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Modified Marker Controlled Watershed Algorithm for the Segmentation Brain MR Image

M. Sreerangappa[1] and D. Jayadevappa[2]
[1]Asst. Professor, Dept. of ECE, Sree Siddartha Institute of Technology, SSAHE, Tumkur Karnataka, India.
sreerangappa.ssit@gmail.com
[2]Professor, Dept. of E&IE, JSS Academy of Technical Education, Bengaluru, VTU, India.
devappa22gmail.com

***Abstract*—The watershed transform is the method of choice for medical image segmentation. Separating overlapping objects in an image is one of the challenging tasks in image processing operations. Segmentation of brain MR image using marker controlled watershed transform works better if we can identify or mark foreground objects and background locations. This paper deals with a novel segmentation method giving realistic results on brain tumor boundary detection using brain MR images. This method can be easily used to diagnose tumor boundary with a faster rate and it is accurate compare to the existing methods.**

***Index Terms*— Watershed Transform, Image Segmentation, MRI.**

I. INTRODUCTION

The watershed transform has proven to be a powerful tool and fast technique for both contour detection and region based segmentation. Many morphological segmentation approaches using the watershed transform [1], [2], [3], [4] are reviewed in these papers. Different watershed methods use slightly different distance measures, but they all share the property that, the watershed lines appear as the points of equidistance between two adjacent minima. Some of the important drawbacks of these methods are over-segmentation, poor detection and sensitivity to noise, but the crucial point is that all important object boundaries are included, and the task is to reduce the undesired ones. A simple region merging method [5] can be applied, but careful intervention from the user or explicit prior knowledge on the image structure is necessary for region merging. Another way of avoiding over-segmentation is that of using low pass filter. However, low pass filtering decreases the precision. To overcome this limitation multiscale hierarchy [6] is proposed. But, this might cause problems when shape information is used to control the merging of segments. The watershed transform can be classified as a region-based segmentation approach. The intuitive idea underlying this method comes from geography: it is that of a landscape or topographic relief which is added by water, watersheds being the divide lines of the domains of attraction of rain falling over the region. An alternative approach is to imagine the landscape being immersed in a lake, with holes pierced in local minima. Basins (also called `catchment basins') will fill up with water starting at these local minima, and, at points where water coming from different basins would meet, dams are built. When the water level has reached the highest peak in the landscape, the process is stopped. As a result, the landscape is partitioned into regions or basins separated by dams, called watershed lines or simply watersheds.

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Watershed transformation is just a way of extracting crest lines from the gradient image. In general, the boundary of each region usually has high gradient value and corresponds to the watershed line while the interior has low gradient value and means the catchment basin.
Assume that the image f is an element of the space $C(D)$ of a connected domain D then the topographical distance between points p and q in D is,

$$T_f(p,q) = \inf_\gamma \int \left\| \nabla f(\gamma(s)) \right\| ds \tag{1}$$

where, $\inf_\gamma$ is over all paths (smooth curve) inside D, defines the watershed as follows.

Let $f \in C(D)$ have a minima $\{m_k\}_{k \in I}$, for some index set I. The catchment basin $CB(m_i)$ of a minimum m_i is defined as the set of points $C \in D$, which are topographically closer to m_i than to any other regional minimum m_j.

$$CB(m_i) = \left\{ x \in D \mid \forall_j \in I \setminus \{i\} : f(m_i) + T_f(x, m_i) < f(m_j) + T_f(x, m_j) \right\} \tag{2}$$

The watershed of f is the set of points which do not belong to any catchment basin;

$$W_{watershed}(f) = D \cap \left(\bigcup_{i \in I} CB(m_i) \right) \tag{3}$$

Let W be some label, $W \in I$. The watershed transform of f is a mapping of $\lambda : D \to I \cup \{W\}$ such that $\lambda(p) = i$ if $p \in CB(m_i)$ and $\lambda(p) = W$ if $p \in W_{watershed}(f)$. So the watershed transforms of f assigns labels to the points D, such that

- Different catchment basins are uniquely labeled.

Special label W is assigned to all points of the watershed of f.

II. RELATED WORK

Marker-controlled watershed segmentation [7], [8] can also be used to reduce the severe over-segmentation. However, the success of the watershed segmentation relies on a situation where the boundaries and ridges are located.
Recently, hybrid models are proposed to overcome these limitations. Watersnakes [9] are applied to regularize the watershed lines. However, due to the small capture range of the snake model will have a problem in tracing the edges at the concave object boundary. Kim et al. [10] and Gauch et al. [11] have proposed other snake models, where a snake zone is defined around the object boundaries. However, the initialization of snake is a difficult task.
Mehena and Adhikary [12] succeeded to tackle the problem of over-segmentation while preventing under-segmentation by introducing improved watershed algorithm, it combines both watershed and balloon snake to ensure automatic initialization of snakes and parameter optimization, but this hybrid model suffers with poor capture range for the overlapping tissues and its inability to extract concave objects. Further, the use of this technique in real applications is limited due to high computational time.
Watershed transforms have also been used in multiresolution methods [13], [14], [15] for producing resolution hierarchies. Although these methods are successful in segmenting certain classes of images, they require significant interactive user guidance or accurate prior knowledge on the image structure. It is aimed to reduce the computational complexity and also to improve the segmentation accuracy.
The marker-controlled watershed expresses an elaborated form over the traditional watershed transform. The laws of the marker-based segmentation are to transform the input image so that the watersheds of the transformed image resemble to the object boundaries. The goal of the marker controlled segmentation is to detect the presence of the homogenous regions from the image by a set of morphological operations. Markers are connected components belonging to an image. Some solutions of the over-segmentation are addressed in the marker-controlled watershed segmentation has been shown to be a robust and flexible method for segmentation of objects with closed contours, where the boundaries are expressed as Markers are placed inside an object of interest; internal markers associate with objects of interest, and external markers associate

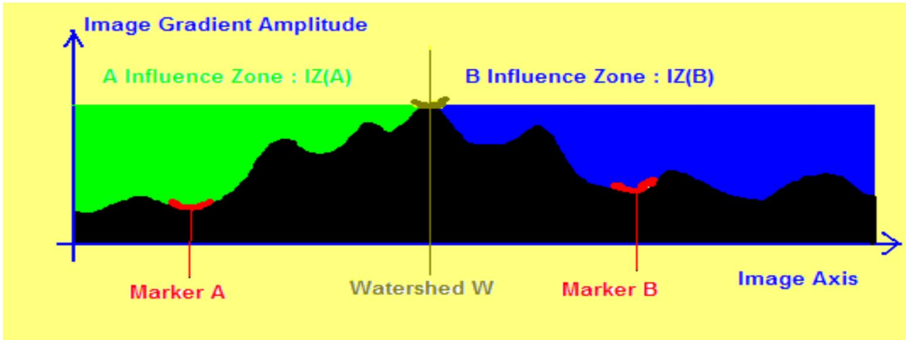

Figure1. Marker based watershed transform principle [7]

with the background. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbors.

III. Proposed Methodology

This method uses different morphological operations to remove noise from structured elements in the images such as dilation, erosion, opening, and closing. To get the better filtered image we used erosion and dilation functions. For getting more refined result we used opening and closing operations with different structuring elements. In this proposed algorithm, we first converted the image into gray-scale and then performed gradient magnitude as the segmentation function. The developed segmentation function results into a resultant image, whose foreground and background markers are the objects we are interested to segment.
The limitations of traditional Watershed algorithm are as follows

- Over-segmentation.
- Sensitivity to noise.
- Poor detection of significant areas with low contrast boundaries.
- Poor detection of thin structures which are common in MR images.

To overcome the deficiencies of traditional watershed algorithm, an improved marker controlled watershed algorithm is proposed. This algorithm is also based on flooding of the image terrain to form catchment basins and watersheds. Unlike the traditional concept of use of gradient image directly for flooding, an adaptive thresholding is applied on the gradient image. Then the markers are imposed on the gradient thresholded image. The following block diagram illustrates the methodology of the proposed model. The main difference is that the immersion of the gradient surface begins only from selected markers and not from all minima. Now, the foreground marker, background marker and object boundaries are found by using some morphological techniques such as opening-by-reconstruction, closing-by-reconstruction, erosion, dilation, reconstruction and thresholding operations. The final watershed segmented output of the original image, where tumor of the brain is extracted out from the original MRI image can be obtained in this method.

A. Advantages of the proposed algorithm

- ➢ The watershed lines always correspond to the most significant edges between the markers. So this technique is not affected by lower contrast edges, due to noise that could produce local minima and thus, erroneous results, in energy minimization methods.
- ➢ Even if there are no strong edges between the markers, the watershed algorithm always detects a contour in that area.

IV. Experimental Results

The performance of the proposed modified Marker controlled watershed algorithm is evaluated by conducting the experiments on MR image datasets. Segmentation results are validated using various performance measures. The proposed hybrid algorithm is compared with existing algorithms. However, there are some issues in the watershed transform by immersion which require some attention. The first is finding the image minima in each grey level, from which the propagation fronts emanate. The second is the transition of the propagation fronts from one grey level to the next, without the storage of unnecessary points. In the

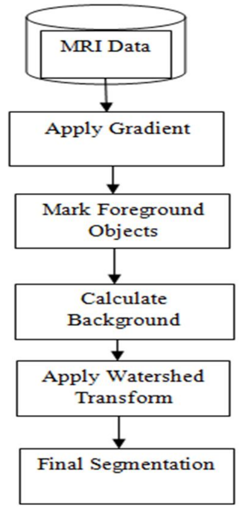

Figure 2. Proposed Marker controlled Watershed transform for the segmentation brain MR Image

proposed method these challenges tackled effectively. Figure 3 and 4 demonstrates the segmentation results of modified marker-controlled watershed algorithm for MR image1 Unlike traditional algorithm the proposed marker controlled watershed algorithm uses the gradient threshold image figures 3(b) and 4(b) well as the marker controlled image figure 3(c) and 4(c) respectively to overcome the over-segmentation.

The speed of the algorithm was satisfactory. It only rises significantly when more marker points are used. Above that number, the number of markers becomes comparable to the number of points in the surface, and the entire algorithm degenerates. It must be noted that the execution time remains constant although the number of iterations decreases with the number of markers, meaning that the time spent on each iteration increases with marker number, as expected. The memory requirements were also reasonable. If we assume a uniform distribution of markers on the image region, the number of points belonging to each influence zone can be approximated.

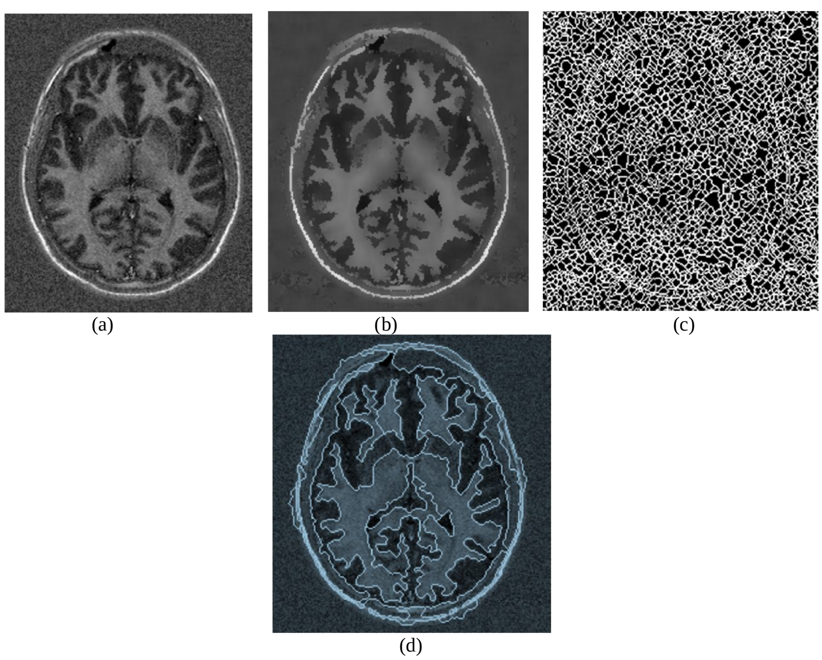

Figure 3. Results for Brain MR Image 1. (a) Original image, (b) Gradient image, (c) Watershed image, (d) Final segmentation

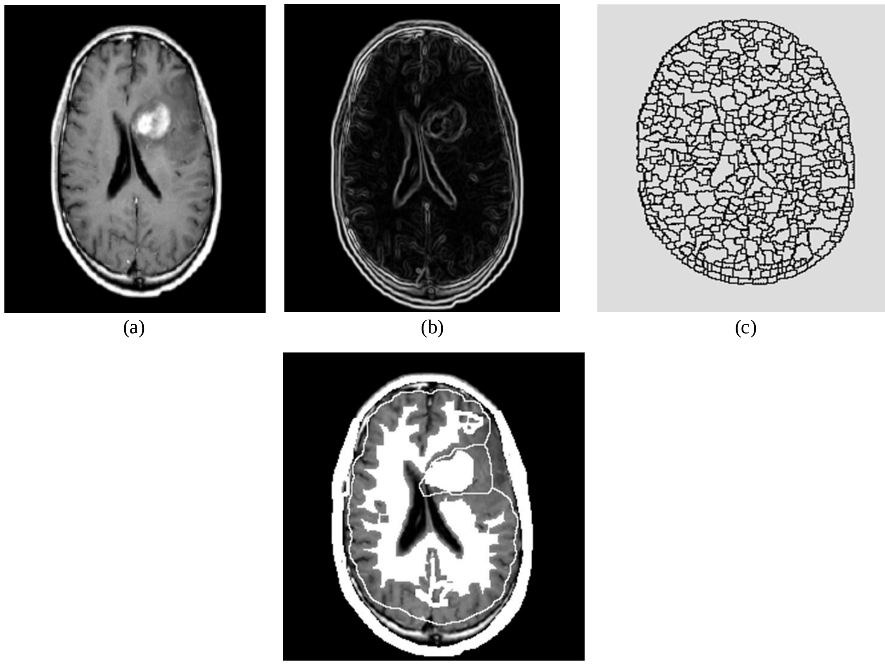

Figure 4. Results for MR Image 2: (a) Original image, (b) Gradient image, (c) Watershed image, (d) Final segmentation

V. CONCLUSION

This paper presented the improved version of the segmentation technique using modified marker controlled watershed transform for the segmentation of brain tumor by using MR images. The experiment was carried using two sets of MR images. The experimental results prove that, the proposed method is fast, efficient and accurate method of segmentation of brain image. Results are very encouraging but great enhancements are still possible. Future work will consist in image enhancement using wavelet and contourlet transform techniques for contrast enhancement.

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