



Testing of Brain Tumor Segmentation Using Hierarchal Self Organizing Map (HSOM)

Dr. M.Anto Bennet , G.Sankar Babu, S.Lokesh, S.Sankaranarayanan
Department of Electronics and Communication Engineering,
VELTECH, Avadi-Chennai- 600062, Tamilnadu, INDIA

Abstract: A forceful segmentation tool for the detection of brain tumor is used to assist clinician and researchers in radio surgery applications. A clustering based approach using hierarchal self organizing map algorithm is proposed for MR image segmentation. Hierarchal self organizing map (HSOM) is a dynamically growing neural network model evolves into a hierarchical structure according to the requirements of the input data during an unsupervised training process. This algorithm proved to be exceptionally successful for data visualization applications. HSOM is the extension of the conventional self organizing map which is used to classify the image row by row. In this technique lowest level of weight vector, a higher value of tumor pixels and the computation speed is achieved by the HSOM with vector quantization. Hierarchal self organizing map (HSOM) segmentation is done in two phases: In the first phase MRI brain image is acquired from patient data base and the image is pre-processed where the noise is removed. In the second phase tumor present in the brain and the severances of the tumor is detected. Finally the numbers of affected cells are counted using the row and column wise scanning method. The proposed system uses HSOM. A self-organizing map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network for unsupervised learning. SOMs operate in two modes: training and mapping. Training is a competitive process, also called vector quantization. Mapping automatically classifies a new input vector. Segmentation is an important process to extract information from complex medical images.

Keywords: HSOM, Image analysis, Magnetic Resonance Imaging (MRI) Segmentation, Tumor detection.

I. INTRODUCTION

The existing system uses cellular automata (CA) based seeded tumor segmentation. Cellular automata (CA) was introduced to provide a formal framework for investigating the behavior of dynamic complex system in which time and space are discrete. CA model is composed of cell, state set of cell, neighborhood and local rule.

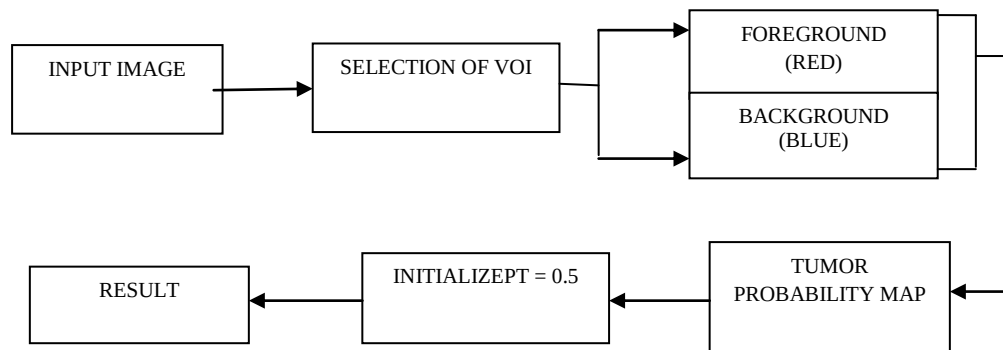


Figure 1 Block Diagram of cellular automata (CA) based seeded tumor segmentation

Figure 1 shows the block diagram of existing system. It shows that the region of interest is selected first and then the process of segmentation is done. The existing system uses cellular automata (CA) based seeded tumor segmentation. Cellular automata (CA) was introduced to provide a formal framework for investigating the behavior of dynamic complex system in which time and space are discrete. CA model is composed of cell, state set of cell, neighborhood and local rule. A cellular automaton is basically a computer algorithm that is discrete in space and time and operates on a lattice of cells. Cellular Automata has attracted researchers from various fields in both physical and social sciences because of its simplicity and potential in modeling complex systems. A cellular automaton (CA) is a triple $A = (S, N, \gamma)$, where S is a nonempty set, called the state set, N is the neighborhood, and γ is the local transition function (rule). Grow-cut method uses continuous state cellular automata to interactively label images using user supplied seeds. The cells are corresponding to image pixels, and the feature vector is RGB or gray scale intensities. The automata are initialized by assigning corresponding labels at seeds with a strength value between 0 and 1 where a higher value reflects a higher confidence in choosing the seed. Strengths for unlabeled cells are set to 0. The ultimate aim of image processing applications is to extract important features from the image data, from which a description, interpretation, or understanding

of the scene can be provided by the machine. The segmentation of brain tumor from magnetic resonance images is an important but time-consuming task performed by medical experts. The digital image processing community has developed several segmentation methods.

II. DIAGNOSIS OF BRAIN TUMOR

Identifying a brain tumor usually involves a neurological examination, brain scans, and/or an analysis of the brain tissue. Doctors use the diagnostic information to classify the tumor from the least aggressive (benign) to the most aggressive (malignant). In most cases, a brain tumor is named for the cell type of origin or its location in the brain. Identifying the type of tumor helps doctors determine the most appropriate course of treatment.

MRI Scan

MRI (Magnetic Resonance Imaging) is a scanning device that uses magnetic fields and computers to capture images of the brain on film. It does not use x-rays. It provides pictures from various planes, which permit doctors to create a three-dimensional image of the tumor. The MRI detects signals emitted from normal and abnormal tissue, providing clear images of most tumors.

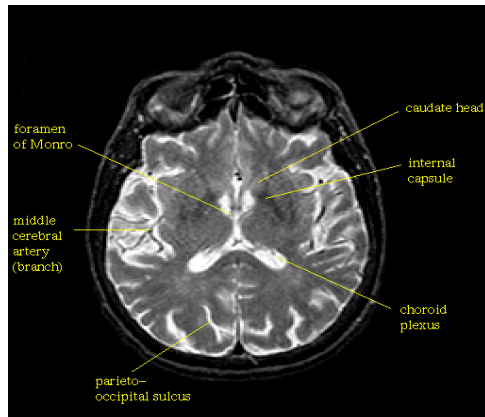


Figure 2. MRI of Normal Brain

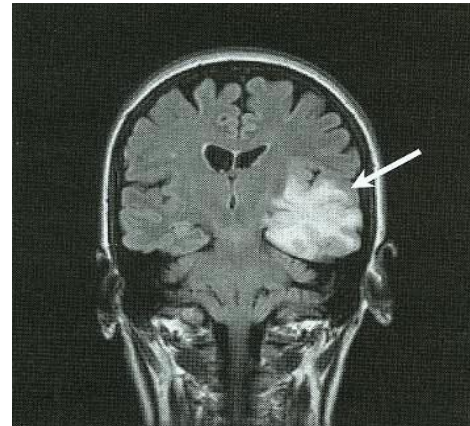


Figure 3. MRI of Tumored Brain

Figure 2 shows the MRI of normal brain which shows the clear view of brain. The brain consists of different parts depending on which the sense organs work. Figure 3 shows the MRI of brain with tumor in it. Tumor may be present in any portion and depending on the number of cells affected it is possible to provide treatment.

CTScan

CT or CAT Scan (Computed Tomography) combines sophisticated x-ray and computer technology. CT can show a combination of soft tissue, bone, and blood vessels. CT images can determine some types of tumors, as well as help detect swelling, bleeding, and bone and tissue calcification. Usually, iodine is the contrast agent used during a CT scan.

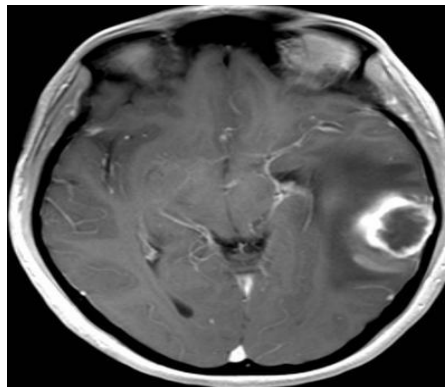


Figure 4. CT Scan Image of Brain Tumor

Figure 4 shows the CT scan image of brain tumor. It is an extended format of X-ray and hence clear description about the tumor cannot be detected.

III. HSOM ALGORITHM

The hierarchical self-organizing map (HSOM) is an artificial neural network model that proved to be exceptionally successful for data visualization applications where the mapping from an usually very high-dimensional data space into a two-dimensional representation space is required. The remarkable benefit of HSOMs in this kind of applications is that the similarity between the input data as measured in the input data space is preserved as faithfully as possible within the representation space. Thus, the similarity of the input data is mirrored to a very large extent in terms of geographical vicinity within the representation space. Image segmentation techniques can be classified as based on edge detection, region or surface growing, threshold level, classifier such as Hierarchical Self Organizing Map (HSOM), and feature vector clustering or vector

quantization. Vector quantization has proved to be a very effective model for image segmentation process. Vector quantization is a process of portioning n -dimensional vector space into M regions so as to optimize a criterion function when all the points in each region are approximated by the representation vector X_i associated with that region. There are two processes involved in the vector quantization: one is the training process which determines the set of codebook vector according to the probability of the input data, the other is the encoding process which assigns input vectors to the codebook vectors. HSOM combine the idea of regarding the image segmentation process as one of data abstraction where the segmented image is the final domain independent abstraction of the input image. The hierarchical segmentation process for a hierarchical structure is called abstraction tree. The abstraction tree bears some resemblance to the major familiar quad tree data structure used in the several image processing and image analysis algorithms. The researchers in this field have used SOM or HSOM separately as one of the tool for the image segmentation of MRI brain for the tumor analysis.

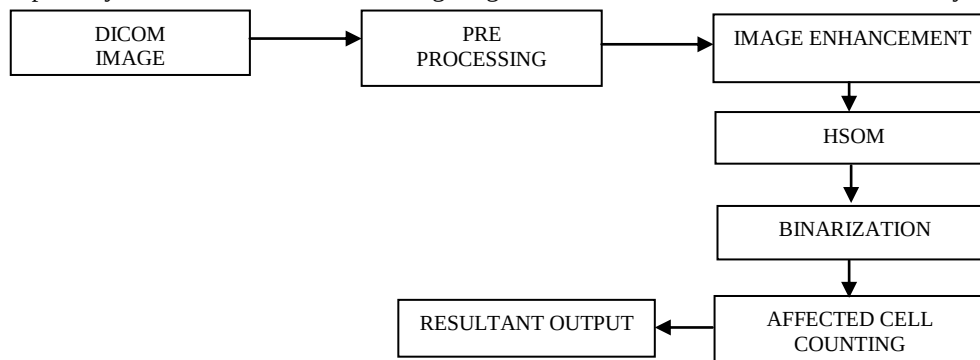


Figure 5 Block Diagram of hierarchal self-organizing map (HSOM)

Figure 5 shows the block diagram of proposed system. The process is done in two phases which is explained in following description. The block diagram of proposed system consists of two phases. First phase composed of segmented output with the help of HSOM algorithm. During the second phase number of cells affected is calculated from which the severity of the tumor is found.

DICOM Image

The Image Processing Toolbox now supports writing files in Digital Imaging and Communications in Medicine (DICOM) format, using the dicom write function. This converts the dicom image format into JPEG image format so that preprocessing of the image becomes easier.

Preprocessing

The MRI consists of film artifact or labels on the MRI such as patient name, age and marks. Film artifacts are removed using tracking algorithm. Here, starting from the first row and the first column, the intensity value, greater than that of the threshold value is removed from MRI. The high intensity value of film artifact is removed from MRI brain image. During removal of film artifacts, the image consist of salt and pepper noise.

Image Enhancement

The image is given to enhancement stage for the removing high intensity component and the above noise. This part is used to enhance the smoothness towards piecewise- homogeneous region and reduce the edge blurring effects. This proposed system describes the information of enhancement using weighted median filter for removing high frequency component. HSOM algorithm is used and segmented output is obtained. Figure 6 shows the satellite image in which the clear details about the image is not found. There are various transformations available from which gamma transformation is used to enhance the above image.



Figure 6. Original Satellite image



Figure7 Enhanced Satellite Image

Figure 7 shows the enhanced satellite image. Using the condition $s = cr \wedge \gamma$ image enhancement process is done considering the value of $\gamma = 5.0$. Finally binarization is done from which the affected numbers of cells are counted. Binarization is the process of converting the grey scale image into black and white image

IV. SYSTEM IMPLEMENTATION

Image segmentation is a technique which divides the image into different feature of region and extract out the interested target. The features can be pixel grayscale, color, texture, etc. Predefined targets can correspond to a single region or multiple regions. To illustrate the level of the image segmentation in image processing, "an image engineering concept" is introduced. It brings the involved theory, methods, algorithms, tools, equipment of image segmentation into an overall framework.

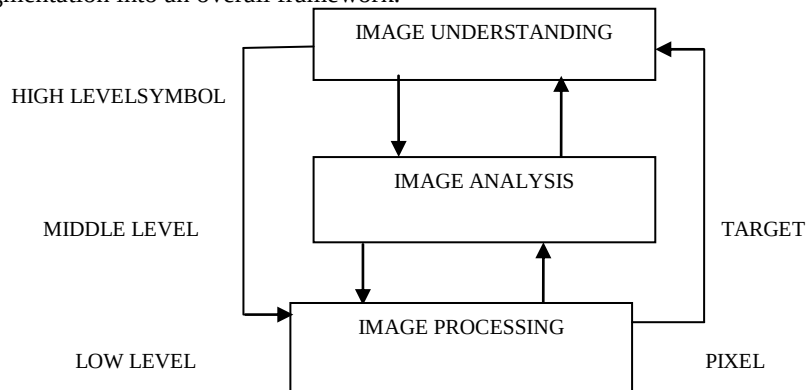


Figure 8 Levels of Segmentation

Figure 8 shows the three levels of segmentation. Image Engineering is a new subject for research and application of image field, its content is very abundant. According to the different of the abstract degree and research methods, it can be divided into three levels as Image processing, image analysis and image understanding. The target expression based on segmentation, the feature extraction and parameter measurement that convert the original image to more abstract and more compact form, it is possible to make high-level image analysis and understanding. In the actual production life, the application of image segmentation is also very wide and almost appeared in all related areas of image processing as well as involved various types of image. For example, satellite image processing in the application of remote sensing. The brain MR image analysis in the applications of medicine, the plates of illegal vehicle region segmentation in the traffic image analysis, the image region of interest extraction in the object oriented image compression and content-based image retrieval. Image segmentation is usually used for image analysis, identification and compress code, etc. The accuracy of regions extraction will directly affect the effectiveness of following task, the method and accuracy of segmentation is very important.

V. METHOD FOR IMAGE SEGMENTATION

Image segmentation is the first important process in numerous applications of computer vision. It partitions the image into different meaningful regions with homogeneous characteristics using discontinuities or similarities of image components, the subsequent processes rely heavily on its performance. In most cases, the segmentation of color image demonstrates to be more useful than the segmentation of monochrome image, because color image expresses much more image features than monochrome image.

Each pixel is characterized by a great number of combinations of RGB chromatic components. However, more complicated segmentation techniques are required to deal with rich chromatic information in the segmentation of color images. According to the usage of prior knowledge of the image, color image can be segmented in an unsupervised or supervised way. The former attempts to construct the "natural grouping" of the image without using any prior knowledge.

Unsupervised Segmentation

The spatial compactness and color homogeneity are two desirable properties in unsupervised segmentation, which lead to image-domain and feature-space based segmentation techniques. According to the strategy of spatial grouping, image-domain techniques include split-and-merge, region growing and edge detection techniques. There have been extensive studies on them in the literature. The Markov Random Field (MRF) is defined in the quad-tree structure to represent the continuity of color regions in the process of split-and-merge. The histogram thresholding is a technique that seeks the peaks or valleys in 3 color histograms or a three dimensional (3-D) histogram. The HSV histograms are used for the segmentation of color image. The achromatic regions are determined by the saturation values, and the remaining chromatic regions are segmented by thresholding the peaks of hue histogram. A 3-D color histogram is built by color components. The valleys of color histogram are identified by the watershed algorithm. The nonparametric clustering is a promising solution in color clustering.

Supervised Segmentation

In supervised segmentation, the pixel classifier is trained for the best partition of color space using the sample of object colors. The image is segmented by assigning the pixel to one of the predefined classes. The common techniques of supervised segmentation are evaluated in, including maximum likelihood, decision tree, nearest neighbor and neural networks. The supervised segmentation is employed for the segmentation of video shots.

The segmentation of image frames is hierarchized by three classifiers, i.e., k nearest neighbor, naive bayes, and support vector machine. In, image segmentation is performed by a procedure of supervised pixel classification. The rule of minimum distance decision is used to assign each pixel to a specific class in a color texture space. Histogram-based approaches can also be quickly adapted to occur over multiple frames, while maintaining their single pass efficiency.

Histogram-Based Methods

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per pixel basis where the information result is used to determine the most frequent color for the pixel location. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in Video tracking.

Edge Detection

Edge detection is one of the fundamental steps in image processing, image analysis, image pattern recognition, and computer vision techniques. During recent years, however, substantial and successful research has also been made on computer vision methods that do not explicitly rely on edge detection as a pre-processing step. The well-known and earlier Sobel operator is based on the following filters: These are the estimates of first- order derivatives, the gradient magnitude is then computed as:

1. Focal blur caused by a finite depth-of-field and finite point spread function.
2. Penumbra blur caused by shadows created by light sources of non-zero radius.
3. Shading at a smooth object.

Region Growing Methods

The first region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean, δ , is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region. Seeded region growing requires seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise in the image can cause the seeds to be poorly placed. Unseeded region growing is a modified algorithm that doesn't require explicit seeds. It starts off with a single region A1 – the pixel chosen here does not significantly influence final segmentation.

Semi-Automatic Segmentation

In this kind of segmentation, the user outlines the region of interest with the mouse clicks and algorithms are applied so that the path that best fits the edge of the image. Techniques like Siox, Livewire, or Intelligent Scissors are used in this kind of segmentation.

Neural Networks Segmentation

Neural Network segmentation relies on processing small areas of an image using an artificial neural network or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network.

VI. SIMULATED RESULTS

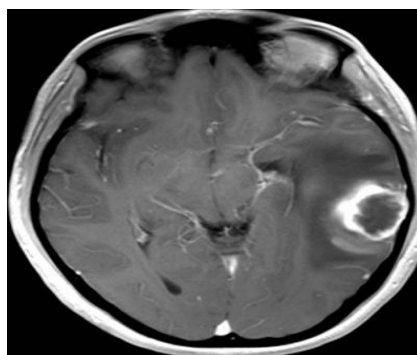


Figure 9. Input Image A

Figure 9 shows the input image which is collected from the tumor diagnosis center. It is an MRI scan in which the tumor is not much severe. GUI programming is done so that the tumor is analyzed and the cells affected by the tumor are found.

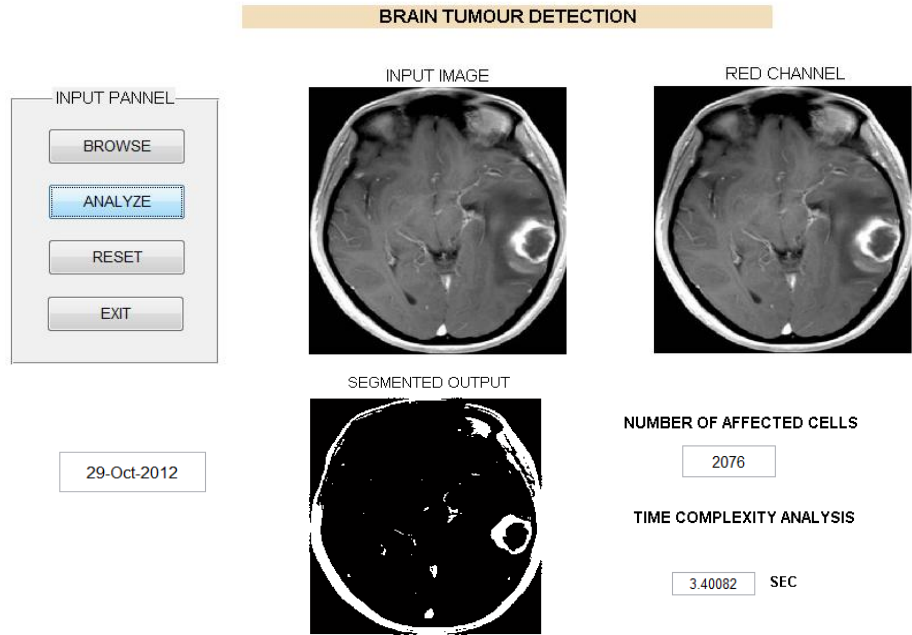


Figure 10. Output of Image A

Figure 10 shows the output of image A. The analysis of the image shows that there are 2076 cells affected cells and the time taken to for the analysis is 3.40082 seconds. The analysis can clearly segment the tumor present in the brain.

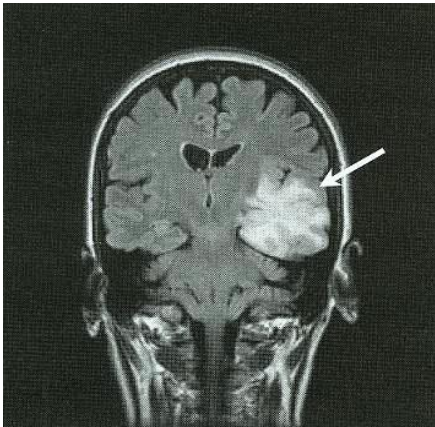
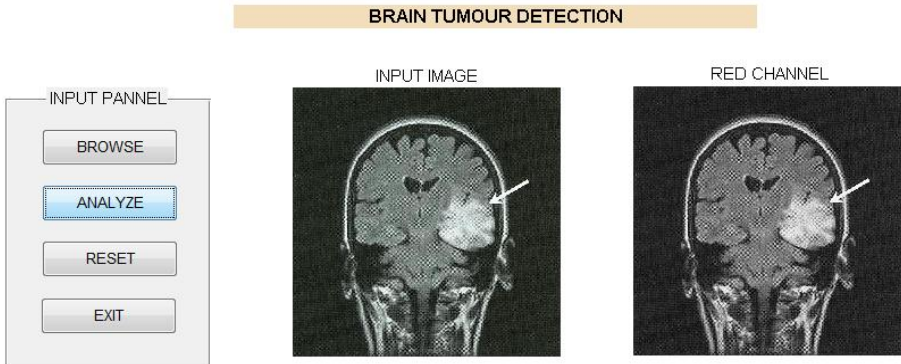


Figure 11 Input Image B

Figure 11 shows the input image which is collected from the tumor diagnosis center. It is an MRI scan in which the tumor is not much severe. GUI programming is done so that the tumor is analyzed and the cells affected by the tumor are found.



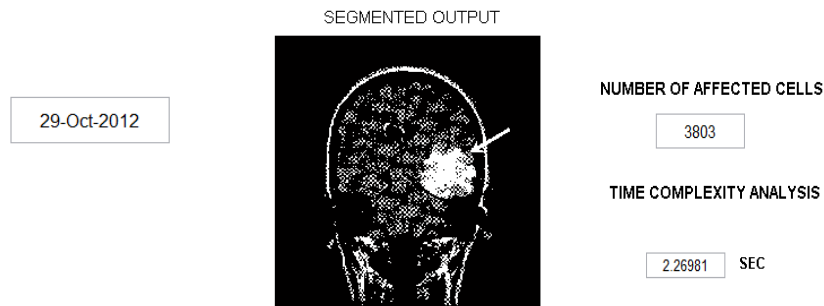


Figure 12. Output of Image B

Figure 12 shows the output of image A. The analysis of the image shows that there are 3803 cells affected cells and the time taken to for the analysis is 2.26981 seconds. The analysis can clearly segment the tumor present in the brain.



Figure 13. Input Image C

Figure 13 shows the input image which is collected from the tumor diagnosis center. It is an MRI scan in which the tumor is not much severe. GUI programming is done so that the tumor is analyzed and the cells affected by the tumor is found.

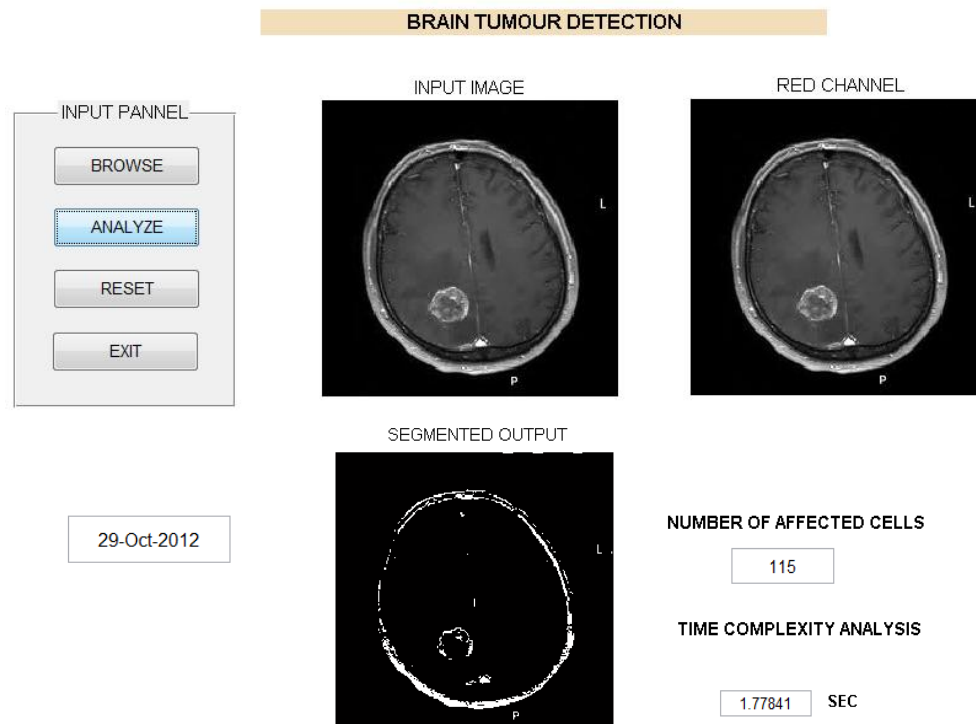


Figure 14 Output of Image C

Figure 14 shows the output of image A. The analysis of the image shows that there are 115 cells affected cells and the time taken to for the analysis is 1.77841 second. The analysis can clearly segment the tumor present in the brain.

VII. CONCLUSION

The proposed method uses hierarchical self organizing map algorithm using which the red blue and green components are separated. During this separation red component is considered to be best suited for the process of segmentation. With the use of red component segmentation is done and the tumor part is identified. The HSOM algorithm provides the information that how many number of tumor cells are affected. The time taken to detect the tumor cells are also provided using HSOM. Segmentation of brain tumor can be done by using different segmentation methodologies. Hence different segmentation techniques such as K-means clustering algorithm, rule based algorithm, fuzzy c-means clustering algorithms will be implemented and the comparative analysis of all the above segmentation will be done. By this the advantage of using HSOM algorithm will be proved.

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