International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.9, No.6 (2016), pp.171-176
http://dx.doi.org/10.14257/ijsip.2016.9.6.15

Review: A Survey on Brain Tumor Extraction from MRI

Jitendra Singh Sengar[1] and Priyanka Chanderiya[2]

[1]JSSRLPSP
Gwalior, India
[2]ITM University
Gwalior, India
[1]jitendrasinghsengar@gmail.com
[2]priyacute.chanderiya@gmail.com

Abstract

It is survey over various approaches applied on brain tumor extraction & detection from magnetic resonance image (MRI). Some of them are completely elaborated below with their strength & weaknesses. Magnetic resonance brain image are segmented & synthetically colored to represent original data through modified fuzzy c-means algorithm, supervised computational neural network approach (SCNNA), knowledge based technique (KBT), fractal-based brain tumor detection (FBTD), automatic segmentation of brain tumor (ASBT).

***Keywords**: Brain MRI, SCNNA, KBT, ASBT, SOM, fuzzy c-means algorithm*

1. Introduction

Brain a complex structure. It is soft, delicate, non-replaceable yet and spongy mass of tissue. A tumor is the name for a neoplasm or a solid lesion formed by an abnormal growth of cells which looks like a swelling. its a mass of tissue that grows out of control of the normal forces that regulates growth. Tumors can destroy rest healthy cells of brain. It can also indirectly damage healthy cells by crowding other parts of the brain and cause inflammation, brain swelling and generate pressure within skull. A tumor can be benign, pre-malignant or malignant, whereas cancer is by definition malignant. Magnetic Resonance Imaging (MRI) a technique of medical imaging [05]. It provides rich set of information about human soft tissues anatomy. MRI is used to analyze and study the behavior of the brain. Segmentation applied on the images for Grey Matter (GM), White Matter (WM), and Cerebra – Spinal Fluid (CSF) and tumor region extraction. Image segmentation partitions an image into different homogeneous regions so that meaningful information about brain MRI image could be obtained. Extraction of brain tumor region requires the segmentation of brain MRI into at least two segments. One segment has the normal brain cells consisting of GM, WM and CSF and the second segment has the timorous cells of brain. Correct segmentation of MRI is important because MR images are not highly contrast thereby these segments can be easily overlapped with each other. Several segmentation methods had been proposed by the digital image processing community.

The four of the most common methods are:

1) Amplitude threshold fixing
2) Texture segmentation
3) Template matching
4) Regional-growing segmentation.

This is very much important for detecting necrotic tissues, edema and tumors.

ISSN: 2005-4254 IJSIP

2. Automatic Segmentation

The three steps are refining process of segmentation

1. K - Means algorithm based segmentation.
2. Local standard deviation guided grid based coarse grain localization.
3. Local standard deviation guided grid based fine grain localization.

Image segmentation is a classical clustering problem where the range of image grey values is clustered in some fixed number of clustered grey values. One of the easiest unsupervised learning algorithms that explain the well acknowledged clustering problem is the K-means [1]. The process follows a straightforward and easy way to categorize given data set during definite number of clusters (assume k clusters) fixed a priori. These centroids must be located in a wiliness way because of dissimilar location cause dissimilar outcome, so locate them as much as possible far away from each other. The most important application is to label k centroids, one for very cluster. The next step is to obtain every point be in the right location to a particular (given) data set and relate it to the adjacent centroid. If there are no point is waiting, the first step is finished and an early group age done.

In this point we want to re-calculate k centroids of the clusters resultant from earlier step. After calculate these k new centroids, a new binding has to be done between the equivalent data set points and the neighboring new centroid. A repetition has been produce. As a effect of this loop we may well notice that the k centroids alter their position step by step until no additional changes are done, in other words centroids do not shift any more. Finally, the algorithms aspire at the minimizing of objective function, in that case a squared error function where the square is calculated of the distance measured between a data point and the cluster centre, which is the pointer of the distance of the n data points from their own bunch centre. The algorithm runs through the following steps:

$$m_i(t+1) = m_i(t) + h_{ci}(t)[x(t) - m(t)],$$

1. Position K points into the image characterize by the objects that are being clustered. These points simply signify initial group centroids.
2. Closest centroides are assigning each object in to a group.
3. After assigning each object then recalculation of the positions of the K centroids is done.
4. Until the centroids no longer move repeat Steps 2 and 3. This is done due to create a disconnection of the objects from the groups from which the metric to be minimized can be calculated.

Although it can be establish that the method will always come to an end, the k-means algorithm does not essentially locate the best possible arrangement, equivalent to the global objective function minimum. The algorithm is also appreciably responsive to the initial arbitrarily chosen cluster centers.

3. Self- Organizing Maps (SOM)

This algorithm used neural network as the segmentation tool. SOM learns cluster input vectors according to how they are naturally grouped in the input space. In its simplest form, the map consists a regular grid unit which learns to represent the statistical data described by model vectors x 2 Rn, where Rn represents n dimension real space. Each map unit i contains a vector mi ðmi 2 RnÞ that is used to represent the data. During the training process the model vectors are changed gradually and finally map forms ordered non-linear regression of model vectors into data space. At the tth step of the learning process, the data sample X(t) is presented to grid. Then the node c is searched for the best representation of the sample. The unit c and its neighbor units are updated according to the below specified learning rule where hci (usually symmetric, monotonically decreasing function of the distance of units i and c on the map grid) is the neighboring function expressing how much unit i is update when unit c is winner. This update process continues for all the data samples as a result of these repeated updates, the model vectors of neighboring map units gradually become similar and eventually the whole grid becomes globally ordered vector model. In addition to other advantages of SOM over other clustering approach, Global ordering property of SOM is attractive. We observe that when we segment a sequence of brain MRI using SOM, any specific tissue (e.g. GM, WM) or tumor is always grouped into a specific location in grid. This helps us to label tumor correctly and unambiguously.

Neural network has been widely used for classification of different tissue regions in MRI. The simplest form of back propagation algorithm which learns network's weights and biases is updated in negative direction of gradient. The objective function of a standard feed forward neural network is as

$$mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2,$$

where N is the number of sample, it is the target output. Similar to any other classifier, the standard back propagation neural network also suffers from over fitting. This over fitting occurs when network memorizes training examples but does not learn to generalize the inputs. To improve the generalization, we obtain the smallest network weights that are large enough to classify the input data with adequate accuracy. We can achieve after modification of objective function as follows:

$$msireg = \gamma \times mse + (1 - \gamma) \times msw,$$

Where c is the performance ratio, and

$$msw = \frac{1}{n}\sum_{j=1}^{n} w_j^2.$$

The objective function in Eq. (13) helps us to build a small network which does not have enough power to over fit. However, how well this function performs depends on the choice of the regularization parameters. In this work, we exploit Bayesian framework to determine the optimal regularization parameters automatically. The weights and biases of the network are assumed to be random variables with specified distributions. Then the unknown variances associated with these distributions are used to estimate the regularization parameters.

4. Critical Evaluation

In this study, we have studied different techniques for segmentation. The prominent intensity models studied in this paper include neural networks, Gaussian mixture models, wavelet based models, finite mixture models, fuzzy adaptive etc. Majority of the researchers preferred MR images, and CT scanned images are rarely used by the researchers. Some studies focused on trained data while other targeted untrained data; some studies used atlas, and some did not. A critical review of the studied literature is summarized in the compare and contrast table (Table I).

Table 1. Compare and Contrast Table

Author	Summary	Proposed Technique	Algorithm Used	Benefits	Identified Problems
Tolba (2003)	MR image segmentation	Gaussian Multi-resolution Analysis	Expectation Maximization	Methodology is lesser sensitive to noise and utilizes strong spatial correlation between neighbouring pixels.	By using this technique, th edges rarely appear in the images.
Li (2004)	Fusing images	Wavelet based	Discrete Wavelet frame transform	Technique uses enhanced version of DWT and is relatively easy to implement.	-
Sing (2005)	Segmentation of MR images	Neural Network	Fuzzy Adaptive radial basis function	The technique removes noise from medical images without losing sharpness of the objects.	Only one task related to fusion was focused. Dynamic ranges were not considered during calculations.
Bayro-Corrochano (2005)	Medical image segmentation using CT scan	Geometric algebra for volume representation and registration	Marching cubes along with region growing strategy	Reduced the number of primitives to model volumetric data and use less primitives for registration process and makes registration process faster.	Images were obtained from CT scan which has its own limitations like blurred boundaries and similar grey level between healthy and non-healthy tissues.
Yu (2008)	3 level image segmentation	Maximum fuzzy partition entropy of 2D histogram	QGA	QGA is selected for optimal combination of parameters.	Compute each possible value QGA is practically not possible.
DiBono (2008)	Decoding cognitive states from MRI data.	Mean intensity	Support Vector Regression	Methodology applies statistical techniques.	Virtual environment sometimes leads to inaccuracy.
Luts (2008)	Segmentation using MRI and MRSI.	T2 Weighted image	Nosologic imaging	Combining MRI with MRSI feature improved classifiers' performance.	The proposed method provides only one dimensional image feature.
Shi1 (2009)	Medical image processing	Neural Network	-	The study offers a comprehensive review of the paper published before 1992.	A review paper.

Roy (2012)	Symmetry analysis	Modular approached to solve MRI segmentation	Symmetry analysis	The proposed can identify the status of increase in the disease by employing quantitative analysis.	MRI segmentation is one of the essential tasks in medical area but is boring and time consuming. Visual study of MRI is generally more interesting and fast.
Padole (2012)	Combination of *mean shift* and *normalized cut*	Normalized cut method		mean shift, normalized cut, component analysis	The brain tumor in the processed data is detected through component analysis.

5. Conclusion

Image segmentation is extensively used in numerous biomedical-imaging applications, *e.g.*, the quantification of tissue Volumes, study of anatomical structure, diagnosis, localization of pathology, treatment planning and computer-integrated surgery. As diagnosis tumor is a complicated and sensitive task; therefore, accuracy and reliability are always assigned much importance. Hence, an elaborated methodology that highlights new vistas for developing more robust image segmentation technique is much sought.

References

[1] T. U Paul and S. K. Bandhyopadhyay, "Segmentation of Brain Tumor from Brain MRI Images Reintroducing K–Means with advanced Dual Localization Method", International Journal of Engineering Research and Applications (IJERA), vol. 2, no. 3, **(2012)** May-Jun, pp. 226-231.

[2] S. Roy and S. K. Bandyopadhyay, "Detection and Quantification of Brain Tumor from MRI of Brain and it’s Symmetric Analysis", International Journal of Informat.

[3] F. Han, H.-F. Yao and Q.-H. Ling, “An improved extreme learning machine based on particle swarm optimization", Proc. of International Conference on Intelligent Computing, **(2012)**, pp. 699 - 704.

[4] S. N. Deepa, and D. B. Aruna, “Second order sequential minimal optimization for brain tumour classi¯cation", European Journal of Scienti¯c Research, vol. 64, no. 3, **(2011)**, pp. 377-386.

[5] J. S. Sengar, “Enhanced Artificial Neural Network Approach to indentify specific binary pattern”, International Journal of Hybrid Information Technology, vol.8, no.6, **(2015)**, pp.391-396.

[6] D. Paddled, and J. Ross, “Validation tools for image segmenta- tion," Proc. of SPIE, Medical Imaging, 72594W, **(2009)**.

[7] E. I. Zacharaki, S. Wang, S. Chawla, D. S. Yoo, R. Wolf, E. R. Melhem and C. Davatzikos, “Classi¯cation of brain tumor type and grade using MRI texture and shape in a machine learning scheme," Magn. Reson. Med., vol. 62, no. 6, **(2009)**, pp. 1609 - 1618.

[8] J. J. Corso, E. Sharo, “Multilevel Brain Tumor Segmentation With Integrated Bayesian Model Classification", IEEE Transactions on Medical Imaging.

[9] J. Luts, T. Laudadio, A. J. Idema, A.W. Simonetti, A. Heerschap, D. Vandermeulen and S. VanHuffel, “Nosologic imaging of the brain: segmentation and classification using MRI and MRSI”, NMR in Biomedicine, **(2008)** May.

[10] Georgiadis, “Improving brain tumor characterization on MRI by probabilistic neural networks and non-linear transformation of textural features”,Computer Methods and program in biomedicine, vol 89, **(2008)**, pp. 24-32.

[11] H. Yu and J. L. Fan, “Three-level Image Segmentation Based on Maximum Fuzzy Partition Entropy of 2-D Histogram and Quantum Genetic Algorithm”, Advanced Intelligent Computing Theories and Applications. With Aspects of Artificial Intelligence. Lecture Notes in Computer Science, Berlin, Heidelberg **(2008)**.