpening operator is sharpening the edges and contours of the objects. This operation gives an opportunity to get noise reduced image and step edged image. After that, multi-scale gradient operator works on noise reduced image in order to get a gradient image. The gradient image is segmented by watershed transform. The approach of region merging is used after watershed transform. The region merging is carried out according to the region area and region homogeneity. The region number of the proposed algorithm is 36% shorter than that of the existing algorithm because the proposed algorithm produces a few irrelevant regions. Moreover, the computational time of the proposed algorithm is relatively fast in comparison with the existing one.

Keywords : Image sharpening, image segmentation, watershed transform, morphological gradient reconstruction.

Ⅰ. Introduction

As image segmentation is a crucial process of range image analysis, a number of range image segmentation techniques have been proposed in the literatures, They can be roughly classified into four categories: threshold based, edge based, region based and hybrid techniques[1,2]. The goal of image segmentation is to partition an image into homogeneous regions and locate the contours of the regions as accurately as possible. The watershed transformation can potentially provide accurate segmentation with very low computational cost[3]. For image segmentation, watershed transformation starts with the gradient of the image to be segmented. It views the gradient image as a three dimensional (3-D) surface where gradient values which appear as watershed lines (also known as mountain ridges) on the 3-D surface, while the interior of each region usually has low gradient value which is considered as a catchment basin on the 3-D surface[4-5]. The watershed lines partition the gradient image into different basins which correspond to homogenous regions of the image to be segmented. The watershed transformation involves a search for watershed lines in the gradient image. Therefore, the performance of watershed based image segmentation method depends largely on the algorithm used to compute the gradient. Generally, the watershed transform produces meaningful image segmentations. Some applications, however, may require further merging of some regions. For region merging, a number of similarity (between regions) criteria have been proposed, each of which has its specific applications. Some criteria are based on edge height along the common contour between two regions. Conventional gradient algorithm produces too many irrelevant regions and it greatly decreases the speed of the entire segmentation method[6].

In this paper, we proposed an algorithm that combines image sharpening and multi-scale gradient operation which is technique to partition the image into several meaningful components. The proposed algorithm works the effectively handling of both step and blurred edged images. The region number of the proposed algorithm is 36% shorter than the existing algorithm because the proposed algorithm produces a few irrelevant regions. In addition, the computational time of the proposed algorithm is extremely fast. This paper is organized as follows. The sectionⅡ contains related theories. First, we introduce the information about the image sharpening in section 2.1. In the section 2.2, we present the multi-scale gradient method. Region merging is presented in section 2.3. The proposed algorithm is presented in sectionⅢ. The experimental results are showed in section Ⅳ. Finally, we give the conclusion in sectionⅤ.

Ⅱ. Related theory

2.1 Image sharpening

The image sharpening is called high pass filter. The filter is capable to detect edge details within a specified radius. Other information is suppressed. In other words, the filter provides

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the raw data that are important for sharpening. Image sharpening increases the contrast between bright and dark regions to bring out features. The sharpening process is basically the application of a high pass filter to an image. The following array is a kernel for a common high pass filter used to sharpen an image

$$\begin{bmatrix} -\frac{1}{9} & -\frac{1}{9} & -\frac{1}{9} \\ -\frac{1}{9} & 1 & -\frac{1}{9} \\ -\frac{1}{9} & -\frac{1}{9} & -\frac{1}{9} \end{bmatrix} \quad (1)$$

The above array (equation 1) is an example of one possible kernel for a sharpening filter. Other filters may include more weighting for the center point. Image filtering is useful for many application, including smoothing, sharpening, removing noise, and edge detection. A filter is defined by a kernel , which is small array applied to each pixel and its neighbors within an image. In most applications, the center of kernel is aligned with the current pixel, and is a square with odd number (3, 5, 7, etc) of elements in each dimension. The process used to apply filters to an image is known as convolution, and may be applied in either the spatial or frequency domain. Within the spatial domain, the first part of the convolution process multiplies the element of the kernel by the matching pixel values when the kernel is centered over pixel. The elements of the resulting array (which is the same size as the kernel) are averaged and the original pixel value is replaced with its result. Within the frequency domain, convolution can be performed by multiplying the FFT (Fast Fourier Transformation) of the image by the FFT of the kernel and then transforming back into the spatial domain. The kernel with zero value to enlarge it to the same size as the image before the forward FFT is applied. These types of filters are usually specified within the frequency domain and do not need to be transformed. The reason the high pass filter technique works so well at image sharpening because any areas in the image which are not an edge are left untouched. The only areas that have sharpening applied to them are the edges, which is exactly what you want.

2.2 Multi-scale gradient

Many gradient operators and edge detection algorithms have been based on the step edge model. However, ideal step edges do not exist in natural images since every edge is blurred to some extent. A blurred edge can be modeled by ramp and the intensity change between two sides of the edge is referred to as edge height. For a ramp edge, the output of a conventional gradient operator, such as Prewitt gradient, is the slope of the edge. The morphological gradient operators used in references can be described as equation 2

$$Grad(f) = (f \oplus B) - (f \ominus B) \quad (2)$$

where $\oplus$ and $\ominus$, respectively, denote dilation and erosion, and B is called structuring element and f is 2D discrete image. This gradient operator is referred to as a mono-scale morphological gradient operator. Its performance depends on the size of structuring element B. If the B is large, the output of gradient operator for ramp edge is equal to the edge height. Unfortunately, large structuring elements result in serious interaction among edges which may lead to gradient maxima not coinciding with edges. However, if the structuring element is very small, this gradient operator has a high spatial resolution, but produces a low output value for ramp edges. In order to exploit the advantages of both small and large structuring elements, we used a multi-scale gradient morphological gradient algorithm. Let B_i, for $0 \leq i \leq n$,, denote a group of square structuring elements. The size of $B_i is\ (2i+1) \times (2i+1)$ pixels, i,e. B_0 contains only one pixel and B_1 is a 3×3 square and so on. The multi-scale gradient is defined by equation3

$$MG(f) = \frac{1}{n} \times \sum_{i=1}^{n} [((f \oplus B_i) - (f \ominus B_i)) \ominus B_{i-1}] \quad (3)$$

The multi-scale gradient algorithm is very robust to edge interaction. The local of gradient maxima corresponding to one edge is not distributed by the presence of other edges. The structuring elements B_i, in equation could be of any shape satisfying the relation $B_0 \subseteq B_1 \subseteq L \subseteq B_n$. We use a group of disk shaped structuring elements because of its low computational cost. We use disk-shaped structuring element to get the multi-scale morphological gradient $MG(f)$.

2.4 Region merging

Some applications, however, may require further merging of some regions. For region merging, a number of similarity (between regions) criteria have been proposed, each of which has its specific applications. In addition to the above over segmentation reduction method, there still remain neighboring regions that could by merging yield meaningful segmentation, on the principal that each region is homogeneous and sufficiently different from its neighbors. Some criteria are based on area of the regions. If the area is very small, it must be redundancy. In this paper, we use these two methods to accomplish the final segmentation. The objective cost function used in this work is the square error of the piecewise constant approximation of the observed image, which yields a measure of the approximation accuracy and is defined over the space of partitions. Let $R_M = R_M^1, R_M^2 \ldots R_M^M$ be M-partition of image Y and $(R_M^k = p_{k,1}, p_{k,2}, \cdots p_{k, \| R_M^k \|})$ be the set of pixels belonging to region (R_M^k). In the piecewise constant approximation of Y, the image intensity in each region $R_M^k, k = 1,2 \ldots M$ of partition R_M^k approximated by one parameter, which minimizes the square error with respect to data Y and is equal to mean value of Y in R_M^k, namely

$$\mu(R_M^k) = \frac{1}{\| R_M^k \|} \sum_{i=1}^{\| R_M^k \|} Y(p_{k,1}) \qquad (4)$$

where $\| R_M^k \|$ denotes the cardinality of set R and μ(R) be the mean gray value. The corresponding square error is

$$(R_M^{*\,k} = E(R_M^k) = \sum_{i=1}^{\| R_M^k \|} [Y(p_{k,i}) - \mu(R_M^k)]^2 \qquad (5)$$

Therefore, the total square error is

$$E(R_M) = \sum_{k=1}^{M} E(R_M^k) \qquad (6)$$

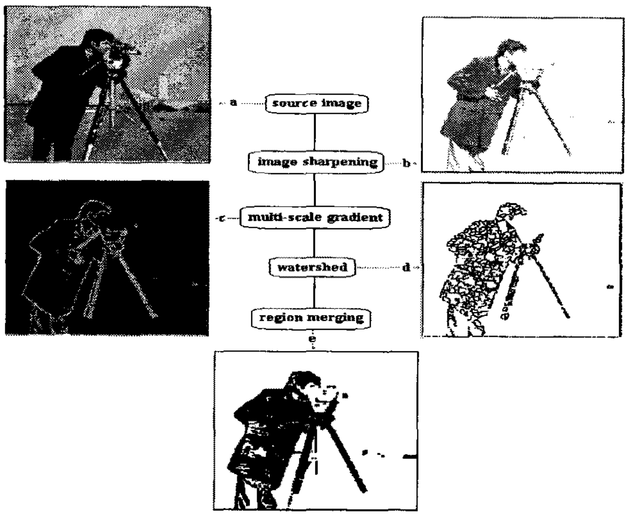
It is clear that, if R_M^k is the optimal M-partition with respect to the squared error, then the optimal (M-1) partition is generated by merging the pair of regions of (R_M^*) which minimizes the following dissimilarity function

$$\delta_{ij}(R_M^{*i}, R_M^{*j}) = \frac{\| R_M^{*i} \| \cdot \| R_M^{*j} \|}{\| R_M^{*i} \| + \| R_M^{*j} \|} [\mu(R_M^{*i}) - \mu(R_M^{*j})]^2 \qquad (7)$$

In the merging algorithm, the two regions having the smallest gray difference are first located. If this dissimilarity function is smaller than thresh holding, the two regions will be merged. The two methods have each own application scope, the former use the area of region to determine region merging. On the stage of the region merging the latter would be clustering the similar regions. The criterion of merging is based on the similarity between the closed regions. The experimental result shows that the proposed algorithm which is based on the above mention region merging criterion effectively partition the original image.

III. The proposed algorithm

In this section, we present the proposed algorithm. In the proposed algorithm, the image sharpening operator is used firstly in order to remove noise and sharpening blurred edges. Usually, we use standard images in the simulation and these images are based on ideal step edged images, but the ideal step edges do not exist in the natural images since every edge is blurred to some extent. A blurred edge can be modelled by ramp and the intensity change between two sides of the edge is referred to as edge height. For the blurred image, the image sharpening method is used to sharpening edge of object. The goal of the image sharpening is to highlight fine details in the image which has been blurred. Fine details in the frequency domain correspond to high frequencies, therefore the using of the high pass filters for the image sharpening. In enhancing fine details the price to pay is also the enhancement of noise. In the proposed algorithm, Laplacian high pass filter is used firstly to sharpening the image and removes noise. Below, the block diagram of the proposed algorithm
is presented. The image sharpening operator is second derivative method of enhancement. It is particularly good at finding the fine detail in an image. Any feature with a sharp discontinuity (like noise) will be enhanced by the image sharpening operator. The ramp edge's height of the sharpened image is higher than before. Hence the edges can be separated from noise and quantization error. After the filtering image by the image sharpening operator, the multi-scale gradient operator is used on the sharpened image. The multi-scale gradient operator which is mentioned before in section 2.2 is used in the proposed algorithm. The multi-scale gradient is very robust to
edge interaction. Afterward the watershed operator is used to segment multi-scale gradient method. In the experiment, the proposed algorithm produces a few irrelevant region because the image sharpening details edges and removes noise.



(a)original image, (b)image sharpeninng result, (c) multi-scale gradient image, (d) result of watershed, (e) region merging result

Fig. 1. segmentation scheme of the proposed algorithm

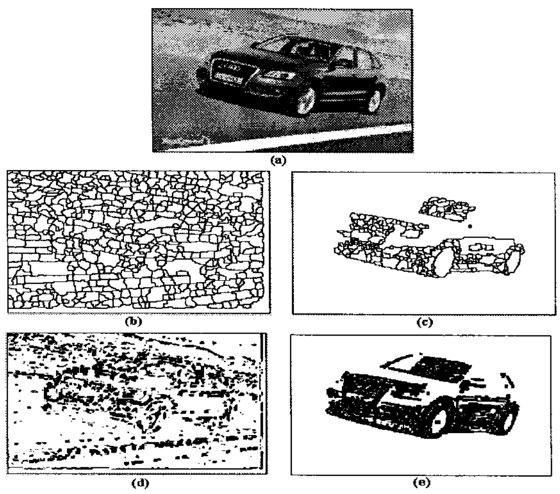
Eventually, the region merging method is used to merge regions in order to remove false contours. For the region merging, some criteria are based on edge height along the common contour between two regions. In the experiment, the criteria is required, the multi-scale gradient method is suitable to provide edge height information since it responds effectively to the blurred edges as well as step edges.

Ⅳ. Simulation and experimental results

In the experiments, a few of the results are obtained by the application of the proposed algorithm on the blurred images. It can be seen from comparison table 1, the proposed algorithm is significantly better than the existing algorithm. The existing algorithm uses the multi-scale gradient method firstly. The watershed transformation is used for on the gradient image and segment image. Finally, region merging method is used in order to merge the segmented image and remove false contour. The existing algorithm produces (conventional watershed algorithm) many irrelevant regions. The proposed algorithm produces a few irrelevant regions. From comparison table 1, we can see the region numbers and time which is used in the proposed algorithm is shorter than the existing algorithm. The images which are used in the experiment which all downloaded from internet, so it means their edges are blurred and all natural images. We use four blurred images in the experiments of this paper. Experiments on the segmentation based on the existing algorithm and proposed algorithm are conducted for comparison. The figure (2.a) is original image. The figure (2.b) is the watershed result of the existing algorithm and figure (2.d) is result of region merging of the existing algorithm which has 542 regions. The figure 2 is computed 89.116(ms) by the existing algorithm. The figure (2.c) is the watershed result of the proposed algorithm and it has 220 regions. Figure (2.e) is final result of the proposed algorithm. The computational time of the proposed algorithm is 68.2486(ms) for the figure 2. The figure (3.b) is watershed result of the existing algorithm and it has 481 regions. The computational time of the existing algorithm is expended 97.9921(ms). The figure (3.c) is the watershed result of the proposed algorithm and it has 156 regions. The computational time of figure 3 is 73.54(ms) by the proposed algorithm. The figure (4.b) is watershed result of the existing algorithm and it has 518 regions. The computational time of figure 4 is 78.70(ms) by the existing algorithm. The figure (4.c) is the watershed result of the proposed algorithm and it has 149 regions. The proposed algorithm is expended 55.22(ms) for figure 4. The figure (5.b) is the watershed result of the existing algorithm and it has 463 regions. The computational time of this image is 86.38(ms). The figure (5.c) is the watershed result of the proposed algorithm and it has 199 regions. The computational time of this image is 64.13(ms) by the proposed algorithm. There are many cars and vans in the figure 4 and 5. The region number of these two test images are a fewer than the other test images. The region number of the figure 2 and 3 are more than figure 4 and 5 because of these two images have only one object or car. From the result, the existing algorithm can not work on the blurred edged images and it takes more computational time because there are many irrelevant regions. Merging many regions take much more time and it extremely decreases the whole segmentation procedure. We can see that the proposed algorithm is a significantly decrease over segmentation from the comparison table 1, the segmentation result and accuracy of the object is clear. The proposed algorithm can handle step and blurred image. The accuracy of final result is clear and computational time is 36% shorter than the existing algorithm.

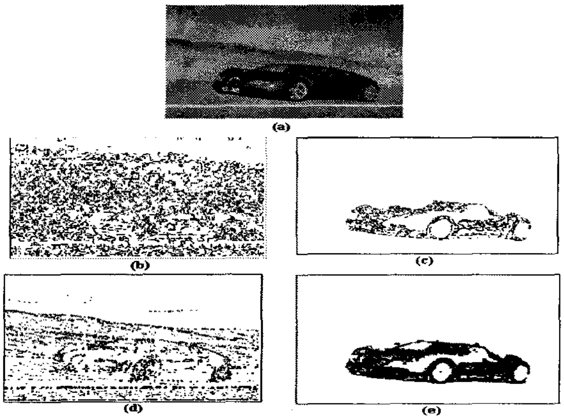
Ⅴ. Conclusion

In this paper, we proposed an improved watershed image segmentation algorithm. Firstly, source image is filtered by the image sharpening and multi-scale gradient morphological filter. Afterward, the watershed transformation segments the filtered image and region merging rules is used in order to merge false contours and get final segmentation image. The region number of the proposed algorithm is 36% shorter than the existing algorithm because the proposed algorithm produces a few irrelevant regions. As we can see, not only the existing algorithm can not work on the blurred edge image, but also computational time is higher than the proposed algorithm. It is proven that the proposed algorithm is valid and more accurate than the other common algorithms of image segmentation.



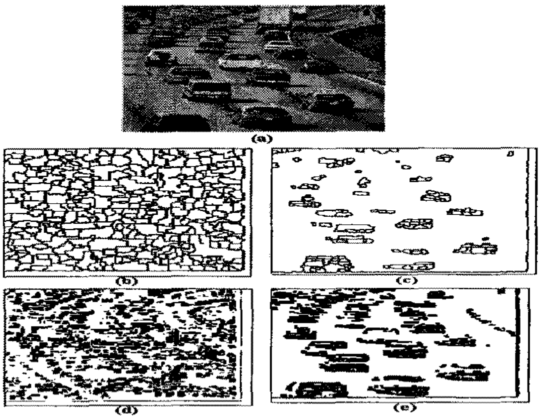
(a) original image, (b) result of watershed of conventional method, (c) watershed result of proposed algorithm, (c) region merging of conventional method, (e) region merging of proposed algorithm

Figure. 2. Segmentation result



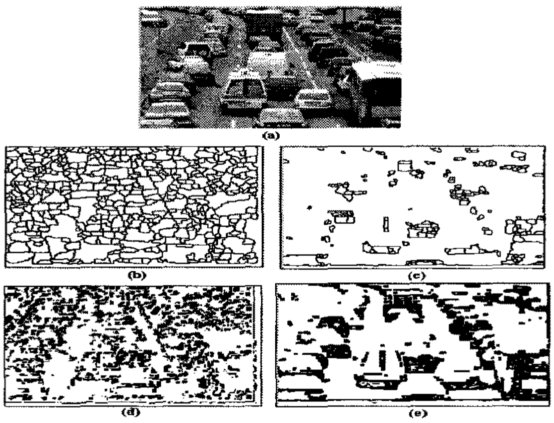
(a) original image, (b) result of watershed of conventional method, (c) watershed result of proposed algorithm, (c) region merging of conventional method, (e) region merging of proposed algorithm

Figure. 3. Segmentation result



(a) original image, (b) result of watershed of conventional method, (c) watershed result of proposed algorithm, (c) region merging of conventional method, (e) region merging of proposed algorithm

Figure. 4. Segmentation result



(a) original image, (b) result of watershed of conventional method, (c) watershed result of proposed algorithm, (c) region merging of conventional method, (e) region merging of proposed algorithm

Figure. 5. Segmentation result

Table 1. Computational time

image	existing		proposed	
	region number	time (ms)	region number	time (ms)
figure2	542	89.9116	220	68.24
figure3	481	97.9921	156	73.54
figure4	518	78.70	149	55.22
figure5	463	86.38	199	64.13

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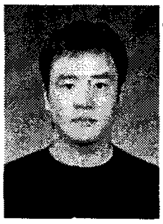

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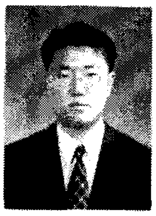

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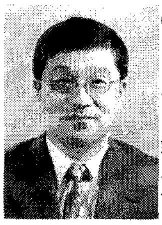

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