THE APPLICATION OF WATERSHED AND REGION MERGING FOR IMAGE SEGMENTATION

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Abstract: *Image segmentation is an important stage in doing image analysis. Among many different techniques in segmenting image, watershed can be noted attracted the attention of the researchers of this field in the past decade. In this paper, we use watershed transform to handle initial segmentation in our system. The vulnerability of watershed from the appearance of noise contained in the image is compensated by the application of region merging mechanism, in which we introduce the merging process relies on the calculation of integer value derived from each region intensity mean. Here we put more intention on merging small regions than big regions by assigning a different merging factor for both regions. From the experimental stage we will show the reduction that can be taken by the system in compromising over-segmentation produced by watershed transform.*

Keywords: Image Processing, Image Segmentation, Watershed Transform, Region Merging

1. Introduction

Image segmentation is a process in dividing and localizing image into a number of meaningful regions. This process is an essential part in doing image analysis. In the area of image analysis, watershed is a method among the others that can be noted does not need any priory knowledge about the object of interest. Due to its elegant way in handling segmentation, many systems have been applying this method although it is known severely suffered from over-segmentation. Noise is the factor accused causing over-segmentation since its appearance fluctuates image intensity. This condition leads to discovering a large number of minima as a result of running minima detection process. Here minima are the pixel having smaller intensity value than its neighbors and are used as a starting point to expand the region.

Many extensions on the watershed method have been proposed by the researchers in the effort to compromise the effect of noise. [17] introduced a marker definition in holding watershed segmentation. A set of marker is used to start the flooding process instead of minima. The drawback of this method is the difficulties encountered when it is applied in the image containing a noisy and complex object. In fact, it is not easy to assign a set of marker for such kind of image.

[15] proposed a spatial distances as a part of minima definition in order to reduce minima number. However, this method tends to become domain specific. Another effort proposed can be noted apply a further processing stage to the segmentation product. [14] introduced a method to merge the resulted regions based on the Minimum Description Length that is represented by image intensity and region boundary. [12] proposed a merging process based on the concept of watershed transformation on graph, while [5] applied a Most Similar Neighbor Graph in reducing

over-segmentation. Although those proposals above proved able to reduce over-segmentation, finding the final product is a difficult task that needs an exhaustive search [5].

This paper aims to introduce a mechanism to compromise over-segmentation. Here we apply the same assumption as used by [14] to conduct a region merging process. This mechanism is applied to the segmented image following watershed transformation that is held as the initial stage. To ease the explanation we divide the paper into six sections. Section 2 explains the basic mechanism of watershed transformation applied in our system, while section 3 discloses the implementation of watershed transformation and several light modification on that method. Section 4 explains an extension to reduce minima number by region merging mechanism, and then it is continued by section 5 that delivers its experimental result. Finally section 6 gives the conclusion of our work.

2. Watershed Transformation

From the literature, it can be found that there are two methods on watershed transform have been proposed up to now, i.e. watershed by immersion [20][18] and watershed by topographical distance [16]. Here we use and focus on watershed by immersion following the presentation on [18]. This technique simulates the flooding process on the surface of the image until all pixels composing the image are reached by the water.

Basically, the mechanism of watershed can be divided into two main stages, i.e. the sorting stage and the flooding process that contains minima detection and basin definition mechanism. The first stage, as shown by its name, aims to sort the pixels in the ascending order based on the intensity. After completing the sorting process, the second stage (i.e. the flooding process) floods the image in the increasing order started from the pixels having lowest intensity to highest ones. Those processes are depicted in figure 1 below.

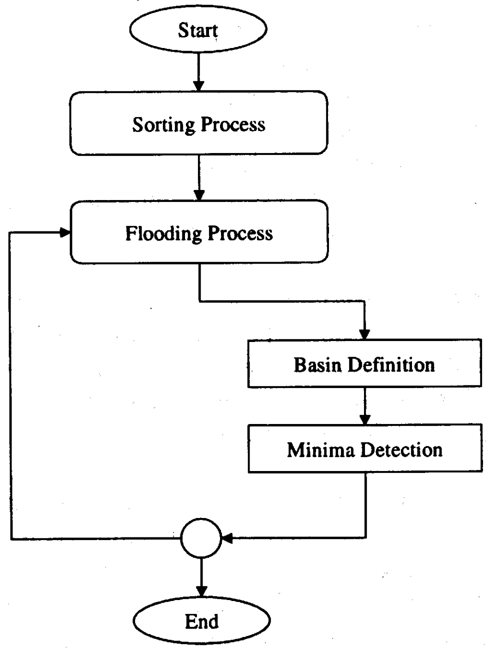


Figure 1. Watershed Transformation

As seen in figure 1 above, the second stage consists of two processes, i.e. minima detection and basin definition. The former aims to define minima contained in the image. Here minima can be defined as the point having lower intensity compared to its neighboring pixels. This point is used to start the flooding process, as it can be pretended as a hole through which the water immerses the image. In [18], minima detection mechanism is possible to produce a set of pixel as minima if it detects minimum intensity on a plateau (a set of points having the same intensity). Whereas the later aims to define the catchment basin by reaching every pixel composing the image and putting them in the defined basin. Those both processes are done step-by-step following the intensity height of the pixels since they reside in the flooding stage. In [18], the flooding process is held relying on the FIFO (First In First Out) queue in order to store neighboring pixels of the current pixel being investigated. At the end of the flooding process, all pixels will be assigned to a particular catchment basin except those belong to watershed lines that separate every basin.

The formalization of the watershed transform following the presentation of [18] is given as follows. Let I denotes the image in domain D □ Z^2 with h_{min} and h_{max} are the minimum and maximum value taken from I respectively. If G a subset of $Z^2 \times Z^2$ is the underlying grid, the neighboring pixels of a pixel p of I can be defined as:

$$N_G(p) = \{p' \in Z^2, (p, p') \in G\} \qquad (1)$$

A minima m of I is the point or area that is darker than neighboring pixels. If minima has the altitude h, it is impossible to reach the point with the lower altitude than h without having to climb. Defined the minima pixel p and non minima pixel q, the definition above can be formulated as the following:

$$p \in m,\ q \notin m,\ h_{(p)} \leq h_{(q)} \qquad (2)$$

To continue with the catchment basin formulation, we previously disclose the definition of threshold value of I at level h as the following:

$$T_h(I) = \{p \in D, I(p) \leq h\} \qquad (3)$$

Let $C(m)$ as the catchment basin that corresponds to the minima m, the subset of the catchment basin with value smaller or equal to h can be defined as:

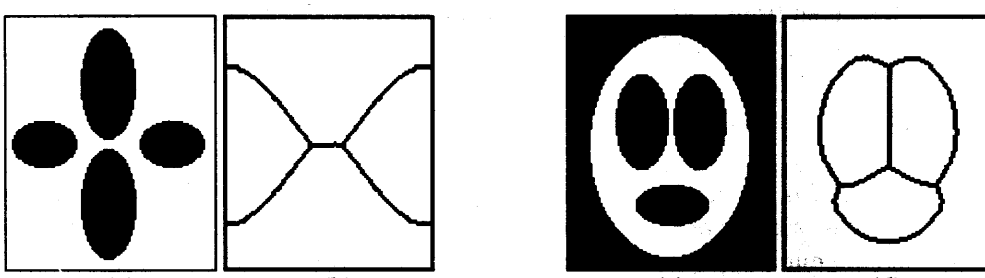
$$C_h(m) = \{p \in C(m), I(p) \leq h\} = C(m) \cap T_h(I) \qquad (4)$$

Intentionally we do not continue with the formulation of watershed lines from geodesic distance, geodesic influence zones and skeleton by influence zones (*SKIZ*) since the watershed lines is eliminated in our system to avoid the appearance of disconnected or incomplete watershed lines [10][18] and a thick watershed lines [2][18]. Therefore the calculation is stopped after completing the definition of catchment basin. The boundary of each basin will definitely be known after this stage is completed without running watershed lines calculation.

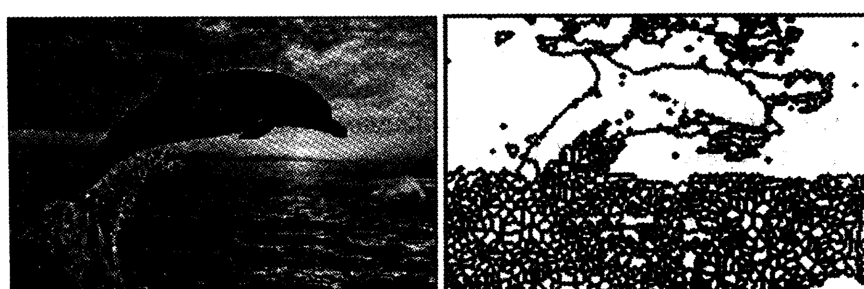
3. Watershed Implementation

In implementing watershed transformation we did not strictly follow the formulation in section 2, instead we held several modification. For the first effort as explained in section 2, we intend to eliminate the existence of watershed lines. Rather than assigning some pixels to compose the lines, we put all pixels in the defined basin since it will be useful in representing the appearance of objects. Second effort is the modification of input image following the statement of [5], in which it states that the application of threshold value in the gradient magnitude can reduce the number of detected catchment basin. Instead of applying watershed transform to the original image, we hold the transformation on the thresholded gradient magnitude image. Other point necessary to disclose here is the four connectivity used to access the neighboring pixel, therefore there are only four neighbor position measured surrounding the pixel being investigated, i.e. left, top, right and bottom position.

Verification to check whether the result of watershed transform violate the presentation of [18] or not was conducted on several images ranging from the simple computer-made image to real images as shown in figure 2 below.



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



(e) (f)

(g) (h)

Figure 2. Original images and watershed transform results

From the figure 2b and 2d that depict the result of segmenting simple computer-made images, it shows that the result of watershed transform implemented in the research follows the presentation of [18] although the watershed lines are eliminated here. And from the result of segmenting real images shown in figure 2f and 2h, it shows that the problem of over-segmentation is remained due to the existence of noise in the image. The over-segmentation here is appeared in the form of a large number of regions resulted from the segmentation.

4. Region Merging

As shown in section 3, the results of watershed transform for the real images are suffering from over-segmentation problem. There are a large number of small regions coming out from the segmented images. To compromise this problem, we apply a region merging mechanism. This method merges the detected basins that are assumed coming from the same object. The assumption applied to measure whether basin are part of the same object or formed from different ones is the mean value of the pixels composing catchment basin. Here we follow [14] that states intensity of the pixels from the same object is rather homogeneous, but differs significantly between different objects. The formalization on the steps taken in this mechanism is given as follows:

Let $i_{C(m)}$ represents the intensity mean of the basin *C(m)* that corresponds to minima *m*, in which it is composed by a set of pixels *p* of the image *I*. The intensity mean of that basin can be computed as:

$$for\ \forall p \in C(m),\ i_{C(m)} = \frac{\sum i_{\forall p}}{\forall p} \tag{5}$$

Let *F* becomes the predefined integer merging value used to produce the divided integer value from the intensity mean of each region, two neighboring basins *C(m)* and *C(n)* correspond to the minima *m* and *n* respectively will be treated as the following:

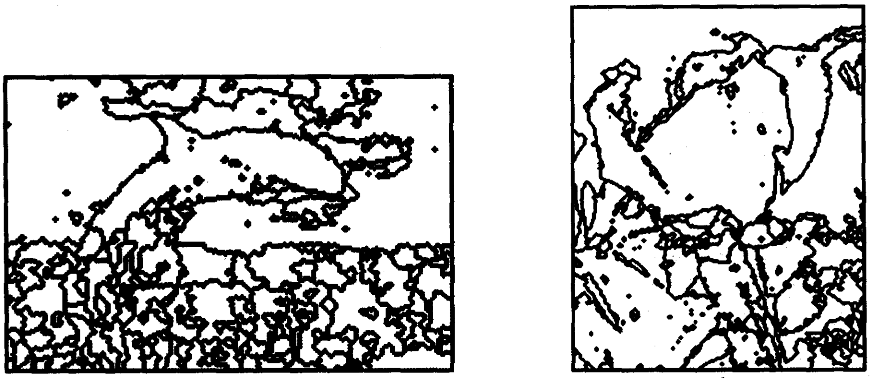
$$C(m) \in I, C(n) \in I \begin{cases} (C(m)\ div\ F) = (C(n)\ div\ F) \Rightarrow C(m)\ and\ C(n)\ merged \\ (C(m)\ div\ F) \neq (C(n)\ div\ F) \Rightarrow C(m)\ and\ C(n)\ left\ intact \end{cases} \tag{6}$$

Equation (6) produces the integer value by dividing intensity mean of each region with the predefined merging factor value. If the derived integer value is the same for two adjacent regions, then those regions will be merged. In our system, we assign two merging factor value, i.e. for the wide and the small regions. As our intention is more to merging the small regions, we put bigger integer value for the merging factor, thus it will produce less variant of integer value to facilitate the merging process.

Using equation (5) and (6) above, the merging process is started to reduce the number of detected basin. Only basins with the similar intensity will be merged as those basins are considered coming from the same object. Here the intensity mean is measured from the original image although we start segmentation from the gradient magnitude image. It is also important to underline that the merging mechanism is only taken for the adjacent regions. This mechanism will not be applied to the regions reside far from the other although the intensity mean of both regions are similar, unless the space lying between two regions are merged previously.

5. Experimental result

The proposed region-merging algorithm has been applied to the segmented images in figure 2f and 2h. As the purpose is to reduce the number of catchment basins, the structure of the picture should be preserved. The results are depicted in figure 3 below.



(c) (d)

Figure 3. Experimental results of dolphin and red rose picture

Figure 3 shows how over-segmentation suffered by each image can be reduced by applying region-merging procedure. Figure 3a is the product of region merging procedure for segmented dolphin picture as the input image shown in figure 2f. It contains 265 basins, a less number of regions compared to 1170 basins contained in figure 2f as the product of watershed transform. Whereas figure 3b shows the output of region merging for the red rose picture that contains 411 basins compared to 1120 regions produced by watershed transform as shown in figure 2h.

The algorithm has also been applied to some other real images as shown in figure 4 that comprises the picture of a tennis player, an astronaut, three F15 jet fighter, a motorcycle racer and a group of person. Here watershed transform was held on each image for initial segmentation, and then it is followed by region merging procedure to reduce the number of the basins. In those figures we present the original images (figure 4a, 4d, 4g, 4j and 4m), the segmented images produced by initial stage using watershed transformation (figure 4b, 4e, 4h, 4k and 4n), and the final results of two stages segmentation system (figure 4c, 4f, 4i, 4l and 4o). The data derived from each image in figure 4 can be seen in table 1. Those data represents the number of the detected catchment basins of each image in each stage. From those data we show that the region merging mechanism can significantly reduce the number of detected basins that represents the contents of the image while preserving the image structure.

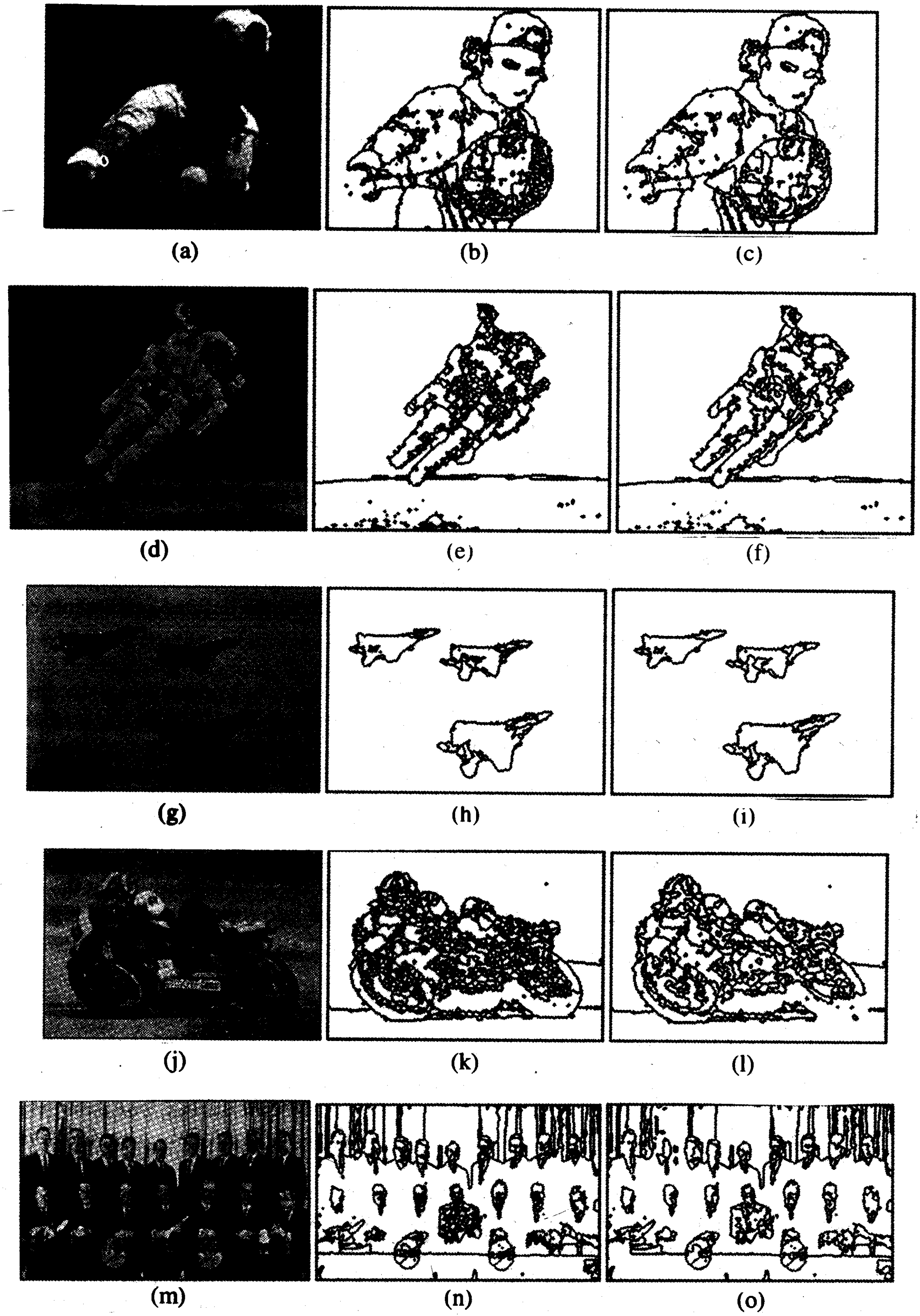


Figure 4. Experimental results of some other images

Table 1. Data of segmenting real images in figure 4

Image Name	Number of Detected Basins	
	Watershed Transform	Region Merging
Tennis player	840	326
Astronaut	644	267
F15 Hornet	182	77
Motorcycle racer	956	313
People	1018	461

6. Conclusion

Watershed transform definitely is an effective technique in segmenting image in order to derive its contents. Started from every pixels having smaller intensity than its neighbors that is called minima, catchments basin are expanded until all pixel can be reached by the flooding process. The results of watershed transform are a set of objects that are represented by the catchments basin, in which each basin is composed by a set of pixels. The vulnerability of watershed transform to the appearance of noise leads to the over-segmented result. In this condition, it is difficult to recognize objects composing image from the defined catchments basin since an object can comprise a large number of basins.

In this paper, two stages segmentation process was presented, which comprises watershed transform and region merging. Watershed is applied as the initial segmentation on the gradient magnitude image. Then region-merging mechanism is held to compensate the over-segmentation produced by the previous stage. Here the regions to merge are having similar intensity mean and residing adjacent to each other. The merging process is held relying on the integer value produced by the division calculation using merging factor. It can also be noted that in the region merging mechanism we intend to merge small regions than big regions as most images suffered from this condition. It is achieved by assigning a different merging factor for both regions. From the experiment we show that the mechanism can partition the image into some meaningful region although we still found the over-segmentation in its product.

7. References

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