A Method for Automatic Tumor Segmentation from Image of Brain

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ABSTRACT
It is difficult to differentiate to between tumor and tissue in the brain when the border and cells overlapped between normal and abnormal tissues in gray level of the medical images. This is a real challenge of the surgeon or physician to distinguish it. When MRI and CT scan are taken for patient brain tumor there is an overlapping between the boundaries of tumor in the cerebellum part and tissue surrounded. If the surgeon has the accurate dimensions of the involved tissue he can do his job with more flexibility. When the image of MRI and CT scan were taken to a patient it is easy to distinguish image gray level overlapping between two or more different parts in the same image.

Keywords: MRI image, CT image, Gray level, Tumor, and Segmentation

1. INTRODUCTION
A brain Image consists of four regions i.e. gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and background. These regions can be considered as four different classes. Therefore, an input image needs to be divided into these four classes. In order to avoid the chances of misclassification, the outer elliptical shaped object should be removed. By removing this object we will get rid of non-brain tissues and will be left with only soft tissues.

Segmentation is a technique used in image processing to locate objects in an image. Computer aided detection of abnormal growth of tissues is primarily motivated by the necessity of achieving maximum possible accuracy. Manual segmentation of these abnormal tissues could not be compared with modern day’s high speed computing machines which enable us to visually observe the volume and location of unwanted tissues.

We are interested in segmentation techniques that can be applied in an efficient way to both image and unstructured data. One solution to this problem is the use of masking techniques such as find out the homogeneity of contours.

There are two forms of deformable models. In the parametric form, also referred to as snakes, an explicit parametric representation of the curve is used. This form is not only compact, but is robust to both image noise and boundary gaps as it constrains the extracted boundaries to be smooth. However, it restricts the degree of topological adaptability of the model, especially if the deformation involves splitting or merging of parts. In comparison, the implicit deformable models, also called implicit active contours or level sets, are designed to handle topological changes naturally. However, unlike the parametric form, they are not robust to boundary gaps and suffer from several other deficiencies. Among the various image segmentation techniques, the level set method offer a powerful approach for image segmentation since it can handle any of the cavities, concavities, splitting/merging and convolution. It has been used in wide fields including medical image processing [4-6]. However, despite all of the advantages, which this method can provide, it requires the prior choice of the most important parameters such as the initial location of seed point, the appropriate propagation speed function and the degree of smoothness[1-2]. The traditional methods only depend on the contrast of the points located near the object boundaries, which cannot be used for the accurate segmentation of complex medical images [5-6].

The idea behind active contours, or deformable models, for image segmentation is quite simple. The user specifies an initial guess for the contour, which is then moved by image driven forces to the boundaries of the desired objects. In such models, two types of forces are considered the internal forces, defined within the curve, are designed to keep the model smooth during the deformation process, while the external forces, which are computed from the underlying image data, are defined to move the model toward an object boundary or other desired features within the image [3-4].

To analyzing brain image, we segmented the image into very small blocks. To reduce the complexity of the algorithm, we first mask the image into 2X2 pixel blocks. Checks the intensity or the pixel value of the blocks and calculate the pixel value which present maximum within the block. Propagate the value in the adjacent pixel of the block is showing in figure 1. Now the entire block contains the same pixel value. So, the whole image now consists of 2X2 mask blocks.

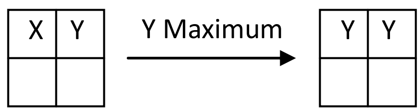


Figure 1 Formation of 2X2 Homogeneous Block

The rest of the paper is organized as follows. Section 2 and 3 summarizes some of the existing segmentation methodologies and proposed method for implementation. Conclusions are drawn in Section 5.

2. REVIEW WORKS
Thresholding method is frequently used for image segmentation. This is simple and effective segmentation method for images with different intensities. [16] The technique basically attempts for finding a threshold value, which enables the classification of pixels into different categories. A major weakness of this segmentation mode is that: it generates only two classes. Therefore, this method fails to deal with multichannel images. It also ignores the spatial characteristics due to which an image becomes noise sensitive and undergoes intensity in-homogeneity problem, which are

expected to be found in MRI. Both these features create the possibility for corrupting the histogram of the image. For overcoming these problems various versions of thresholding technique have been introduced that segments medical images by using the information based on local intensities and connectivity [17]. Though this is a simple technique, still there are some factors that can complicate the thresholding operation, for example, non-stationary and correlated noise, ambient illumination, busyness of gray levels within the object and its background, inadequate contrast, and object size not commensurate with the scene. [18]. [19] introduced a new image thresholding method based on the divergence function. In this method, the objective function is constructed using the divergence function between the classes, the object and the background. The required threshold is found where this divergence function shows a global minimum.

Snakes [7] are appealing to users as they require only a coarse initialization and converge to a stable, reproducible boundary. Snakes based on level set evolution are especially appealing for volumetric data processing [8-10]. The formalism can be naturally extended from 2D to higher dimensions and the result zero level set offers flexible topology. Level set with fixed propagation direction is either initialized inside or outside sought objects and the propagation force is opposed by a strong gradient magnitude at image discontinuities. At locations of missing or fuzzy boundaries, the internal force is often strong enough to counteract global smoothness and leaks through these gaps. Thus, there is no convergence and the evolution has to be halted manually. This observation led to a new concept of region competition, where two adjacent regions compete for the common boundary [11-12] and are additionally constrained by a smoothness term. The driving problem discussed in this paper is the segmentation of 3-D brain tumors from magnetic resonance image data. Tumors vary in shape, size, location and internal texture and tumor segmentation is therefore known to be a very challenging and difficult problem. Intensity thresholding followed by erosion, connectivity and dilation is a common procedure but only applicable to a small class of tumors presenting simple shape and homogeneous interior structure. Warfield et al. [13-15] suggested a methodology based on elastic atlas warping for brain extraction and statistical pattern recognition for brain interior structures. The intensity feature was augmented by a distance from the boundary feature to account for overlapping probability density functions. This method was found to be successful for simple-shaped tumors with homogeneous texture.

3. PROPOSED METHOD

As discussed earlier 2X2 mask blocks or 4X4 pixel block, and do the same process as above of 2X2 block. Now, the whole image consists of 4X4 mask blocks. We repeat the same process to produce image to the 8X8 mask blocks. This block is made to identify the segmented area of interest (Figure 2). The following two algorithms segmented tumor for the further analysis and diagnosis.

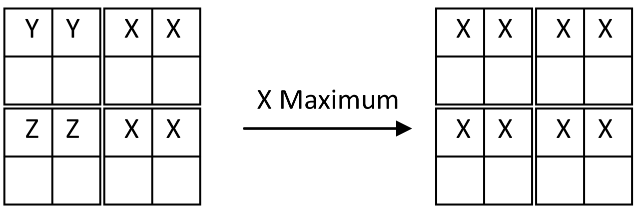


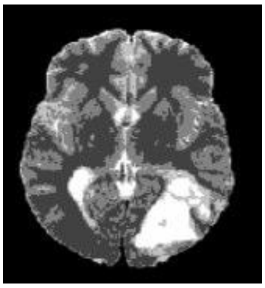
Figure 2 Formation of 4X4 mask Block.

Algorithm1:

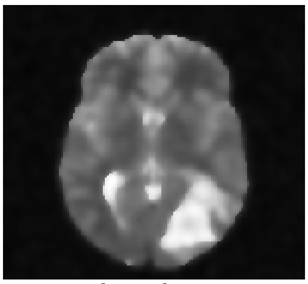
```
Input: Pre-processed   Image (PI)

Isize = Size of the Image

B = Block Size i.e. 2, 4, 8 etc

P [255] = Calculate the Maximum Occurrence Pixel Value

Iseg [B][1024] = Segment of Image Read Each Time

Output: Mask Image (HI)

Begin

    Step1. Open PI file.

    Step2. Open HI file.

    Step3. Loop J=0, Isize/(1024*B)

              Read 1024*B from PI

              Loop I=0, 1024/B

                  Loop K=0, 255

                      P[K]=0

                      K = K + 1

                  End Loop

                  Loop R=0, B-1

    Loop C = I*B, (I*B) + (B-1)

    P[Iseg[R][C]]= P[Iseg[R][C]]+1

                        C=C+1

                      End Loop

                      R=R+1

                  End Loop

                  Hvalue=0

                  Maxvalue=0

                  Loop K=0, 255

                      IF Maxvalue <= P[K]

                        Hvalue = K

                        Maxvalue = P[K]

                      End IF

                      K=K+1
```

```
            End Loop

            Loop R=0, B-1

        Loop C = I*B, (I*B) + (B-1)

                Iseg[R][C]= Hvalue

                C=C+1

              End Loop

              R=R+1

            End Loop

            I=I+1

          End Loop

          Write Iseg to HI

          J=J+1

      End Loop
Step4. Close PI and HI
        End
```

The following outputs are obtained:



Noisy Image



Enhanced Image

Algorithm2:

Input: Mask Image (HI)

Isize = Size of the Image

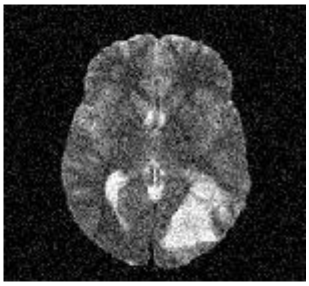
Byte = one byte of data offset

Pbyte = to hold the previous value of byte

Output: Segmented Image (SI)

Begin

```
    Step1. Open PI file

    Step2. Open HI file

    Step3. Loop J=0, Isize
                Read one Byte from HI
                Loop I=0, 256                    IF
Byte < I
                Byte = I - 32
                Break
                End IF
                I = I + 32
                End Loop
                IF J=0
                  Pbyte = Byte
                ELSE
                  IF Pbyte–Byte>32 OR Byte–Pbyte>32
                        Pbyte = Byte
                  ELSE
                        Byte = Pbyte
                  End IF
                End IF
                Write one byte to SI
                J = J + 1
          End Loop
    Step4. Close HI, SI
End
```



Segmented Image

4. CONCLUSIONS

Mathematical modeling of tumor growth dynamics gives us an insight on the physiology of the process by linking different types of observations under theoretical frameworks. There has been a large amount of models proposed to describe the growth dynamics of glial tumors. Different approaches can be coarsely classified into two groups, macroscopic and microscopic ones.

Tumor extracted from a noisy image marks various portions of the MR slice which even contain the normal tissues. The results obtained from enhanced image and the clean image is almost similar. The accuracy of the proposed method is encouraging in terms of results.

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