

Markerpixel using Watershed Transformation

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Abstract— We describe a new method for the generation of superpixels which can be implemented using watershed transformation. Our method aims at the extraction process of local and global impression of a given image. We propose a gradient-based low level segmentation process in order to fulfill the adherence property of the segmented image. We also show this as an efficient method to achieve the regularity and adherence property of the segmented image. Since we are dealing with marker controlled Watershed transformation technique, the problem of oversegmentation can be avoided to a great extent. Here, we try to showcase 'markerpixels' as an efficient tool for the creation of superpixels using Watershed transformation.

Index Terms— markerpixels, segmentation, watershed, clusters

I. INTRODUCTION

Improper image segmentation is the most worst situation in various fields of digital imaging. It include mainly the construction of symbolized and differentiated depiction of a provided image . So that the image can be mark out as regions in accordance with a single or more prior constraints. Through the literature survey, various algorithms for segmenting can be found. The first procedure has been revealed during the 1960's followed by different algorithms and more works are still going on.. The main purpose of this paper is to formulate a new criteria for proper image segmentation by the morphological gradient technique along with the transforming technique. Here we use watershed transformation technique as a main tool. The watershed transformation is the most widely used segmentation technique due to its boundary-based segmentation.. Gray level images can be used for this by treating it as topological reliefs. Each relief is subjected to flooding process. It is done from its minima and a dam is built at the time when two lakes merge, and these developed dams represent watershed.. Always providing closed contours is the most reputed merits of the watershed to decrement the rate of unwanted segmentation several



Fig. 1. Superpixels illustration. First figure shows the original image and the second one shows the Marker pixels

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enhancement several mediums like markers, region merging methods, scale space approaches, etc can be used.

Detection of boundary lines between dissimilar regions can be made using the WS approach. WS has been defined as a combined process of dilations and erosion processes. It include flooding process and can be treated as a topological region. Each with its own advantages and drawbacks, so many approaches to generate superpixel are there. transformation , which makes it very useful in image segmentation field. Minimized computation time in comparison with prevailing segmentation methods is another advantage. Then also, an oversegmented image is the final output by using this approach on either of the original image or on its gradient , which act as a main drawback of watershed transformation .

- Adhere well to image boundaries should be obeyed by superpixels.
- As a preprocessing step, when it is used to reduce computational complexity.
- Increasing the fastness and improving the efficiency of the performance when it is used for segmentation purposes can also be achieved by superpixels.

The classification of prevailing superpixel generation can be done dually: Those algorithms that is not aware of the constraints determining the compactness during the required procedure, like [1], and [2] algorithms are the first classification (see Figure 1 for an illustration). These algorithms do not take into account of the compactness factors, which may lead to the production of superpixels with high irregularities especially the geometry and sizes. The later classification of proposed algorithms gives more importance to the compactness factors, such as [3] and [4] approaches. Through [3] their work described an image superpixel segmentation approach by performing segmentation by normalized cuts method.. That is by segmenting the image onto a large piece of homogeneous, small compact spaces.

The main part of this paper is to perform segmentation by satisfying the requirements of regularity and adherence. Infact these two are oppositional in nature , but through this paper we found a good solution in order to compromise these two requirements. In addition to these some other qualities like superpixel quality, computational efficiency, implementation cost etc were achieved. Even though various methods: mainly graphical based , geometrical or k-means are existing, watershed transformation is well suited for SP generation. More the number of advantages that it have, make it more reasonable: it is simple, fast and an almost linear speedup. Even if the contrast is poor, it produces a complete segmenting of the image. Thus the need for any kind of contour joining can be avoided.

1.1 RELATED WORKS

[5] and [4] are the most popular superpixel generation algorithms. However, they produce superpixels with irregular

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geometry which leads to irrelevant multiple objects. Generation of superpixels with similar sizes and compact shapes which can be used for some vision algorithms [6] is the main property of NCut [3]. The computational requirement-it takes for segmenting an image is the demerit of NCut.. [6,7] propose an optional method for alignment of superpixels with a network. Inorder to sequentially cleave images along some upright and straight strips.], an entirely different algorithm is used in [4]; Whereas, the problem is resolved using a method in [7].

1.2 CONTRIBUTION OF WORK

The main contributions of the paper are listed below:

- This paper is actually an extended version of [6] work. It introduces Mate pixels generation method, by giving more preference to boundary adherence property and regularity condition, as well as computation time.
- Our work makes it one among the fastest superpixel generation methods.
- The achievement of trade-off between regularity and segmentation quality by markerpixels.

II. METHODOLOGY

There are mainly three methods to implement watershed. They are listed below:

- Distance Transform Approach
- Gradient method
- Marker Controlled Approach

Due to noise, applying the watershed transform straight forwardly to a gradient can result in uncontrollable segmentation, which seem to be a disadvantage of WS transformation. The concept of markers can be used for this. For that, marker can be depicted in such a way that it is a part belonging to an image, helpful to improvisation of the gradient of the image. Markers are of two types:

- Internal markers
- External markers

Internal markers are assigned for object and external markers for boundary. For closed contours segmentation, the robustness and flexibility of the marker-controlled watershed segmentation has been shown to be an extravagant method.. Marker –controlled WS segmenting follows the basic procedures as shown below:

- Computation of a segmentation function is the first step.
- Define the foreground markers.
- Define background markers.
- Modification of segmentation function in a manner such that it contains only minimas in any locations.
- Computation of WS transform of the modified segmentation function.

By performing WS transform along with some more procedures will help in obtaining the regularity and adherence of the segmented image.

A ‘markerpixel’ generation method can be made clear through the following steps:

- Compute the image gradient, g (of the original image).
- Allocation of clusters for the image by centering it over the endpoints of a hexagonal network.

- Spatial regularization of the clusters by updating the distance, δ and label.
- Merge the nearby islands by cleaning up small islands around the cluster to obtain Mp_image .
- Apply the watershed transformation on gray-level image of the original image to get the ws_image .
- Then add both the Mp_image and Ws_image in order to obtain the markerpixels

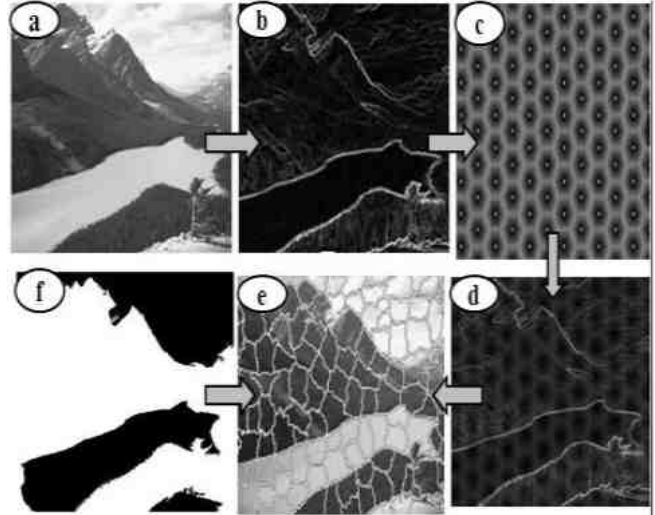


Fig. 2 .Markerpixels generation illustration: (a): Actual image; (b) Lab gradient of corresponding image; (c): selected markers within the regular network of hexagonal clusters; (d) spatially regularized gradient; (f) Watershed transformed image; (e) Markerpixels.

Algorithm

1. Read the image and compute its gradient.
2. Formation of hexagonal shaped regular grids.
 - 2.1. Convert the image to Lab space.
 - 2.2. Define the spacing between the grid elements for hexagonal grid as,
$$S = \frac{\sqrt{nr+nc}}{k+\sqrt{3}/2} \quad (1)$$
 - 2.3. Compute
$$K = \text{nodesperrow} \times \text{nodeRows} \quad (2)$$
 - 2.4. Allocate memory and initialize clusters, labels and distances.
 - 2.5. Loop L1:
 - 2.6. Compute the distance between cluster and subimage..
 - 2.7. If any pixel distance from the cluster centers is less than its previous value, update its distance and label.
 - 2.8. Spatially regularize the clusters and clean up the small islands to nearby regions to obtain the image with hexagonal grids, Mp_im .
3. Perform WS transformation in the gradient of image, g to obtain Ws_im .
4. On combining both the Mp_im and Ws_im , we get markerpixels which provide adherence and regularity property to the segmented image.

The content included in the g in this segmented region is then

studied to choose the required marker. The corresponding marker is chosen for each cluster, from among the minimas present in this defined cell,. If more minimas are found to be present, then a minima having the most surface extinction value is selected.

The selectiveness of markers contains not only the data of future markerpixel-boundaries but also the regularness and homogeneity of patterns. In the final step, the gradient is subjected to watershed transformation technique, The unwanted details from the expected markerpixel area can be removed efficiently through this method.

Here the centers correspond to the edges of a hexagonal network of step size δ . The network is computed by passing over the original image, That is, by first calculating the three coordinate values (nr, nc, np) belonging to each cell and then assigning to them the label and cluster of their corresponding cell. The main problem faced in Superpixel methods is poor performance. First importance is given the one which not every methods guarantee. That is the ability to specify the amount of superpixels. Finally, the ability to control the compactibility of the markerpixels is the most preferable one. In image processing, compact and regular superpixels are often desirable.

Table-1 : Definition of various abbreviations used in explanation

Terms	Definition
MP	markerpixels
WS	watershed
g	Gradient image
nr,nc	Number of rows, number of columns
Mp_im	Markerpixel image
Ws_im	Watershed image
K	Number of markerpixels
S	Vertical spacing
δ	Distance of neighbouring pixels from the hexagonal centre

III. CONCLUSIONS

The high cost of computing segments can be avoided by the task of efficiently computing a highly regular over segmentation of an image. This proposed method outperforms other superpixel generation methods, both in terms of regularness and computational efficiency. The covenant between computation efficiency and regularity in segmenting process can be gained by marker pixels offer this superpixels generation method, an interesting one. Both adherence and regularity properties leads to efficient segmentation. The problem of over-segmentation can be avoided since watershed transformation method is used here. This method is computationally efficient, since it reduces the infinite pixels to limited marker pixels. Superpixels have been showcased an essential menu for the object detection and medical imaging. In addition, a new method for generation of markerpixels is proposed here, inorder to outperform available superpixel methods.

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