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TUMOR DETECTION IN MEDICAL IMAGES USING SELF ORGANIZING MAP

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ABSTRACT

Boundary is very commonly defined as line that distinguishes two different regions. Boundary provides clarity to human eye in understanding any view. It plays a major role in Medical field, as finding the correct boundary in noisy images is still a difficult task. This paper introduces the new technique of detection using the information of intensity and texture of an image. Our proposed technique detects the boundaries of objects in noisy images using the information from the intensity gradient via the vector image model and the texture gradient via the edge map. we discuss the proposed technique on various medical images using Self organizing map (SOM) clustering provides correct boundaries even in an ill-defined images and multi grey level images. This method is robust and applicable on various kinds of noisy images without prior knowledge of noise properties.

Key Word: Boundary Extraction, Edge Following, SOM Clustering.

I. INTRODUCTION

Image segmentation is an initial step before performing high level tasks. While considering the case of a brain tumor patient, the MRI scan of his brain shows the tumor but not clearly. If the boundaries of tumor are detected then its size can be calculated and further medication can be planned. So in order to find the boundary we need to understand the basic image processing step [1] i.e., segmentation. Segmentation partitions an input image into its constituent parts or objects. Output of segmentation is usually raw pixel data constituting either boundary of a region or all points in that region. Segmentation algorithms are generally based on two properties of grey level values, discontinuity and similarity. First one is based on abrupt changes in grey levels usually detects lines and edges. Second one is based on thresholding, region splitting and merging. So many edge based algorithms as Sobel, Prewitt, Laplacian and region based approaches as region growing, merging, clustering have been implemented. However the performance evaluation of image segmentation results is still a challenging problem as they fail to extract the correct boundaries of objects in noisy images.

Boundary can be detected in an noisy image by the above mentioned algorithms but most of the algorithms have difficulties in detecting boundaries in images with ill-defined edges. In many medical images like in scanned images of lungs and brain, the accumulations of organs with blockages or damages cannot be figured out correctly as they are too complex and noisy. As a remedy to this problem, we propose the technique of edge following method based on the intensity and texture values of the image. Intensity refers to the brightness of a point in an image and is determined by several quantities including the local concentration, the quantum efficiency of the fluorophore, and sensitivity of the light sensor in the imaging system. Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image and this is one way that can be used for segmentation [2].The intensity gradient is defined as the directional change in the color value of an image. Since the intensity function of a digital image is only known at discrete points, derivative of this function is considered usually. A complete description of an image we consider both directions and magnitudes of image edges as vector image model. The vector image model, a derivative based edge operator [3] is applied to get the edge vector field which is obtained by averaging magnitudes and directions in the vector image. Number of methods [7] has been proposed ,One of the best techniques is edge map which is derived from law's texture and the canny edge detection. The vector image model and edge map are applied to select the best edges.

The process of boundary detection carried out using intensity gradient and texture gradient is useful and gives good results if the image has minimum range of gray values. If more variations in gray values is found in an image then it will be time consuming. Moreover the values of α,β *and* ε need to fed manually for every image which makes it more time consuming, hence an automatic method is required. Self-Organizing map (SOM) plays an important role in clustering. Its attractive features are input space approximation, topological ordering and density matching helps in simple implementation of boundary detection

The paper is organized as follows. Section II and III describes the boundary detection using vector image model and edge map. Section IV, V describes the self-organizing map clustering method for boundary detection and compare the results with edge based method. Section VI concludes the paper.

II.BOUNDARY DETECTION ALGORITHM

The proposed algorithm consists of four phases

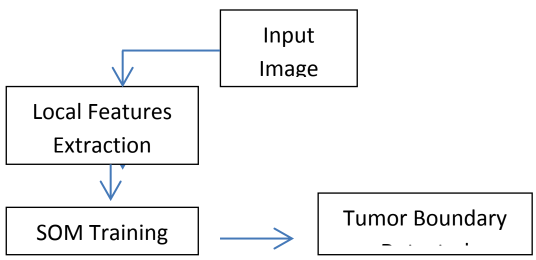


Fig -1: Block Diagram of the Proposed Method

- Phase1:In our proposed method we consider the MRI scan of brain tumor image is consider as input image the tumor but not clearly
- Phase2:The local features of an input image are extracted for further processing. Histogram features of an image is consider as a local features.
- Phase3: Self-organizing map is applied in on the local features of an image for clustering operation.
- Phase 4:the boundary of the tumor is detected from the clustered data.

III. SOM CLUSTERING

The boundary of tumor is not detected using using intensity gradient and texture gradient method shown in Fig. 2(a) So to get the boundary of the tumor, we proceed with SOM clustering. In SOM the clustering is carried out using a two level approach, where image is first clustered using SOM [14, 15] and then, the SOM is clustered. At first, local features of medical image pixels are extracted to feed a self-organizing map (SOM) after a preprocessing step. The output prototypes of SOM are then filtered with a hits map and a clustering method is applied to the prototypes. Compared to Davies-Bolden (DB) clustering index and entropy image segmentation index, a quantitative image evaluation index is at last selected for a best segmentation. The segmentation results after the post-processing show the proposed method to be effective and promising [8,9].The typical features of SOM are topology visualization of the input patterns and representation of a large number of input patterns with a small number of prototypes. The most important attribute of SOM is that the input patterns which are similar in the input space are also close to each other topologically in the output space.

The Self-Organizing Feature Map provides a compact representation of the data, has been widely applied in the visualization of high-dimensional data. In [2, 15] SOFM is a unsupervised learning technique which retains principle 'features' of the input data. In SOFM topological structure imposed on the nodes which preserves neighborhood details has been presented in [14, 15].A self-organizing map structure consists of components called map node or neurons. A single map node contains a weight vector pseudo-Zernike moments have better features representation capabilities. These moments are invariant under image rotation, multilevel moments of an image are used weight vector which have better features representation capabilities. The arrangement of nodes is a rectangular grid. Map nodes are not connected to each other but all the nodes are connected to each input node.

Self-organizing maps (SOMs) are a data visualization technique invented by Professor Teuvo Kohonen which reduces the dimensions of data through the use of self-organizing neural networks. In this configuration, each map node has a unique coordinate. This makes it easy to reference a node in the network, and to calculate the distances between nodes. Because of the connections only to the input nodes, the map nodes are oblivious as to what values their neighbors have [10, 11]. A map node will only update its' weights based on what the input vector tells it. Each weight vector has two components. The first part of a weight vector is its data. This is of the same dimensions as the sample vectors and the second part of a weight vector [12, 13] is its natural location is the position of the pixel of the image.

The SOM Steps:

- M dimensional input

$$I= [I1, I2, I3.........In] \qquad (1)$$

- Each node's weights are initialized.

$$W_j= [w_1, w2, w3.........wm] \qquad (2)$$

- A texture feature vector (histogram) is presented to the network as a weight vector.
- Every node in the network is examined to calculate Best Matching Unit (BMU). The node with a weight vector closest to the input vector is tagged as winning node which done with the help of Euclidian distance between input and weight vector.

$$\sum_{i=0}^{n} (Ii - Wi)^\wedge 2 \qquad (3)$$

- The radius of the neighborhood of the best matching unit is calculated.

$$\sigma (t) = \sigma_0 e^{(t/\lambda)} \qquad (4)$$

- Each neighboring nodes are adjusted with new weight to make them more toward the input vector. New weight of the node.

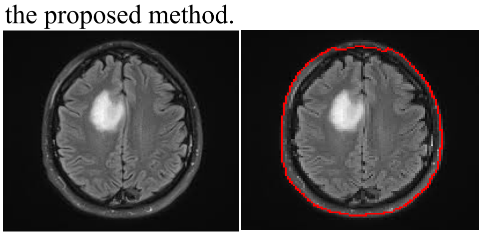
$$W (t+1) =W(t)+ L_0 e^{((-t/\lambda)h(t)0^\wedge 2/}2\ \sigma^{2\,(t)}(I(t)-W(t)) \qquad (5)$$

$$h (t)= {}^{e-(\text{distance from BMU})} \qquad (6)$$

- The above process is repeated for each input vector for a number of cycles. The network winds up associating output nodes with groups in the input data set.

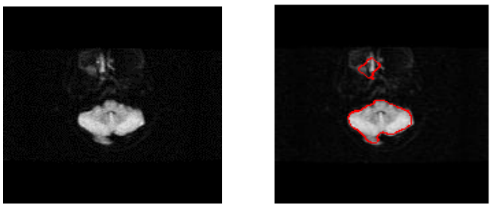
IV. EXPERIMENTAL RESULTS

We tested the performance of the proposed technique by considering many medical images of Brain. Some of the images are too noisy and some with ill-defined edges, But still the boundaries were detected by using the proposed method.



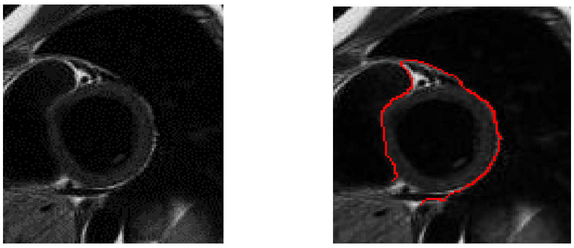
(a) (b)

Fig. 2 (a) Brain MR image (b) Boundary of brain is detected but not the tumor.



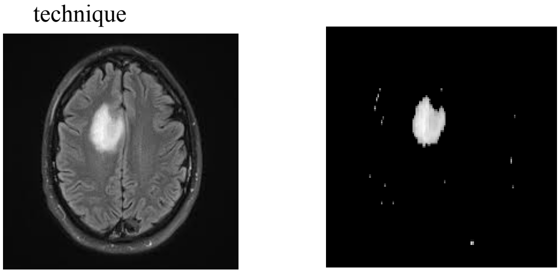
(a) (b)

Fig. (2.b) The MR image of Brain. (a) Original image with tumor (b) tumor being highlighted by its boundary



(a) (b)

Fig. (2c) Aorta in cardiovascular MR image (a) Original image (b) The boundary is detected by the proposed technique



(a) (b)

Fig 3 (a) Brain MR image with tumor, Tumor being extracted by its boundary detection.

V. CONCLUSION

In this paper, SOM clustering method are combined to achieve segmentation of medical images. Local features of mean and standard variance of pixels are selected to be trained in SOM. Output prototypes are filtered by a hits map .The best cluster number can found under the guidance Final segmentation result is obtained for brain MR images show that the proposed method is effective and promising for detecting the tumor efficiently.

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