

Segmentation of Cerebral Tumors Using Coactive Transform Approach

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Abstract—The main topic of this work is to segment brain tumors based on a hybrid approach. For tumor segmentation a coactive approach of wavelet and watershed transform is proposed. If only watershed algorithm be used for segmentation of image, then over clusters in segmentation is obtained. To solve this, an approach of using wavelet transformer is proposed to produce initial images, then watershed algorithm is applied for the segmentation of the initial image, then by using the inverse wavelet transform, the segmented image is projected up to a higher resolution. Even MR images are noise free, usage of wavelet decomposition involving a low-pass filter decreases the amount of the minute noise if any in the image and in turn leads to a robust segmentation. The results demonstrate that combining wavelet and watershed transform can help us to get the high accuracy segmentation for tumor detection.

Keywords—MR image, Region merging, Segmentation, Wavelet, Watershed transform.

I. INTRODUCTION

Brain tumor is one of the most deadly and intractable diseases. A brain tumor can be defined as a disease in which cells grow uncontrollably in the brain. Brain tumor is basically of two types:

- 1) Benign tumors
- 2) Malignant tumors

Benign tumors do not have the ability to spread beyond the brain itself. Benign tumors in the brain have limited self-growth and it do not to be treated. But they can create problem due to their location and has to be treated as early as possible.

Malignant tumor is the actual brain cancer. These tumors can even spread outside of the brain rapidly. Malignant tumors are left almost untreated most of the time as the growth is so fast that it gets too late for the surgeon to control or operate it. Brain malignancies again of two types:

- i) Primary brain cancer originated in the brain.
- ii) Secondary or metastatic brain cancer spread to the brain from another site in the body.

Tumors can be benign or malignant. Imaging plays a central role in the diagnosis and treatment planning of brain tumor. Tumor volume is an important diagnostic indicator in treatment planning and results assessment for brain tumor. The measurement of brain tumor volume could assist tumor staging for effective treatment surgical planning. Imaging of the tumors can be done by CT scan, Ultrasound and MRI etc. The MR imaging method is the best due to its higher resolution (~100 microns). The methods to segment brain tumors are snakes segmentation, level set segmentation, watershed segmentation, region-growing segmentation etc.

The Watershed segmentation [1] is preferred for its wide range of applications and automatic features. Preprocessing experiments are carried out to find which type of filtering will be more beneficial. This reduces the effect of the speckle and preserves the tumor edges: thereby provide the foundation for a successful segmentation. The desired tumor area is selected from the segmented image to calculate the volume. MR imaging is currently the method of choice for early detection of brain tumor [2]. However, the interpretation of MRI is largely based on radiologist's opinion. Computer aided detection systems can now assist in the detection of suspicious brain lesions and suspicious masses. The task of manually segmenting brain tumors from MR imaging is generally time consuming and difficult. An automated segmentation method is desirable because it reduces the load on the operator and generates satisfactory results.

II. OVERVIEW

Basically segmentation deals with dividing an image into distinct regions. In fact each region is equivalent with an object. There are many approaches to image segmentation such as classifications of edges or regions. Mathematical morphology (MM) is a powerful tool for image segmentation. Watershed algorithm is based on MM and is a useful tool to image segmentation but is very sensitive to noise and leads to over segmentation in image. In this work watershed algorithm is used for image segmentation [3]. Multi resolution technique by wavelet transformer is applied to reduce over segmentation problems caused by watershed algorithm[4]. Using this method, amount of noise and also the small details will be removed from image and only large objects will remain. This idea has many advantages in segmentation of brain tumor MR images, which greatly involve the classification among Malignant and Benign tumors. In this paper, a collective use of wavelet transform and watershed transform is proposed, To do this, first the wavelet transform is used for denoising, which in turn

leads to the production of four images, approximation image and detail images, then Sobel operator is applied for the estimation of edges. Additional edge is eliminated by a threshold then initial segmentation image by applied watershed transform is obtained. To reach the high resolution in the projected segmented image, the inverse wavelet could be repeatedly used until we get a resolution segmented image that is similar to the initial image.

III. METHODOLOGY

The diagram of the algorithm is presented in figure 1. In the first step wavelet transform is used for producing approximation and detail images, then by Sobel mask, approximation image gradient is obtained and additional edge is eliminated by a threshold then watershed transform is done and the segmented image is projected to high resolution by inverse wavelet. Region merging is applied in the last phase and cropping of tumor is done.

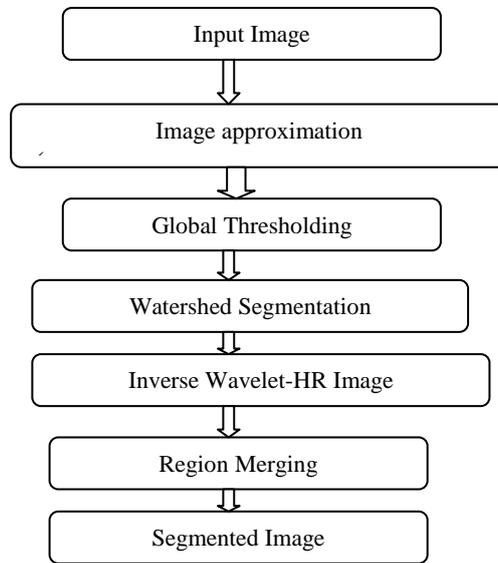


Fig 1.Overall system architecture

Step 1: Wavelet Transform

The 1-D DWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. As depicted in Figure 2(c), the four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

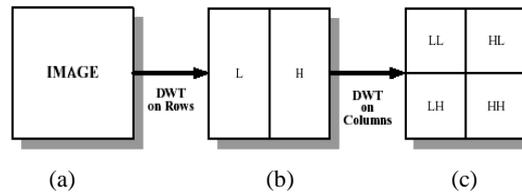


Fig. 2 Block Diagram of DWT

(a)Original Image (b) Output image after the 1D applied on Row input (c) Output image after the second 1-D applied on row input.

SAMPLE CODING:

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and subsampled data. Figure 3 depicts, how wavelet transform is applied to an MRI brain image by the following code:

```

input_im = handles.input_im;
[LL LH HL HH] = dwt2(input_im,'haar');
Dec = [LL LH;HL HH];
axes(handles.axes2);
imshow(Dec,[]);
title('DWT Image');
handles.LL = LL;
handles.LH = LH;
handles.HL = HL;
  
```

```
handles.HH = HH;
handles.Dec = Dec;
helpdlg('Process Completed');
```

The wavelet transform can describe an image in a different scale, and due to existence of the low pass filter in wavelet, noise magnitude is reduced. Before using the wavelet, the wavelet function should be determined. To do this, we used the Haar method, because it requires small computational complexity (linear with respect to the size of the input image). [7] By applying the wavelet on an image, four images will be produced, that the size of each one is half of the original image; they are called: HH, HL, LH, and LL. The first and second components correspond to horizontal and vertical position respectively, and the letter H and L are representing the high and low frequency respectively, (Jung, 2007). Figure 3 demonstrates the output of this

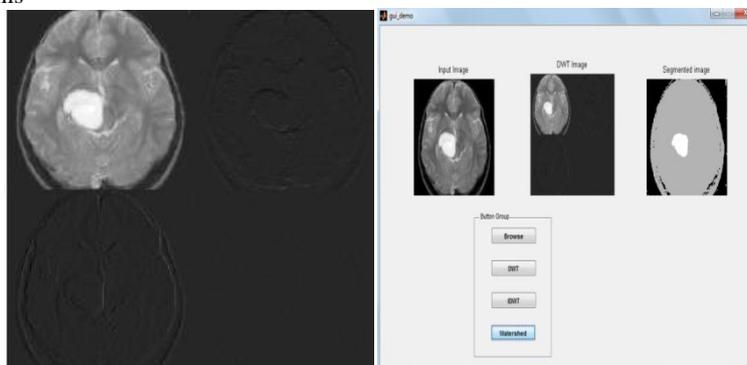


Fig 3.(a)LL,LH,HL,HH sets of Wavelet Transform (b)Initial,Band and final output of Wavelet Transform

Step 2: Edge Detection and Removal of Additional edge

One of the most fundamental segmentation techniques is edge detection. [1] There are many methods for edge detection. Convolution of the approximation image is done by Sobel mask.

Step 3: Watershed Transform

In the next step, by applying the watershed transform,[5][6] initial segmentation at the lowest resolution is obtained. Figure 4 shows the output of Watershed Transform.

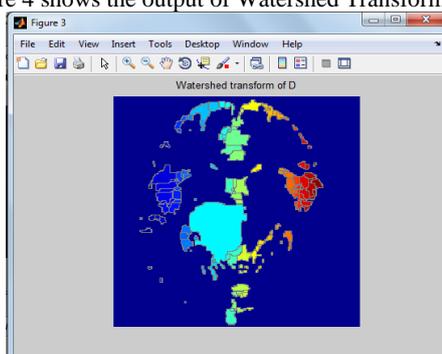


Fig 4.Output of Watershed Transform

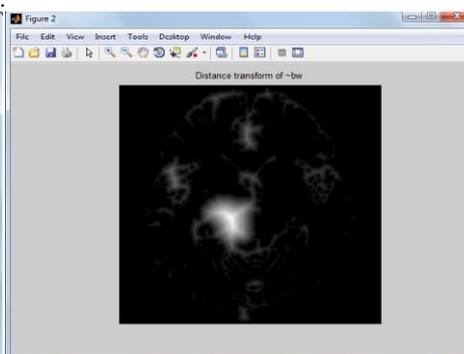


Fig 5. High Resolution Image.

Step 4: Low Resolution to High Resolution Segmented Image

The segmented image has a low resolution with respect to the original image. By applying the inverse wavelet transform and using detail images, a higher resolution image will be obtained from the segmented image [8]. With repeating this step, the segmented image and original image will have the same resolution. It should be noticed that before using the inverse wavelet, only the information of the edge on the details image should be kept [9]. See figure 6 for original and noisy images. As shown in this figure, there are some pixels which are belong to no region, they are lost pixels. In the next step, we use an approach for solving this problem.

Step 5: Finding the Lost Pixel

For appointing the lost pixels, the intensity of the lost pixels was compared to the eight non lost neighbors' pixels and the intensity difference between lost pixel and non lost neighbor's pixels are computed.[10] Lost pixel appointed to the region that has a minimum intensity difference. By repeating the steps 4 and 5, the segmented image will have the same resolution as the original image.

Step 6: Region Merging

In order to have more reduction of the regions in the high resolution image, region merging was used [12]. It means that, if the intensity of the two adjacent regions was smaller than a threshold, they will be combined. It will reduce the number of regions.

Step 7: Image Cropping:

Cropping is the process of selecting desired region from an image that is to be processed [11].The image shows the desired tumor portion. The cropped tumor set is identified by the regional maxima image obtained through watershed algorithm. This image is used to calculate the tumor volume for further analysis.

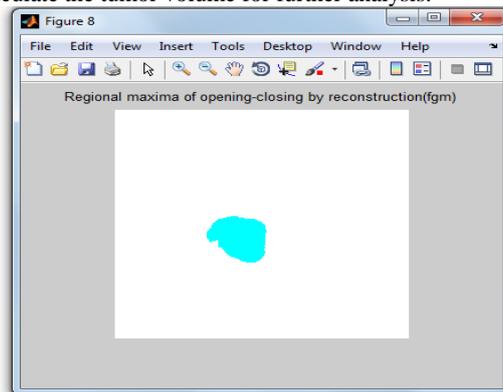


Fig. 6 Cropped tumor image for area calculation

IV. CONCLUSION & FUTURE WORK

This type of segmentation can be used to detect tumor early and provide improved results with the help of coactive approach. Semantics can be incorporated in region merging phase.This work enables to detect the suspicious region and the future work would be calculating area and volume of tumor and storing the output in a database so that it can be matched with the some of the sample which will be pre-stored in a database, so that according to the symptoms and detection of tumor can be done in improved manner. The future work includes the integration with the concept of ontology that can be used for better and accurate results.

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