Automated Preliminary Brain Tumor Segmentation Using MRI Images

Shamla Mantri[1], Aditi Jahagirdar[2], Kuldeep Ghate[3], Aniket Jiddigouder[4], Neha Senjit[5] and Saurabh Sathaye[6]

**[1] Computer Engineering, University of Pune, MIT College of Engineering
Pune, Maharashtra 411038, India**

**[2] Information Technology, University of Pune, MIT College of Engineering
Pune, Maharashtra 411038, India**

**[3] Computer Engineering, University of Pune, MIT College of Engineering
Pune, Maharashtra 411038, India**

**[4] Information Technology, University of Pune, MIT College of Engineering
Pune, Maharashtra 411038, India**

**[5] Information Technology, University of Pune, MIT College of Engineering
Pune, Maharashtra 411038, India**

**[6] Information Technology, University of Pune, MIT College of Engineering
Pune, Maharashtra 411038, India**

Abstract

Brain tumour has ample variations from person to person, in terms of size, texture or distribution. Experienced oncologists can easily identify the tumour region. But given its variations, training an algorithm to detect the tumour is a challenging task. Many algorithms have been developed to segment and detect the tumours, taking into consideration various aspects of an image. In this paper, we discussed a survey of brain tumour segmentation algorithms in image processing, and our proposed approach to detect brain tumors using texture and feature vectors and one-class classification methods.

Keywords: *Brain Tumor, Image Segmentation, Histogram of Oriented Gradients, One Class Classification.*

1. Introduction

Brain, which is an essential part of the body, can be thought to be divided into four parts- Grey Matter (GM), White Matter (WM), Cerebrospinal Fluid (CSF) and background. In human brain, the cells are generated and simultaneously destroyed. Thus the operation of cells in human brain is carried out in a controlled environment. It contains of around 100 billion neurons, with every single neuron performing a vital function. Damage to even a single neuron can result impairment to any body organ. Brain tumours are abnormal proliferations of the cells. They can be either cancerous (malignant) or non-cancerous (benign). However, the malignant tumours are of utmost concern since they pose a direct threat to the body and also, their proliferation is unpredictable. It depends on a number of factors like the tumour size, location and state of development. Brain tumours are graded from 1 to 4 according to their behavior, such as how fast they grow and their likeliness to spread. Grade 1 tumours are the least aggressive and grade 4 tumours are the most harmful and cancerous.

1.1 Benign Tumors

Benign tumours are noncancerous tumours, usually having clear defined borders. Unlike malignant tumours, benign tumours are not deeply rooted in brain tissues. Their growth is slow and usually stays at one place and does not spread. Benign tumours can be removed and the possibility of their re growth is also very low. The symptoms of benign tumours are not specific, but include bleeding, pain due to pressure of the tumour, vision problems, hearing problems and balance problems along with other problems. [1]

1.2 Malignant Tumors

Malignant tumours consist of cancerous cells, capable of multiplying in an unpredictable fashion. They can be either of primary or secondary type. Primary brain tumours are those that started in the brain while secondary brain tumours are those that started in another part of the body and reached brain for instance through bloodstream or lymphatic system. These are of invading nature and hence a serious threat to human body. The symptoms of malignant tumour depend of the size, position and rate of multiplicity of the carcinogenic cells. Typically it includes epilepsy, severe headache, vomiting, dizziness, and hallucinations along with other symptoms.

Enhancing brain tumour segmentation thus extremely important for detection and precise response to the life-threatening disease. Automated quantitative analysis relieves the medical experts from the tedious task of manual segmentation which is very time consuming and can introduce errors. Numerous computerized methods have been developed over time to automatically detect brain tumours. However, the importance of tumour appearance features was not well exploited, which may limit the performance of those methods on enhancing tumor segmentation. [1]

MRI stands for Magnetic Resonance Imaging and is a medical imaging technique used in radiology to visualize detailed internal structures. It uses magnetic field and pulses of radio wave energy to make picture of brain and other elements in brain. Multi-parametric MRI images typically consist of pre-contrast T1 weighted (T1 pre), post-contrast T1 weighted (T1 post) [Fig 1], T2 weighted (T2) and fluid attenuated inversion recovery (FLAIR) images [Fig 2].

An MRI machine uses a powerful magnetic field to align the magnetization of some atomic nuclei in the body, and radio frequency fields to systematically alter the alignment of this magnetization. The atoms thus gain energy and align themselves in a particular direction. During the "relaxation" period, they emit the gained magnetic energy which is detected by the scanner and this information is recorded to construct an accurate image of the scanned area of the brain. MRI does not use ionizing radiation unlike CT scans or X-Rays.

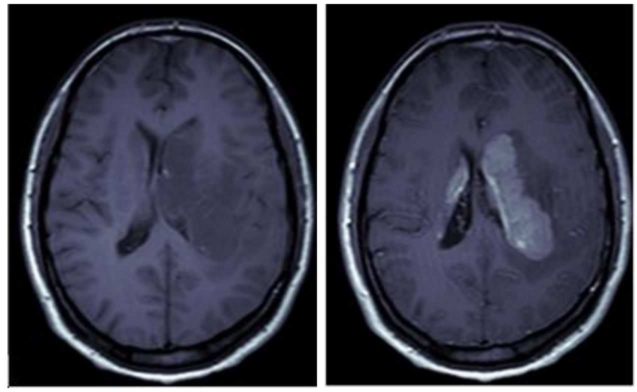


Fig 1 Input T1-pre and T1-post images

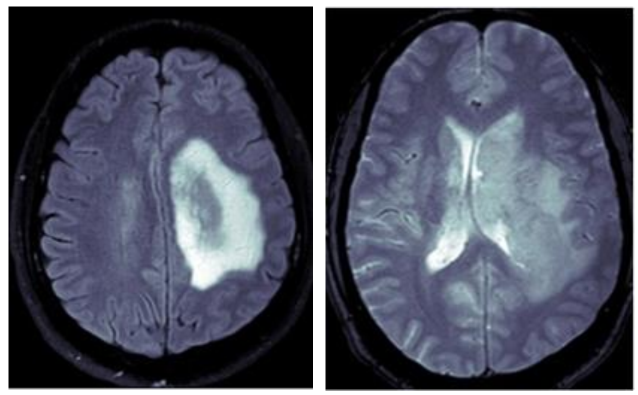


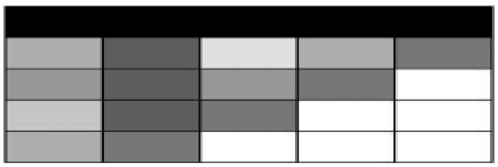
Fig 2 Input FLAIR and T2 images

2. Feature Extractors

Feature extractors play a pivotal role in ultimate segmentation of images. The types of features that can be extracted from any image are colour features, shape features, intensity features and texture features. [2] For color features, extraction is straightforward in any image. Shape Features include parameters like area, perimeter, shape, irregularity, circularity. Intensity is one of the most widely used for brain tumour segmentation. Intensity features include mean, variance, standard variance, median intensity, skewness, and kurtosis. However, it is not sufficient for tumour segmentation in MRI due to tumour intensity variation and also overlaps with intensities of normal tissues. Other features must be considered along with intensity feature for accurate detection of tumour.

2.1 Texture Features

Texture concept in digital images refers to the distribution of grey values among the pixels of a given region of interest in the image. Texture features are mathematical parameters computed from the distribution of pixels, which characterize the texture type and thus the underlying structure of the objects in the image. Histogram is one of the texture feature parameter, which is the count of how may pixels in the image process a given grey value [Fig 3]. Many parameters can be derived from the histogram of an image, like its mean, variance and percentiles. Also, Auto-Regressive model, which is another parameter of texture feature, is a way of describing shapes within the image by finding relations between groups of neighboring pixels. [1] Some of the texture features include energy, contrast, correlation, entropy, homogeneity, sum of square variance.



0	0	0	0	0
4	1	6	4	2
3	1	3	2	7
5	1	2	7	7
4	2	7	7	7

Fig 3: Example of Histogram

Processing an image involves operations on multiple dimensions of that image. Analysis with a large number of variables generally requires a large amount of memory and computational power. With reduced dimensions, processing the image becomes more feasible and also, the desired output is obtained. Extracting only the required features reduces the dimensions and thus the errors in the image. Feature extraction is thus a very important step in segmentation of images.

2.2 Intensity Features

Homogeneous regions in an image have similar intensities. Intensity can thus show greater detail in some areas in certain cases. This property can be exploited by intensity features. Images can be enhanced by changing the intensity values of pixels.

3. Segmentation

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). It is used to locate objects and boundaries in images. Segmentation algorithms generally are based on one of the two basic properties of intensity values-

Discontinuity- partitioning an image based on sharp changes in intensity.

Similarity- partitioning an image into regions that are similar according to a set of predefined criteria [Gonzales]

Some of the methods that can segment an image are as follows-

3.1 Thresholding

Thresholding is an operation used to convert grey scale brain image into binary image where the two levels are assigned to pixels, below or above the specified threshold value. For example, for a possible threshold of 30% grey in grayscale, all pixels darker than 30% belong to one segment and rest to other. Several popular thresholding methods are used for brain tumour segmentation including the Otsu's method and K-means clustering. Thresholding may be viewed as an operation that involves tests against a function T of the form –

$$T = \mathrm{T}\,[\,x, y, (\,p\,(x, y)\,, f\,(x, y))\,] \tag{1}$$

Where f(x, y) is the grey level at point (x, y) and p(x, y) denotes some local property of the point (such as the average grey level if a neighborhood centred on (x, y)). A thresholded image is defined as –

$$g(x,y) = \begin{cases} 1\ if\ f(x,y) > T \\ 0\ if\ f(x,y) \leq= T \end{cases} \tag{2}$$

Global Thresholding- If T depends only on f(x, y), and then the thresholding is called global.

Local Thresholding- If T depends on both f(x, y) and p(x, y) the thresholding is called local.

3.2 Edge Based Segmentation

Edge based segmentation is an effective type of segmentation for images with less features, like grey scale MRI image. This technique consists of making decision as to whether the pixels under consideration are an edge or not. Edge based segmentation techniques include high-emphasis spatial frequency filtering, gradient operators, adaptive local operators, functional approximations and line and curve fitting. [2]

For brain tumor detection, various edge detection operators like sobel edge detection, prewitt edge detection and canny edge detector operator are used.

3.2.1 Sobel Edge Detection

Sobel operator is a gradient operator. It performs a 2-D spatial gradient measurement of an image and emphasizes regions of high spatial frequency that corresponds to edges. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grey scale image.

3.2.2 Canny Edge Detection

It is also known as optimal edge detector. The canny edge detection operator takes as input a grey scale image and produces as output an image showing the positions of tracked intensity discontinuities. After removal of noise from the image, the gradient of the image is computed by feeding the smoothed image through convolution operation with the derivative of Gaussian in both the vertical and horizontal directions.

3.2.3 Prewitt Edge Detection

The Prewitt edge detector operator is used to detect edges by applying a horizontal and vertical filter in sequence. It uses two 3*3 kernels which are convolved with the original image to calculate approximations of the derivatives – one for horizontal, and one for vertical change. [3]

3.1 Region Based Segmentation

Region based segmentation techniques are generally better in noisy images where edges are extremely difficult to detect. Homogeneity of images is the main criteria used for region based segmentation. This technique attempts to group regions in an image according to common image properties like intensity values, textures or patterns, etc. We need a rule describing the growth mechanism and a rule describing the homogeneity of the regions after each growth stage. An initial set of small areas is iteratively merged according to similar constraints. An arbitrary seed pixel is selected and compared with neighbouring pixels. Region is grown from the seed pixels by adding in neighbouring pixels that are similar, increasing the size of region. When the growth of one region stops, we choose another seed pixel which does not yet belong to any region and start again. The whole process is continued until all pixels belong to some region.

4. Proposed Approach

The proposed approach assumes that only human brain MR Images of jpeg format may be inputted to the algorithm. The range for tumor pixels was experimentally found to be 115 to 251 and the MR images are of the transverse slice and not longitudinal or Sagittal. Also, the original MRI images input to the algorithm must be of a resolution greater than 400X500 pixels. Our algorithm intends to provide a simple yet preliminary approach towards classification of tumor pixels [Fig 4]. We consider just the intensity and HOG feature vectors for classification. Training is based on one class classification in which only positive samples are given to train the algorithm. The training phase involves determination of thresholds. Thresholds for intensity and HOG values of tumor regions are determined from the ground truth. Our proposed classification algorithm determines the likely neighborhood/locality of the tumor. After determining the bins falling within the thresholds, we explore and highlight the pixels only in this identified locality and its immediately adjacent regions at pixel level.

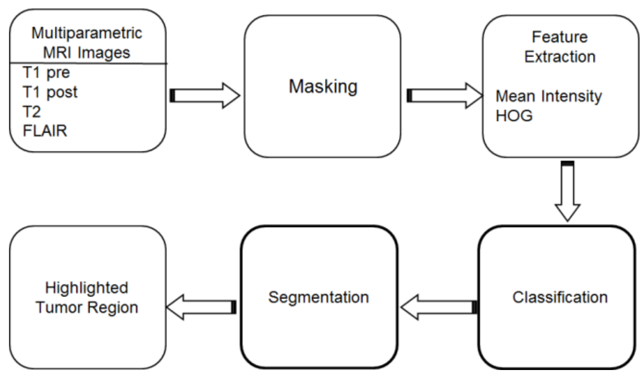


Fig. 4 Flowchart for overall procedure

4.1 Experiment Modules

Our proposed approach comprises of three main phases:

4.1.1 Preprocessing

This is the first phase of the project. It is responsible for selecting an image, resizing it to 400X500px, creating a mask and returning masked images. The dimensions of 400X500 have been chosen since cropping the image to this dimension yields the portion of interest i.e. the brain. Resizing thus helps to eliminate unnecessary areas from the original MRI image. Masking is important, since the generated masks, once used, help to extract the distinctive features which may be used in the further phases for identifying thresholds and highlighting pixels. The mask is generated by subtracting the T1-pre and T1-post images (bitwise subtraction). This mask, so generated [Fig 5], is then AND-end with each of the four images [Fig 6].

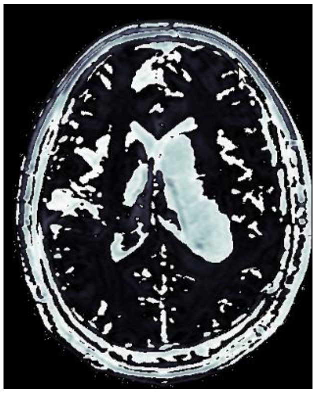
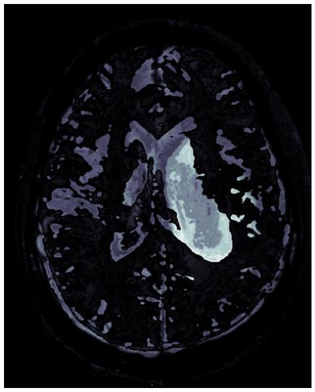
 

Fig. 5 Generated mask Fig 6 Mask applied on image

4.1.2 Classification

The classification algorithm first divides the image into patches or bins of 10X10 pixels. CSV files contain information on features extracted from known tumors (the ground truth). The algorithm involves two phases:

- Training:
  The primary purpose of this phase is to establish thresholds for the feature vectors which are to be used in classification: MI and HOG. It is based in the concept of single class classification. This means that only positive examples are provided to determine thresholds (unlike 2- class classification where both positive as well as negative samples are provided). Prior to this module, a masked image of the ground truth (i.e. with known location of the tumor) has been divided into bins/patches of 10X10px each. The features of MI and HOG have been extracted from them. The details of the features extracted from the bins/patches containing the tumor have then been stored in a CSV (Comma Separated Values) file. The CSV files form the training set. The values stored in these files are used to establish a threshold range for MI and HOG values which can assist in the classification of an unknown image.

- Testing:
  The main purpose of this phase is to identify the locality of the tumor. In this module, an image is first divided into bins/patches of size 10X10 pixels. The HOG and MI values are extracted from these bins/patches. The obtained values are compared with the range established by the Training Phase module. The bins that lie within the expected range (considering an error of 10%) contain the tumor. This module builds an array which contains the sets of the locality containing the tumor [Fig 7].

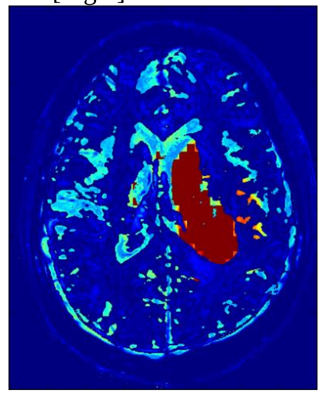


Fig. 7 Output after classification

4.1.3 Segmentation

The main objective of this phase is to highlight pixels in the identified tumor locality. The unique approach herein is that unlike other established algorithms, only the region of interest (rather than the whole image) is explored at the pixel level. The pixels lying within a predefined range are highlighted. This provides a simplistic approach which offers reasonable accuracy. Another unique feature of this is that once tumor regions are detected, the regions adjacent to these are also examined for tumor. This helps to improve accuracy in cases where a small part of the tumor may lie in the adjacent region [Fig 8]

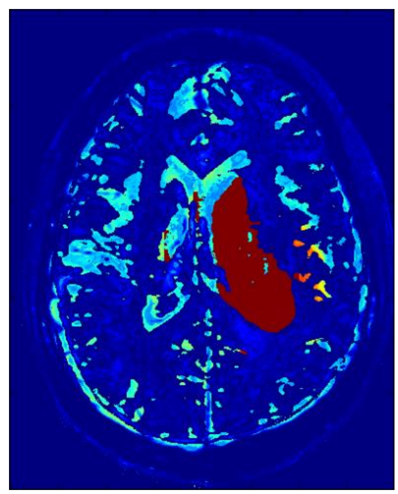


Fig 8 Final output after segmentation

5. Results and Analysis

Our algorithm is based on the concept of single class classification. The training phase of the classification considers only positive examples that are images with brain tumor. Amongst the following figures the first four depict the preprocessed input to our algorithm. The next four images depict the highlighted tumor. These are obtained after exploring the neighborhood of the bins/patches after the testing phase of the classification. From the readings noted in our reference/base paper [4], it can be seen that the results obtained (by us) yield approximately the same accuracy as those obtained by them.

The Sorensen Dice index is a statistic used for comparing the similarity of two samples. The index is known by several other names, usually Sorensen index or Dice's coefficient. Sorensen's original formula was intended to be applied to presence/absence data, and is:

$$QS = 2C/A + B = 2|A B|/|A| + |B| \qquad (3)$$

The output is obtained as shown in the figures

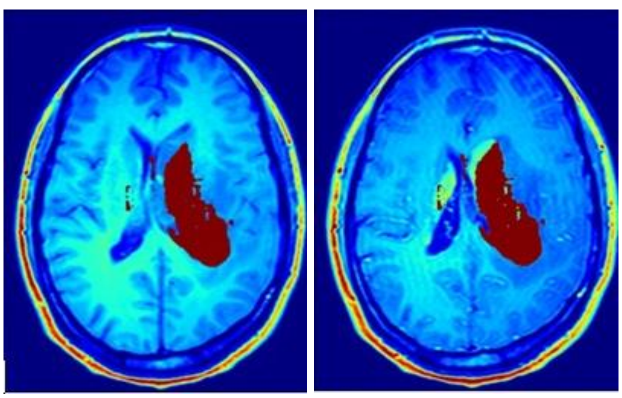


Fig 9 Output T1-Pre and T1-Post Images

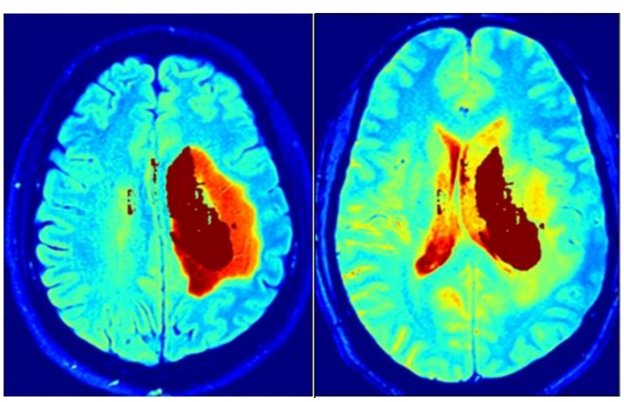


Fig 10 Output FLAIR and T2 Images

Patient	Pixels Marked	Ground Truth	DSS
P1	7881	6635	0.8075
P2	3298	4064	0.7379
P3	6585	9771	0.6772
P4	5487	7693	0.6995

Fig 11 Output comparing ground truth with marked values

6. Conclusion and Future Scope

In this paper, a simplistic approach towards fairly accurate preliminary brain tumour detection is presented. The proposed algorithms effectively exploit texture and intensity features from MRI images. The proposed framework provides a way of incorporating expert knowledge into image segmentation by using the concept of single class classification which leads to an automatic enhancing brain tumor labelling research tool to assist radiologists and which could also be useful in the preliminary stages of diagnosis. Our proposed algorithms produce results similar to conventional algorithms. Our proposed algorithm is also portable to various platforms since it has been implemented in Python. As compared to the implementations of our base paper which utilized AdaBoost, our algorithm utilizes less space.
This methodology has been used to segment/highlight tumors in brain images. It could also be adapted to segment or highlight tumors in other organs as well. Besides the proposed algorithm, other more accurate segmentation and classification algorithms could be incorporated to produce improved results. Coordinates of the tumor can be determined in 3D space and a 3D model of the brain with the highlighted tumor area can be constructed. The co-ordinates determined in 3D space could aid in the preliminary stages of robotic surgery.

Acknowledgments

The authors would like to thank Dr. Ashish Atre for providing the MRI images used in this project and Mrs. Ayesha Butalia for her guidance in the research of the topic.

References

[1] M. Choubey and S. Agrawal, “A Fully Automatic Approach to Detect Brain Cancer Using Random Walk Algorithm”, International Journal of Computer Technology and Applications, Vol. 3, No. 1, 2012, pp.265-268.

[2] V.P. Gladis, P. Rathi and S. Palani, “Brain Tumor MRI Image Classification With Feature Selection and Extraction Using Linear Discriminant Analysis”, International Journal

of Information Science and Techniques, Vol. 2, No. 4, 2012, pp. 131-146.

[3] G.Castellano, L.Bonilha, L.M.Li, and F.Cendes, "Texture Analysis of medical images", Clinical Radiology-Elsevier, 2004.

[4] T. Uemura, G. Koutaki, and K. Uchimura, "Image Segmentation Based on Edge Detection Using Boundary Code", IJICIC, Vol. 7, No. 10, October 2011.

[5] Priyanka, B. Singh, "A Review on Brain Tumor Detection Using Segmentation", IJCSMC, Vol. 2, No. 7, pp. 48-50, July 2013.

[6] K. K. Reddy, B. Solmaz, P. Yan, N. G. Avgeropoulos, D.J. Rippe, and M. Shah. "Confidence guided enhancing brain tumor segmentation in multi-parametric MRI", Biomedical Imaging (ISBI), Vol 6, No. 1, 2012, pp.366-369.