A Study on Seeded Region Based Improved Watershed Transformation for Brain Tumor segmentation

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Abstract

The objective of segmentation is to partition an image into regions. In present work authors have presented an innovative image segmentation technique based on mathematical morphology using watershed transformation. Present approach is an intuitive method that produces a complete division of the image in separated regions avoiding the need for any kind of edge linking. We have further proposed seed-region based improved watersheds which removes drawbacks of conventional watersheds utilizing the prior knowledge of the test images.

1. Introduction

Segmentation subdivides an image into its constituent regions or objects. The level to which the subdivision is carried depends on the problem being solved. The process of *segmentation* should stop when the objects of interest in an application have been isolated [1]. Medical image segmentation is one of the difficult tasks in image processing and accuracy of segmentation of *region of interest ROI* from an medical image determines the eventual success or failure of proper diagnosis. In this context of segmentation of medical images authors have developed a robust technique for segmentation using *watershed transform* using mathematical morphology [2]. We visualize an image with two spatial coordinates and gray levels and to understand the *watershed transform* let us imagine that there is a hole in each local minimum and that the topographic surface is immersed in water. Water starts filling all catchment basins at a uniform rate. If two catchment basins would merge as a result of further immersion, a dam is built all the way to the highest surface altitude and the dam represents the watershed lines. Final dam represents the continuous boundaries extracted by watershed segmentation algorithm [3]. It produces a complete contour of the images and avoids the need for any kind of contour joining. To avoid oversegmentation [4] some pre or post processing methods have been proposed in order to produce a more reasonable segmentation that reflects the layout of objects [5],[6-8],[9]. Local variations of the image can change the results immensely. Due to noise and other local irregularities of the gradient, some times watershed transformation produces fatal effect. This effect can be removed by blurring the images, which suppresses the noise and other local irregularity [10].

In proposed method, we have implemented marker-based improved watershed algorithm for segmentation of tumors appearing in human brain where seeded region-growing method has been used as the marker of the region of interests. In present paper, we have set the seed point on the basis of prior knowledge of the tumor regions with a consultation of the physician.

2. Algorithms of Improved Watershed Transform

Our proposed method is based on improved watershed transform. In order to avoid oversegmentation images are being blurred. Then markers have been used to achieve meaningful segmentation. This marker is selected on the basis of seeded region growing method. Proposed watershed algorithm has been implemented on brain images having space occupying tumor lesions in order to segment the tumors from normal brain tissues. Each of the steps has been discussed in details.

2.1 Smoothing of Images

Smoothing filters are used for blurring and for noise reduction. In present problem, blurring is used as preprocessing steps for removal of small details from the images prior to watershed transform. The output response of a smoothing filter is simply the average of the pixels contained in the neighborhood of the filter mask. These types of filters sometimes are called averaging filters or lowpass filters. This process results in an image with reduced sharp transitions in gray levels. Since noises and other local irregularities of the image some times produce meaningless watershed transformation, blurring is a necessary to suppress the noises and other local irregularities.

2.2 Marker using Seeded Region Growing

Direct application of the watershed segmentation algorithm generally leads to oversegmentation due to noise and other local irregularities of the images. To control oversegmentation the concept of marker has been used. A marker is a connected component belonging to an image. In the present problem, marker is selected on the basis of tumor region intensity and texture. The marker selection procedure follows the methodology of region growing. In X-ray brain images, it is known that tumor pixels tend to have maximum brightness. Based on this information we have selected the seed points containing the brightest pixel and a set of 8-adjacent pixels. On the other hand, darker pixels represent the tumor region in brain MRI. Not only the pixel intensity represents the tumor cell characteristics, the texture of affected region is another important demarcation. Thus combined effect of tumor pixels' intensity and texture introduces better and accurate region growing algorithm than a single one.

2.3 Morphological watershed Transform

In a topographic image, three types of points are obtained: (a) points belonging to a regional minimum, (b) points at which a drop of water if placed, would fall with certainty to a single minimum and (c) points at which water would be equally likely to fall to more than one such minimum. For a particular regional minimum, the set of points satisfying condition (b) is called the catchment basin or watershed of that minimum. The points satisfying condition (c) form the crest lines on the topographic surface and termed as watershed lines. The principal objective of segmentation algorithms based on these concepts is to find the watershed lines. The basic idea is that the catchment basins fill from the bottom.

2.3.1 Watershed Segmentation Algorithm

Let $M_1, M_2, \ldots, M_R$ be sets denoting the coordinates of the points in the regional minima of an image $g(x,y)$ and $C(M_i)$ be a set denoting the coordinates of the points in the catchment basin associated with regional minimum M_i. Finally $T[n]$ represents the set of coordinates (s, t) for which $g(s, t) < n$.

$$T[n] = \{(s,t) | g(s,t) < n\} \tag{1}$$

Geometrically, $T[n]$ is the set of coordinates of points in $g(x, y)$ lying below the plane $g(x,y) = n$. The topography is flooded in integer flood increments from $n = min + 1$ to $n = max + 1$. At any step n of the flooding process, the algorithm needs to know the number of points below the flood depth. Conceptually the coordinates in $T[n]$ that are below the plane $g(x,y) = n$ are marked black and all other points marked white.

Consider $C_n(M_i)$ denotes the set of coordinates of points in the catchment basin associated with minimum M_i that are flooded at stage n. Thus $C_n(M_i)$ may be viewed as a binary image given by

$$C_n(M_i) = C(M_i) \cap T[n] \tag{2}$$

Next we consider $C[n]$ denotes the union of the flooded catchment basins portions at stage n:

$$C[n] = \bigcup_{i=1}^{R} C_n(M_i) \tag{3}$$

Then $C[max + 1]$ is the union of all catchment basins:

$$C[\max \quad +1] = \bigcup_{i=1}^{R} C(M_i) \tag{4}$$

According to equation (2) and (3), *C[n]* is a subset of *T[n]*, so it follows that *C[n−1]* is a subset of *T[n]*. From this the important result can be drawn that each connected component of *C[n−1]* is contained in exactly one connected component of *T[n]*. The algorithm for finding the watershed lines is initialized with *C[min+1] = T[min+1]*. The algorithm then proceeds recursively, assuming at step n that *C[n−1]* has been constructed. A procedure for obtaining *C[n]* from *C[n−1]* is as follows. Let *Q* denotes the set of connected components in *T*[n]. Then for each connected component $q \in Q$[n], there are three possibilities:

(a) $q \cap C[n-1]$ is empty.

(b) $q \cap C[n-1]$ contains one connected component of *C*[n−1].

(c) $q \cap C[n-1]$ contains more than one connected component of *C*[n−1].

Construction of *C[n]* from *C[n+1]* depends on which of these three conditions holds. Condition (a) occurs when a new minimum is encountered, in which case connected component *q* is incorporated into *C[n−1]* to form *C[n]*. Condition (b) occurs when *q* lies within the catchment basin of some regional minimum, in that case *q* is incorporated into *C[n−1]* to form *C[n]*. Condition (c) occurs when all or part of a ridge separating two or more catchment basins is encountered. Further flooding would cause the water level in these catchment basins to merge. Thus a dam or dams must be built within *q* to prevent overflow between the catchment basins. A one pixel thick dam can be constructed when needed by dilating $q \cap C[n-1]$ with 3 × 3 structuring element of 1's.

3. Experimental Results

We have applied the proposed algorithm to segment the brain tumors accurately. The dataset contains more than 20 brain images. In present problem texture and gray level intensity based region growing techniques have been used as marker of watershed algorithm. Texture measures the relative smoothness, average uniformity of the images. The conditions for texture based region growing are stated below.

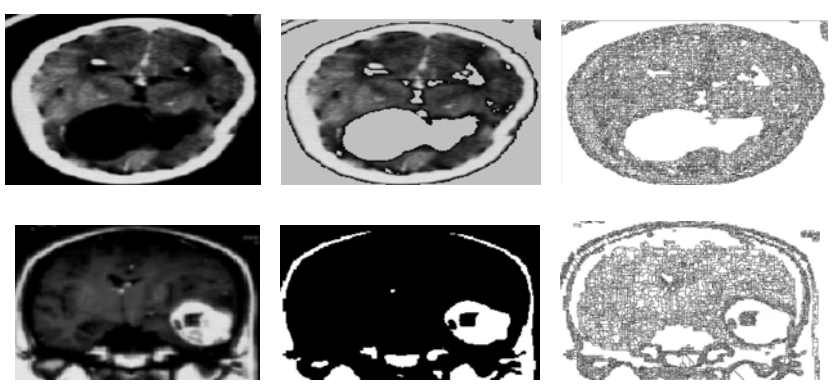
$$|m_i - m_s| \le 0.05 \quad \text{and} \quad |\sigma_i - \sigma_s| \le 0.05 \quad \text{and} \quad |U_i - U_s| \le 0.05$$

where m_i, σ_i and U_i are mean, standard deviation and average uniformity of ith window location respectively and m_s, σ_s and U_s are mean, standard deviation and average uniformity of the seed region respectively.

The condition for gray level intensity based region growing stated below.

$$|A(G_i) - A(G_s)| \le 0.1$$

where $A(G_i)$ is average gray level intensity of ith window location and $A(G_s)$ is the average gray level intensity of seeded region.



[a] [b] [c]

Fig. 1: [a] Brain images with tumor [b] marker selection by region growing method [c] watershed segmentation of tumor with marker

4. Conclusion

In the proposed methodology for brain tumor segmentation, we have attempted to develop a seeded region growing based improved watershed algorithm to be implemented on medical images for segmentation of region of interest *ROI.* Both texture and gray level intensity based region growing methods were adopted for rough tumor regions. Finally watershed transform was applied to segment fine tumor boundary. To describe the texture of the seeded region, we have developed statistical moments of the gray-level histogram of that region.. Marker selection depends on prior knowledge of tumor region. In general an approximate tumor region was indicated by the physician and center of this region has been used as seed points. In some cases, seed region is being grown up on the basis of information of the brighter/darker pixels of the tumor region. Since blurring of the images has been done as a preprocessing step, sensitivity on the noises and other irregularities are also being removed which results more accurate segmentation and fine boundary detection of tumor lesion from brain images. This method will help for further diagnosis and therapeutic planning using medical images.

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6. References

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