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# Brain Tumor Segmentation Based on Self Organising Map and Discrete Wavelet Transform

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***Abstract-One of the serious kind of disease in the medical field is considered to be the brain tumor. So it must to have the fast and accurate detection. Different algorithms are provided for the tumour detection and segmentation. The important approach in the brain tumor segmentation is to identify the various stages includes benign, malignant and the normal. For the process of classifying voxels, a classifier called Self Organising Map(SOM) is used. Self-Organizing Map (SOM) which includes the unsupervised learning algorithm and Learning Vector Quantization (LVQ) with high diversity data like tumour appearance and its contour deformation. On comparing with the other approaches, instead of using Multimodal MRI images for clustering of voxels SOM has been used. A feature vector has been constructed in which the features for the constructing vector have been gained from the Discrete Wavelet Transform (DWT) coefficients. This has been constructed mainly for identifying tissue types which includes White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF) and sometimes pathological tissues. The accuracies and the performance are provided in terms of training performance and the classification accuracies. The results which has been simulated, shows the better accuracies of classifier and segmentation on comparing with the previous method.***

***Keywords-Brain Tumor Segmentation, Self Organising Map, Discrete Wavelet Transform, Learning Vector Quantization, Grey Matter, White Matter.***

## I. INTRODUCTION

Brain tumor segmentation is considered to be an important process in the clinical research.Braintumor, is the growth of abnormal cells, which can be either cancerous or non-cancerous.Depending on the type,tumors are classified as Benign Tumor and Malignant Tumor.The earlier stage of detection is necessary in such a way that to prevent the complications of loss of vision and speech which could lead to paralysis and even to death.

Currently, in segmenting brain tumor multimodal MRI images are used simultaneously.The radiologist's uses multimodal MRI images because it provides the complementary information regarding on tumor area.Although it provides immense data regarding tumor area,the segmentation of tumor is defined to be the complicated and difficult task.This is because of their heterogeneity and they are visually vague.The heterogeneity of tumor makes the process tedious,since they have different shapes and sizes which appearing different location.In addition to this,noise in the brain also increases the complexity in segmenting tumor.Therefore automatic brain tumor segmentation is considered in order to provide the acceptable performance.[4]

### Types of tumor

The Brain tumor is classified into two main types,namely:
a) Primary tumor
b) Secondarytumor

Primary tumors are again classified into:
a) Benign tumor
b) Malignant tumor

The brain tumor are generally named and classified according to either of the following:
a) The type of brain cells in which they originate
b) The type of location in which the cancer develops.

### Primary tumor

Primary tumors are those which develop in the brain.Theinitial growth of the abnormal and the unwanted tissues in the brain is called as the primary tumor.From the brain,thetumor has been spread to various parts of the body.Depending on the concentration the primary tumor are classified in to two types.[3]

### Benign tumor

Benign tumor is a tumor where they are having their boundaries or the edges in which they does not spread over the other parts of the body.Benigntumor is considerably quite serious if they are meant to be in the vital areas of the brain.On another hand,benigntumor can step in to the disability and even it lead to the death.[2]

 

**Malignant tumor**

In malignant tumor are considered to be the most serious one and they develop rapidly.They affect the various vital organs which may leads to the death.About 80% of the malignant tumors arereferred to as the gliomas,Gliomas refers to the tumors which have been originated from the gilial cells of the brain.[2]

**Secondary brain tumor**

Secondary brain tumor is a tumor where the tumor in the brain is arisen from the other tumor in the body.They are mainly formed from the cells that have broken away from the primary tumor and have spread in the bloodstream to the brain.The primary source for the secondary tumor is the lung or the blood cancer.[2]

## II. REVIEW ON LITERATURE

### *A. Atlas-based segmentation*

In this method,a method for the brain atlas deformation has been analyzed on the presence of the large space occupying tumors.This can be done mainly by the apriori model oflesion growth in which it predicts the growth of the lesion from its starting point.

This method takes three steps,they are namely as follows:

a) Atfirst,the atlas and the patient are getting into global correspondence through the method of affine registration
b) The template for the lesion can be employed by the embedding the synthetic tumor in to the brain
c) Theprocessof combining optical flow principles and model of the lesion growth can be done by the deformation of seeded atlas.[1]

### *B. Discriminative model-constrained graph cuts approach*

In this method,the method of segmenting the pediatric brain tumors which is in the multi-spectral 3-D magnetic resonance images is fully automatic and it has been analyzed.

It is mainly based on the Markov random field (MRF) model which is an top down approach in which they joins the functionalities of probabilistic boosting trees (PBT) and lower-level segmentation via graph cuts.The discriminative observation modelhas been provided by the PBT algorithm that may classifies the appearance of the tumor and the pair wise homogeneity can be given in the words of the classification labels and multi-spectral voxel intensities.The integrating the two approaches into a unified statistical framework have been given by the mathematical sound formulation.This method has been mainly given for the prediction and analysis of the pediatric brain tumors.The high non-uniformity of the pathological and non-pathological brain tissue is characterized by the segmentation process.Therobustness of this method is employed by the quantitative approach.The result which has obtained for the pediatric brain tumor iscomparatively greater when comparing with the current approaches.[4]

### *C. Tumor- Cut: segmentation of brain tumors*

In this method, a robust tool for segmenting the solid tumors with the reduced user interaction. In order to assist the assist clinicians and researchers in radiosurgery planning and assessment of the response to the therapy has been discussed. The technique which used is, cellular automata (CA) based seeded tumor segmentation method on enhancing the contrast of the magnetic resonance images(MR images),in which it formulates the volume of interest (VO) and their seed selection,has been obtained.

In the first step we have studied about the connection of the CA-based segmentation to the graph-theoretic methods in which it explores the iterative CA framework and the resolves the shortest path problem. On that circumstances' we obtain information in order to change a state transition function of the CA to calculate the exact shortest path solution. Additionally, a sensitivity parameter has been gained in order to accept heterogeneous tumor segmentation problem, and an implicit level set surface is evolved on a tumor probability map constructed from CA states to impose spatial smoothness. The information for initializing the algorithm has been collected from the user simply by a line drawn on the maximum diameter of the tumor, in line with the clinical practice. The differentiation among necrotic and enhancing tumor tissue content has been addressed by this algorithm.[2]

### *D. Decision forests for tissue specific segmentation*

In this method,a method of the automatic segmentation has been employed in which segmenting of high grade gliomas and their structures has been analyzed.In addition to this,differentiation among the active cells,necroticcore,and edema has also been taken in to the consideration.The method of discriminative approach is mainly depends on the decision forests in which they uses the context-aware spatial features,and also combines the generative model of tissue appearance in which the probabilities has been gained from the Gaussian mixture models.Theproposed method classifies the unique tissue type's parallel,which has the capability to simplify the classification mechanism.[5]

### *E. Contextsensitive classification forests for segmentation*

In this method,classification process of the segmentation and discriminative power of context information has been analyzed.This idea has been explored by gaining the classification forest (CF) with spatially non-local features in order to structure thedata,by giving the CF with initial probability estimates for the single tissue classes as additional input (along-side the MRI channels).The initial probabilities which are given is mainly patient specific,and they are computed at the time basis of a learned model of the intensity.By combining the initial probabilities along with the non-localfeatures,our method is designed for capturing the context information from the all data points.[6]

 

Table I. Comparison Table for Different Techniques

| METHODS | FUNCTIONALITIES | ADVANTAGES | LIMITATION |
|---|---|---|---|
| **1.Atlas-based segmentation** | Affine registration followed by embedding synthetic tumor and combining optical flow principles and lesion growth. | Automatic segmentation of structures and substructures in brain | The most important structures and their shapes is not considered as well as to the existence of the edema. |
| **2.Discriminativemodel-constrainedgraph cuts approach** | It is mainly based on the Markov random field (MRF) model and this focuses on identifying the Heterogeneity of the regions i.e., it finds the different sizes and shapes of the tumor areas in the brain. | Since it uses the multi spectral data for the entire spectral processing, therefore it minimizes the manual user interaction and processing time. Therefore it has the better performance. | Different shapes and the locations of the tumor area has not been taken in to the consideration. So it may find the Selected Tumor area in the smallest amount of processing time. |
| **3.Tumor-Cut: segmentation of brain tumors** | The technique which used is, cellular automata (CA) based seeded tumor segmentation method. The differentiation among necrotic and enhancing tumor tissue content has been addressed by this method. | This tumor cut segmentation is mainly emphasizing on the less sensitivity to seed initialization, robustness with respect to different and heterogeneous tumor types, and their efficiency has been enhanced by their less time computation. | They do not consider the difference of changes in the necrotic and enhancing tumor tissue content in radiation oncology practices. |
| **4.Decision forests for tissue specific segmentation** | This classifies the unique tissue type's parallel, which has the capability to simplify the classification mechanism. | They are having the better computational efficiency, and they exhibits high accuracy and of low model complexity | Segmentation can be carried out with explicit regularization for high accuracy which leads to high computation cost. |
| **5.Context sensitive classification forests for segmentation** | The classification process of the segmentation and discriminative power of context information has been analyzed. | The method is fully automatic, and process of segmentation is easy | Its produces the low segmentation results to the low graded tumors. |

## III. PROPOSED SYSTEM

Initially as in fig.2,brain tumor data (image) has been pre-processed,For the process of classifying voxels,a classifier called Self Organising Map(SOM) is used. Self-Organizing Map (SOM) which includes the unsupervised learning algorithm and Learning Vector Quantization (LVQ) with high diversity data like tumour appearance and its contour deformation.On comparing with other techniques,Instead of using Multimodal MRI images for clustering of voxels SOM has been used.A feature vector has been constructed in which the features for constructing vector have been gained from the Discrete Wavelet Transform (DWT) coefficients.This has been constructed mainly for identifying tissue types which includes White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF) and sometimes pathological tissues. The accuracies and the performance are provided in terms of training performance and the classification accuracies.The results which has simulated shows the better accuracies for the classifiers.

Apart from the previous mentioned techniques some of the other techniques involved in the paper are described below:-

### *A. Image Segmentation*

The image segmentation is mainly based on the Thresholdingcondition.It is based on the principle of converting the grey-scale image into a binary image.Each pixel assigned a value depending upon the threshold condition.Forexample,if the pixel value exceeds the threshold value it assigns either the value of 0 or either the value of 1,i.e white or else black. Brain tumor image has different lighting conditions in different areas. So, in that case, we may want to use adaptive Thresholding. It uses the algorithm that calculates the threshold for small regions of the image so that we can get different thresholds for different regions of the same image and it gives us better results for images with varying light conditions

### *B. Fast Bounding Box Technique*

The bounding box method is based on the property of the symmetrical structure of the brain. That is left and right lobes are almost identical. The left right parts are similar until an abnormality occurs in any part of the brain. For creating a bounding box, first the skull is detected. Then line of symmetry is drawn to create left right symmetry of brain. Assumption is made that tumor is located in one of the two halves of the brain. One half acts as reference image while other as test image. The vertical and horizontal scan is performed on both sides, comparing to obtain the region of abnormality. This is done by obtaining a score plot function 'E' based on average intensities of the region of abnormality. All maximum and minimum points are obtained from the graph. From all the pairs, the pair (m, n) is found for which difference (E(m)-E(n)) is maximum. This defines the boundary of bounding box. The score plot function is defined by the Bhattacharya coefficient. This method uses the probability mass function, that is, normalized grey level intensity histograms.The bounding box of an object is constructed using a simple yet effective binary test and a decision tree. We show that this method reduces the miss detections while increasing the scanning grid spacing

### *C. Classification Technique*

It is a method is used to classify each voxel into different classes. Local independent projection-based classification method is modelled for brain tumor segmentation without using explicit regularization. Then, the training samples are divided into different groups and subsequently used to construct different dictionaries. The testing sample is independently projected on these different dictionaries using the local anchor embedding method

### *D. Classification Optimisation*

The data distribution of different classes (i.e., tumor, edema, and brain tissue) may widely vary. Therefore, the data distribution of each class should be considered when segmenting brain tumors. a patch-based technique was used in extracting the image feature. The intensity values in a patch around a voxel *v* were obtained and rearranged as a feature vector. The proposed classification technique based on Softmax regression is modelled against the tumor tissues. The proposed classification method requires no explicit regularization because the patch feature contains the contextual information of a voxel in the image. The proposed method leads a natural smoothness to the segmentation results without explicit regularization by using this contextual information. However, the patch feature may be insufficient to discriminate the brain tumor segmentation task because of the complex characteristics of brain MRI images in terms of accuracy and efficiency to the various colorintensity of the tumors. Also reconstruction error norm and error rate are also reduced

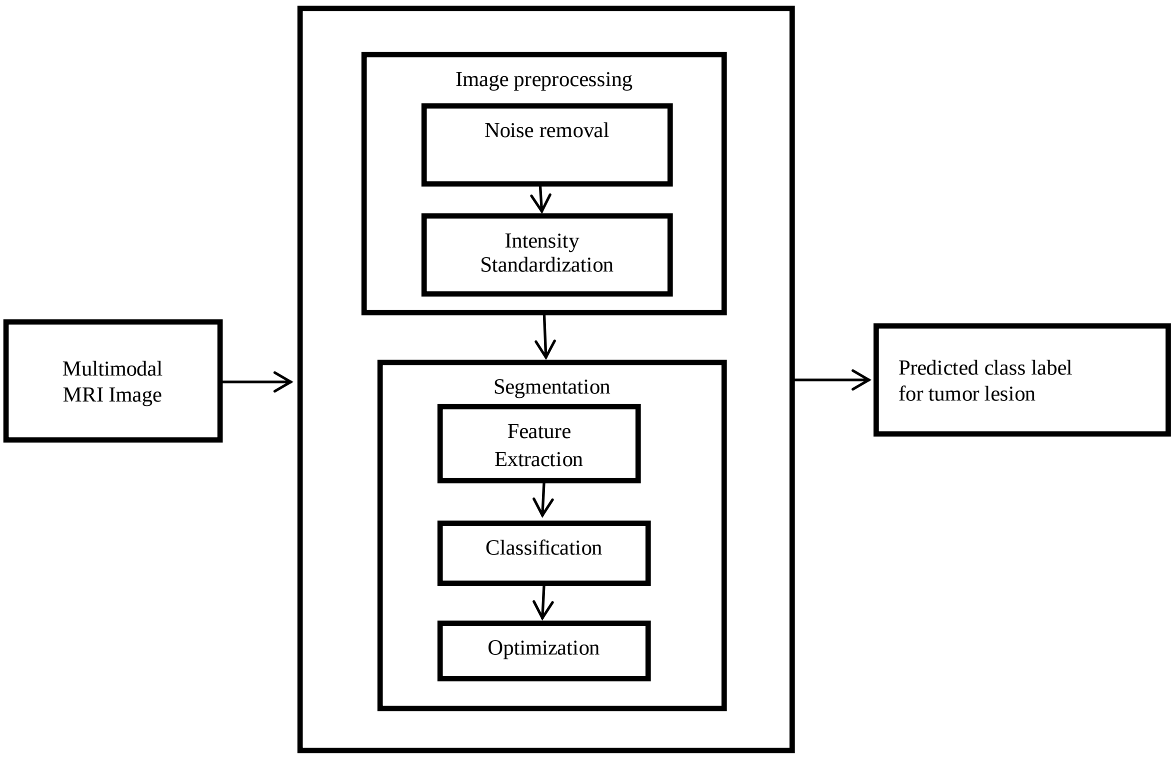


Fig 1. Architecture Diagram

## IV. CONCLUSION

The method of segmenting tumor is quiet exacting,the reason is because brain tumor MRI images exposes the heterogeneity in terms of their appearances,visually vague and they demand the high diversity in the tumor area. Brain tumors can have various sizes and shapes and may appear at different locations. In addition to tumor heterogeneity, tumor edges can be complex and visually vague.Hence the segmentation is done through the Self Organising map.Therefore it reduces the classification error rate and they provide the better accuracies.

## V. FUTURE ENHANCEMENT

In the process of segmenting,the future research will take to the accuracies,exactness and performances.In addition to this it also considerably minimizes the work of manual interaction.In this brain tumor segmentation, various contextual features have been additioned in order to deliver the better performance accuracies.

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