RESEARCH ARTICLE OPEN ACCESS

Feature Extraction Based Hybrid Method for Segmentation of Brain Tumor in MRI Brain Images

P.Kalavathi [1], R.Ilakkiyamuthu [2]

The Gandhigram Rural Institute [1]
Deemed University, Dindigul
M.Phil Research Scholar [2],
Madurai Kamaraj University (Evening College), Dindigul
Tamil Nadu - India

ABSTRACT

Brain tumor occurs when there is growth of enormous cells inside the brain. Brain tumors are of two types; benign tumors and malignant tumors. Benign tumors are the starting stage of brain tumor and can be cured with medicines and surgery. Malignant are the cancerous tumors which lead to death of human. To identify the benign tumors, many techniques and algorithms are used based on image processing techniques. Our proposed method uses Fuzzy C-means Clustering for segmentation and classification based on wavelets and GLCM feature extraction methods. The proposed method provides effective results for identifying and classifying the tumors. The performance of the proposed method is evaluated based on Jaccard similarity and Dice coefficient values. Our proposed method shows better experimental results for segmenting and classification of brain tumor.

Keywords :– Brain tumor, Segmentation, Wavelet, GLCM

I. INTRODUCTION

A brain tumor is a growth of abnormal cells within the brain. Tumors are two types: malignant or cancerous tumors and benign tumors. Cancerous tumors can be spitted into primary tumors that start within the brain, and secondary tumors that have spread from metastasis tumors. All types of brain tumors may produce symptoms that vary depending on the part of the brain involved. They cause headaches, seizures, problem with vision, vomiting, and mental changes. The headache is worse in the morning and goes away with vomiting. More problems may include such as difficultly in walking, speaking and with sensation. As the disease progresses unconsciousness may occur. The cause of most brain tumors is unknown. The most common primary tumors occur in adults are: meningiomas (benign), and astrocytomas as glioblastomas. Diagnosis of brain tumor is generally by medical examination along with computed tomography or magnetic resonance imaging. This is confirmed by a biopsy. Based on the findings, the tumors are divided into different grades of severity.

Lala et al [1], expressed that extracting the tumor from brain images by manually will not produce proper result to diagnosis. So they use computer aided segmentation techniques such as Fuzzy C-Means techniques to produce accurate results. Enhancement method and the clustering techniques such as Fuzzy C-Means are applied to the 3D brain tumor MRI images, the result showed that Fuzzy C-Means are much closer to each other than the enhancement method and it easily detect and extract the brain tumor in MRI images. They reviewed that adaptive clustering automatically select the cluster value and the process continued until all the pixels belongs to some region and finally level set method was used for smoothing of image.

A method by Kannan et al [2], is a novel FCM algorithm using weighted bias estimation and segmentation of MRI. In this method, the objective function of standard algorithm was modified and applied at the earlier stage in automated analysis and they proposed center knowledge method in order to reduce the running time of the proposed algorithm. The proposed method produced the better result even in the brain image having intensity homogeneities and various image noises. In [3], the intensity and texture based image segmentation with two levels of the level set method uses both intensity and texture based image segmentation which provides better results than the traditional methods. Anand and Kaur [4] proposed a method to segment the brain tumor in a vital step for the initial detection of tumor in the medical field. Although various methods have been presented for brain tumor segmentation, but enhancing tumor is a challenging task since tumor possess complex characteristics in appearance and must be done with precision in the clinical practices. Prajapati and Jadhav [5] developed an approach by introducing the morphological operations which are useful for the detection of the tumor but not all tumors can be specifically detected by this technique. Therefore they extended to use region growing which provide seed point approach to segment ROI region so that the tumor is easily detected and also further used for the classification purpose. Ghoniemy et al,[6] devised a procedure which is used to detect the best possible seeds from a set of data distributed all over the image as a high accumulator of the histogram. Detection of tumor in the earlier stages makes the treatment easier. A brief review of different segmentation methods used for detection of tumor from Magnetic Resonance Imaging (MRI) of brain has been discussed in [7].

MRI imaging plays an important role in brain tumor for analysis, diagnosis and treatment planning. It is helpful to doctor for determining the previous steps of brain tumor. Brain tumor detections are using MRI images is a challenging task, because the complex structure of the brain [8]. It is also possible to segment tumor region accurately, which helps in measuring the area of tumor region from brain tumor MRI image [9].

The authors Swatikhurana and Garg [10] reviewed that MRI based brain tumors segmentation methods are getting more and more attention and coming closer to clinical acceptance, as it providers non invasive images with high resolution and excellent contrast between different soft tissues [11]. Brain tumors vary depending upon its distinct components like location, shape, size and image intensities. Segmentation of brain tumor takes into account the detachment of tumor tissues (tumor, edema and necrosis) from normal brain tissues : Gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) [12]. In supervised learning, the network is provided with series of sample inputs and output is compared with expected response. It involves both training phase that uses labelled data that maps features to labels and testing phase is used to map labels to unlabeled data . Brain tissues segmentation especially tumor and edema is an intricate task because of artifacts in tumor, complex shape, heterogeneous intensity distribution and variability of the position of tumor [13] [14].

Manual segmentation requires software tools for the ease of drawing regions of interest (ROI), is a tedious and exhausting task. MRI scanners produce multiple 2-D slices and the human expert has to mark tumor regions carefully, otherwise it will generate jaggy images that lead to poor segmentation results. There is no intervention of human and segmentation of tumor is determined with the help of computer. It involves the human intelligence and is developed with soft computing techniques, which is a difficult task. Brain tumor segmentation has various properties which reduce the advantage of humans over machines. These methods are likely to be used for large batch of image in research environment. However; these methods have not gained popularity for clinical practice, due to lack of transparency and interpretability [15].

Image segmentation is to segregate the image into exclusive regions, which are similar with respect some condition. This can be accomplished using two methods of segmentations; Supervised and Unsupervised methods [16]. If for training input vectors, target output is unknown, training method adopted is unsupervised learning. In the previous years, various unsupervised learning methods such as K-means and fuzzy clustering have gained popularity for brain tumor segmentation [17]. The main aim of this type of segmentation is to segment the image into areas that have similar intensity and has well defined anatomic properties. Unsupervised segmentation of brain tumor achieve its anatomic goal by segmenting the image into atleast two anatomical regions, one is tumor and other is edema. The advantage of this type is that it can handle very difficult tasks such as brain tumor segmentation [18]. Disadvantages of this segmentation are: number of regions is to be known before, tumors may not be specified clearly. This disadvantage can be avoided using skull stripping. Skull stripping is a pre-processing step to wipe out noncerebral tissue such as fat, muscle, skin, skull which are not desired region of interest [19]. There are many skull stripping technique are available in the literature [20-28].

II. PROPOSED METHODOLOGY

In our proposed work we use different methodologies and algorithms to identify the presence of brain tumor cells in the given image. For the purpose of good localization and identification we start with wavelet transformation in which the noise is removed then its features are extracted using GLCM and then we segment the tumor by using Fuzzy C-means clustering.

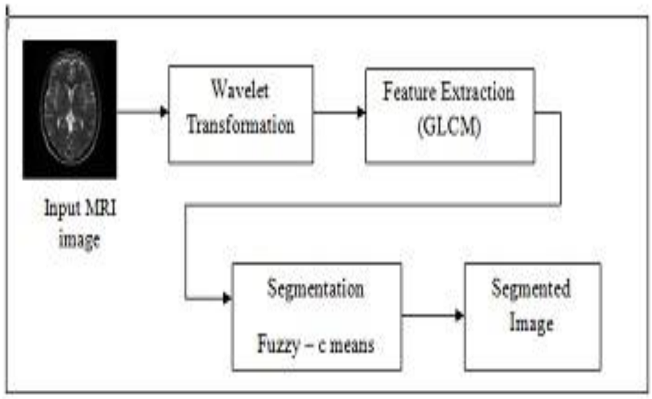


Fig1. Block Diagram of the Propose Method

Fig 1 illustrates the overall process of our proposed work in the block diagram, in which we start our process with gray scale MRI images and the noise is removed by wavelet transform. Further sequentially we perform the feature extraction using GLCM and finally the tumor is segmented by applying the fuzzy – c means method.

A. Wavelet Transform

Wavelet transformation is used since we have considered higher resolution of MRI images. Wavelets could effectively analyze and represent the multi-resolution images that are given. This is an effective method for the removal of noise. This wavelet transforms used changes only the time extension but not the shapes. The wavelet transform includes two inputs as 'a' scaling and 'b' time, this transform is represented as follows,

$$X(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} \overline{\Psi\left(\frac{t-b}{a}\right)}\, x(t)\,dt \qquad (1)$$

In this wavelet transform we initially estimate the mean value for the first order momentum. Mean is estimated since it consists of perfect intensity information of the given image. Then we predict the horizontal, vertical and diagonal details of the image by using this wavelet transform.

B. Gray Level Co-occurrence Matrix

This Gray Level Co-occurrence Matrix is called in short as GLCM which is formulated for obtaining statistical texture features. We extract features as,

- Angular Second Momentum (Homogeneity)
- Contrast
- Entropy
- Correlation
- Energy

1) Angular Second Momentum

Angular Second Momentum is referred as the measure of the number of repeated pairs. This statistical textural feature of Angular Second Momentum is high in case if the image has good homogeneity. This Angular Second Momentum is considered to be one of the significant features that are to be computed for the segmentation of brain tumor. Hence, this feature is mathematically formulated as given in the equation below,

$$SM = \sum_{i}^{y} P^2[i.j] \qquad (2)$$

2) Correlation

Correlation is defined as the measure of the correlated pixels, here the correlated pixels are identified with the pixels of the neighbors present on the image. Correlation is a value that is either '1' or '-1' (i.e.) perfectly positive or negatively correlation. Therefore correlation is computed using the following mathematical formula:

$$Correlation = \sum_{i}^{y} \sum_{j}^{y} \frac{(i-\mu)(j-\mu)P[i,j]}{\sigma^2} \qquad (3)$$

The term 'μ' in the above formula represent the mean value of the image and the term 'σ' denotes the standard deviation of the image.

3) Entropy

Entropy is the measure of the randomness which is being used for characterizing the texture of the given input image. This feature entropy is '0' in case if all 'P_{ij}' was estimated as '0'. Here we compute this statistical texture features by using,

$$Entropy = -\sum_{i}^{y} \sum_{j}^{y} P[i,j] \log P[i,j] \qquad (4)$$

4) Contrast

Contrast is a significant statistical textural feature which is defined as the measure of the intensity of contrast present between a pixel and its neighboring pixel of the image. In some cases the contrast of the images is '0' that is known constant for an image. In simple contrast can be defined as the local intensity variation of the image which contributes from '$P(i,j)$' away from the diagonal, which represents the condition that '$i \neq j$'.We measure contrast by using the following equation given as follows,

$$Contrast = \sum_{i}^{y} \sum_{j}^{y} (i-j)^2 P[i,j] \qquad (5)$$

5) Energy

Energy is a statistical textural feature which returns the sum of the squared elements that are present in GLMC which ranges between '$[0,1]$'. The value '1' is termed to be constant for an image. Hereby we measure energy by using,

$$Energy = \sum_{i,j} p\,(i,j)^2 \qquad (6)$$

In the above mathematical formula, 'i', 'j' are defined as the coordinates of the co-occurrence matrix. With these values of the GLCM, we compute five different elements to extract the statistical textural feature. By using this process; our further processing with the image is simpler and also effective. Features play a significant part in each image and so we consider such features and extract them to improve our final brain tumor segmentation result.

C. Segmentation by Fuzzy C-means algorithm

Fuzzy C-Means algorithm is used for performing segmentation process, this algorithm executes by assigning membership functions to each data point. Then each data point will be corresponding to each cluster center which is constructed over the basis of distance between the cluster center and the data point. Here, if large amount of data are present very near to that of the cluster center then it shows that there will be larger membership functions towards that particular cluster center. In FCM algorithm, the value of the summation of all the membership function present at each data point must be equal to one. Hence after each iteration, the membership function and cluster centers will be updated by using the formula that are given as follows,

$$\mu_{ij} = 1/\sum_{k=1}^{c} (d_{ij}/d_{ik})^{(\frac{2}{m}-1)} \qquad (7)$$

$$v_j = \left(\sum_{i=1}^{n} \mu_{ij}{}^{m} x_i\right) / \left(\sum_{i=1}^{n} \mu_{ij}{}^{m}\right), \forall_j = 1,2,\ldots,c \qquad (8)$$

where, the term 'n' represents the number of data points, 'v_j' represents the 'j^{th}' cluster center, 'm' defines the fuzziness index (i.e.) '$m \in [1,\infty]$', here 'c' denotes the number of cluster center, 'μ_{ij}' represents the membership function of 'i^{th}' data to that of the 'j^{th}' cluster center and then 'd_{ij}' represents the Euclidean distance between 'i^{th}' data and 'j^{th}' cluster center. Hereby the major objective of the Fuzzy C-means algorithm is to minimize the following as given,

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} \mu_{ij}{}^{m} \,||x_i - v_j||^2 \qquad (9)$$

In the above equation, '$||x_i - v_j||$' denotes the Euclidean distance present between the 'i^{th}' data and the 'j^{th}' cluster center. Finally we have segmented the MRI brain tumor image.

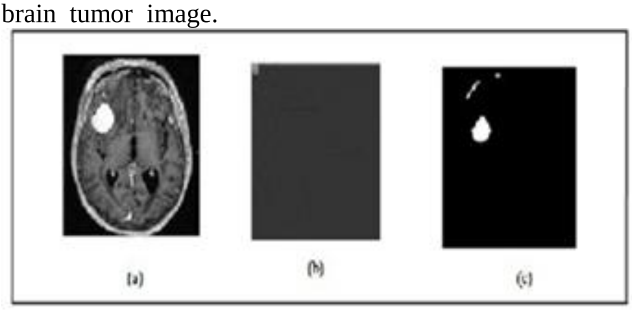


Fig2. Brain Tumor Segmentation (a) Original Image, (b) Pre-Processed Image, (c) Segmented Tumor

The summary of the steps involved in the proposed method is given below:

Step 1: Read the original image
Step 2: Remove the noise in the input image by using wavelet transform(preprocessing)
Step 3: Feature extraction by using the GLCM.
Step 4: Obtain the segmented image by forwarding the values from step 3.
Step 5: Obtain the final segmented tumor image.
Step 6: Compute the similarity measure using the segmented image by the proposed and Expert segmentation image.

III. RESULTS AND DISCUSSION

i) Dataset

In our proposed work we have used a dataset of brain imaging resources. This dataset [29] is comprised into MRI brain images which are affected by tumor and hence we evaluate our performance of brain tumor segmentation by using these images present in the dataset.

ii) Performance Evaluation

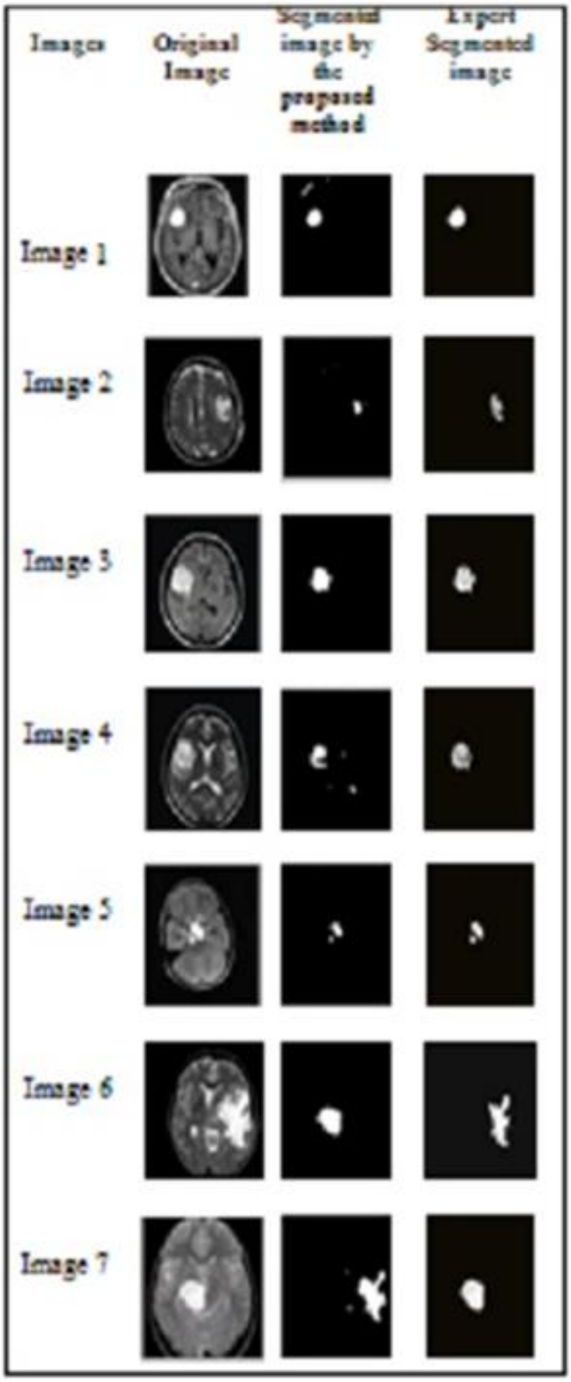
The evaluation of our proposed work is done by using Jaccard (J) and Dice (D) similarity measures. The value of Jaccard and Dice are estimated using the mathematical formula as given below:

$$J(S_1,S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \qquad (10)$$

$$D(S_1,S_2) = 2\frac{|S_1 \cap S_2|}{|S_1|+|S_2|} \qquad (11)$$

From the above equation the terms 'S_1' represents the segmented image and 'S_2' represents the gold standard image. Jaccard is a statistic which is being used for comparing the similarity and the diversity of the sample sets, similarly Dice is also used for the purpose of comparing the similarity between the samples sets that are present.

The values of estimated Jaccard and Dice for the output images shown in Figure 3 are listed in the following Table 1. From this estimation we could evaluate the performance of our proposed algorithms for detection of tumor in brain based on segmentation. By computing the values of Jaccard and Dice, we show improvements in the identification of the brain tumor.



(a) (b) (c)

Table 2. Segmentation result by the proposed method (a)Original images (b) Segmented tumor image by the proposed method and (c) Expert segmented tumor image

Table 1 Computed Jaccard and Dice value for the MRI brain tumor images. These values are estimated using the mathematical formula (10) and (11).

IMAGES	JACCARD VALUE	DICE VALUE
1	0.8714	0.9469
2	0.8867	0.9520
3	0.8987	0.9266
4	0.6078	0.7227
5	0.8760	0.9584
6	0.8800	0.9822
7	0.8784	0.9132

IV. CONCLUSIONS

Our proposed method describes the segmentation of brain tumors. Here we use FCM (Fuzzy C-Means) Algorithm for segmentation. These algorithms helps to identify the tumor and classify them effectively and our proposed process is effectively proved by Jaccard similarity and Dice Coefficient values which are calculated based on comparing the segmented output with expert segmented image.

REFERENCES

[1] A.A.Lala Image Segmentation: A Short Survey on detecting brain tumor segmentation image.

[2] A.Sindhu and S.Meera A Survey on Detecting Brain Tumorinmri Images Using Image Processing Techniques vol. 3,Issue 1,January 2015.

[3] A.A.Taneja, D.P.Ranjan, and A.A.Ujjlayan, A Performance Study of Image Segmentation Techniques Reliability, Infocom Technologies and Optimization,2015 4th International Conference on Year 2015.

[4] S. A.Anand, and H.Kaur, Survey on Segmentation of Brain Tumor A Review of Literature.

[5] J. Prajapati, A.Kalpesh and Jadhav, Brain Tumor Detection By Various Image Segmentation Techniques With Introducation To Non Negative Matrix Factorization ,Vol. 4, Issue 3, March 2015.

[6] A. Afifi, S. Ghoniemy, E.A. Zanaty and S. F. El-Zoghdy, New Region Growing based on Thresholding Technique Applied to MRI Data, *Computer Network and Information Security*, 2015, 7, 61-67.

[7] E.Amrutha Ravi, and S.Sreejith A Review on Brain Tumor Detection Using Image Segmentation, ISSN 2250 - 2459, ISO 9001:2008 Certified Journal, Volume 5, Issue 6, June 2015.

[8] Y. Borole, K.Sunil, S. Nimbhore, D. Seema, and S.Kawthekar Image Processing Techniques for Brain Tumor Detection: A Review, volume 4,Issue 5(2), September – october 2015.

[9] S.Shubhangi, S. Veer, and P.M. Patil, An efficient method for Segmentation and Detection of Brain Tumor in MRI images ,Volume: 02 Issue: 09 | Dec-2015.

[10] K.Swati Khurana, and M.L.Garg, MRI based Brain Tumor Segmentation methods a critical Review volume 3, issue 4,april 2015.

[11] D. Langleben and G.M. Segall, PET in differentiation of recurrent brain tumor from radiation injury, J. Nucl. Med., vol. 41, pp: 1861–1867, 2000.

[12] R.Nelly Gordillo, G.Eduard Montseny and Pilar Sobrevilla, State of the art survey on MRI brain tumor segmentation, Elsevier 2013, pp:1-13.

[13] H. Chang, J. Valentino, G. R. Duckwiler, and A. W. Toga, Segmentation of brain MR images using a charged fluid model, Eng., vol. 54, no. 10, pp. 1798–1813, Oct. 2007.

[14] J. Yao, Image processing in tumor imaging. New techniques in oncologic imaging 2006, pp:79-102.

[15] E. Papageorgiou, P. Spyridonos, D Glotsos, C. Stylios , P. Ravazoula, and G. Nikiforidis Brain tumor characterization using the soft computing technique of fuzzy cognitive maps. Appl Soft Comput 2008; 8:820–

[16] M. Schmid, Automatic brain tumor segmentation. Master's thesis, University of Alberta, 2005.

[17] E. Meiyan Huang, S.Wei Yang, k. Yaown, Y.Jun Jiang, and F. Wufan Chen, brain Tumor Segmentetion based classification, IEEE transaction an Biomedical Engineering, Vol.61,No.10 October 2014,app:2633-2645.

[18] G.Wiseline, L. Ganesan, Un supervised segmentation using Fuzzy Logic based texture spectrum for MRI brain Images World Acad Sci Eng Technol 2005; 5: 155-7.

[19] E.Ayse Demirhan, S. Mustafa Toru, and G. Inan Guler, segmentation of Tumor and Edema along with Healthy Tissues of Brain Using Wavelets and Neural Networks , IEEE Journl of biomedical amd health Informatics vol.19,no.4 July 2015.

[20] P.Kalavathi and V.B.Surya Prasath, Method on skull shipping of MRI Head Scan Image - a Review, Tournal of Digital Smaging, Spring, ,29(3),365-379,2016.

[21] P.Kalavathi, Improved Brian Extraction tool using marker-controlled watershed segmentation, IOSR Journal of computer Engineering, 16(5), 106-111,2014.

[22] K.Somassundaram and P. Kalavathi, Brain segmentation in magnetic Resonance Human Head scans using multi - seeded Region Growing, Imaging Science Journal,62(5),273 -284, 2014.

[23] K.Somasundaram and P.Kalavathi, Contour – based Brain Segmentation Method for Magnetic Resonance Imaging Human Head scans, Journal of computer Assisted Tomography,37(3), 353 – 368, 2013.

[24] K. Somasundaram and P.Kalavathi, A Novel skull stripping techniques for TI – Weight MRI Human Head scans, ACM Digital Library, 1 – 8,2012.

[25] K.Somasundaram and P. Kalavathi ,Skull stripping of MRI Head scans based on Chan-Vese Active

contour model, International Journal of knowledgement & e- learning, 3(1), 7 – 14,2011.

[26] K.Somasundaram and P.Kalavathi , A Hybrid Method for Automatic skull stripping of magnetic Resonance Images (MRI) of Human Head Scans, IEEE Xplorer Digital Library, 1 – 5, 2010.

[27] P.Kalavathi and K.Somasundaram, Segmentation of Brain from MRI Head Images using Modified Chan-Vese Active Contour Model, The International Arab Journal of Information Technology, 13(6A), pp:858-866, 2016.

[28] K.Somasundaram and P.Kalavathi, Automatic Skull Stripping of Magnetic Resonance Images (MRI) of Human Head Scans using Image Contour, Image Processing, Allied Publisher, New Delhi, pp. 147-151, 2010.

[29] http://pubs.sciepub.com.