International Journal on Recent Researches in Science, Engineering & Technology (IJRRSET)
A Journal Established in early 2000 as National journal and upgraded to International journal in 2013 and is in existence for the last 10 years. It is run by Retired Professors from NIT, Trichy. Journal Indexed in JIR, DIIF and SJIF.
Research Paper
Available online at: www.jrrset.com

ISSN (Print) : 2347-6729
ISSN (Online) : 2348-3105
Volume 6, Issue 12
December 2018.
JIR IF : 2.54
SJIF IF : 4.334
Cosmos: 5.395

Received on: 01.12.2018 Published on: 19.12.2018 Pages : 29 - 35

NEURAL NETWORK BASED SEGMENTATION OF TUMOR AND EDEMA USING MR IMAGES

Dr.A.G.Vadivelan
Department of Science and Humanities,Shadan College of Engineering and Technology HYD,T.S,INDIA

Abstract
Image processing plays an important role in various medical applications to support the computerized disease examination. Brain tumor, such as Glioma is one of the life threatening cancers in humans and the premature diagnosis will improve the survival rate. Magnetic Resonance Image (MRI) is the widely considered imaging practice to record the glioma for the clinical study. Due to its complexity and varied modality, brain MRI needs the automated assessment technique. In this paper, a novel methodology based on meta-heuristic optimization approach is proposed to assist the brain MRI examination. This approach enhances and extracts the tumor core and edema sector from the brain MRI integrating the Teaching Learning Based Optimization (TLBO), entropy value, and level set / active contour based segmentation. The proposed method is tested on the images acquired using the Flair, T1C and T2 modalities. The experimental work is implemented and is evaluated using the CEREBRIX and BRAINIX dataset. Further, TLBO assisted approach is validated on the MICCAI brain tumor segmentation (BRATS) challenge 2012 dataset and achieved better values of Jaccard index, dice co-efficient, precision, sensitivity, specificity and accuracy. Hence the proposed segmentation approach is clinically significant.
Keywords: Image processing**,** MRI, Glioma, CEREBRIX

1. Introduction
Brain tumor is one of the life threatening diseases for human community. The mainstream of brain tumor commences in the regions and associated parts of the brain. Bauer et al. [1] reported that, glioma is the most common brain tumor with the maximum morbidity and mortality rates. Based on its severity, brain tumor can be classified as the low and high grade gliomas [2].
The availability of the latest therapeutic technology can help the human community in the early detection and examination of the gliomas during the screening inspection process. When the location and nature of glioma is identified, then the possible treatment procedure can be provided to cure the disease. After detecting the tumor, the oncologist will plan the one of the following treatment procedures; (i) radiation therapy, (ii) chemotherapy and (iii) surgery. In which the radiation and chemotherapy are recommended to slow down the tumor growth and the surgical procedure can be used to completely remove the tumor region.
Magnetic Resonance Image (MRI) is the widely adopted procedure to record the brain abnormality using various modalities for the clinical study. The recent advancement in MRI technology helps to provide the complete details about the internal brain sections in the form of a three dimensional (3D) picture. After recording the image, 3D or slice based analysis is carried out using a chosen image processing scheme to locate and localize the tumor for superior diagnosis and treatment planning. The

brain image processing literature presents a number of methods to examine the abnormality using the MRI. The modern MRI examining procedures includes the neural network based approach [3], watershed segmentation [4], clustering techniques [5], fuzzy c-means algorithm [6], edge detection algorithm [7], ANFIS approach [8], cellular automata [9], Gaussian mixture models [10], multi-level thresholding, and heuristic approaches [11]. Moreover, recent work by Despotovic et al. [12] highlights that, combination of several techniques is essential to achieve better segmentation accuracy. Except the neural network based approaches, most of the above said tumor segmentation methods are modality based approaches, works well on the brain MRI registered with a particular modality. Hence, it is recommended to develop a unique segmentation and analysis tool for the MRI dataset, registered with a variety of modalities, such as Fluid Attenuation Inversion Recovery (Flair), spin lattice relaxation (T1), T1-contrast enhanced (T1C) and spin-spin relaxation (T2). In this paper, a novel procedure based on meta-heuristic optimization is proposed to segment the tumor core and the edema regions from the brain MRI dataset recorded using Flair, T1C and T2 modalities.

The proposed computer aided brain MRI segmentation methodology is grouped as (i) Pre-processing and (ii) Post-processing sections. Pre-processing section includes the skull stripping operation along with the global multi-thresholding scheme based on entropy function. In order to improve the multi-thresholding accuracy, maximal entropy function is integrated with the recent metaheuristic algorithm called the Teaching Learning Based Optimization (TLBO) algorithm introduced by Rao et al. [13]. Image quality based analysis is carried out between the original brain MRI image and the multi-threshold image in order to identify the best entropy function approaches. The post-processing section is used to extract the tumor core and edema based on chosen segmentation procedure. This section presents examination with some well-known segmentation procedures such as the level set approach [14], local active contour and global active contour. After the segmentation, a comparative study involving the segmented tumor region and the expert's ground truth is performed to evaluate the significance of proposed segmentation approaches.

During the experimental work, various appearances of brain images such as coronal, sagittal and axial views obtained from Cerebrix and Brainix dataset are initially considered for the analysis. The validation of the proposed procedure is done using the MICCAI brain tumor segmentation (BRATS) challenge 2012 dataset .Further, few abnormal MRI images of brain deviations like, Craniophryngioma (CP), High Grade Glioma (HGG) and Microadenoma (MA) of Radiopaedia [15] is also considered for the analysis. This study, confirms that, the brain tumor segmented using the Shannon's entropy function and level set approach offers better result compared with the Kapur's function and Tsallis functions. Finally, the performance of Shannon's entropy and level set based procedure is validated against the Fuzzy c-means algorithm (FCM) ,Particle Swarm Optimization with Markov Random Field (PSO-MRF) and Principal Component Analysis (PCA) existing in the literature.

2. Methodology

This paper focuses on developing the meta-heuristic algorithm supported tool to extract tumor and edema from the brain MRI irrespective of modalities. The proposed work is segregated as the pre-processing and post-processing section.

2.1. Pre-processing

The overall accuracy of the proposed meta-heuristic assisted segmentation approach depends mainly on the pre-processing stage.

2.1.1. TLBO

Teaching Learning Based Optimization (TLBO) algorithm is a recently developed meta-heuristic procedure based on the mathematical model of the teaching-learning practice existing in the classroom scenario. It is an optimal search procedure among two closed linked set, such as teacher phase and learner phase. The teacher stage starts learning from a most outstanding teacher and the scholar stage authorize the students to learn through interactions. Due to its superiority, TLBO approaches are widely implemented by the researchers to solve a variety of engineering optimization problems. A comprehensive description about the TLBO can be found in Fig. 1 depicts the pseudo code of the traditional TLBO algorithm adopted in this paper.

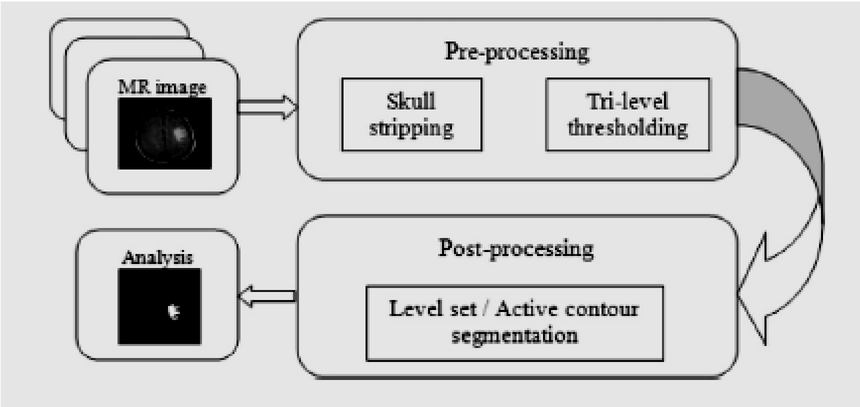

Fig. 1. Structure of the proposed segmentation process.

Pseudo code of the TLBO algorithm

START;

Initialize the algorithm with number of learners (NT), search dimension (D), Maximum iteration (Miter) and the objective value (Jmax);

Arbitrarily initialize 'NT' learners for xj (j = 1, 2, … n);

Assess the routine and choose the finest solution f(xbest);

WHILE iter = 1:Miter;

%TEACHER PHASE%

Use f(xbest) as teacher;

Sort based on f(x), chose new teachers based on:

f(x)s = f(xbest) – rand for f(x)s = 2,3, . . ., T;

FOR j = 1:n

Compute T j

F = round[1 + rand(0, 1){2 − 1}];xj

new = xj + rand(0, 1)[xteacher − (T jF .xmean)];

% Calculate objective value; f(xj new)%

If f(xj new) < f(xj), then xj = xj new;

End If % End of TEACHER PHASE%

%STUDENT PHASE%

Randomly chose the learner xj, such that k = j;

If f(xj) < f(xk), then xjnew = xj + rand(0,1)(xj − xk);

Else xj new = xj + rand(0,1)(xk – xj);

End If

If xj new is better than xj, then xj = xj new;

End If % End of STUDENT PHASE%

End FOR

Set m = m+ 1;

End WHILE

Record the threshold values, Jmax, and performance measures and CPU time;

STOP;

2.1.2. Skull stripping

Skull stripping is the initial step in the brain MRI segmentation process. It is necessary to eliminate the skull from the background area from MRI for quantitative analysis. Skull stripping is usually performed using an image filter which separated the skull and the rest of the image sections by masking the pixels having similar intensity levels. In MR image, normally the skull/bone section will have a maximum threshold value (threshold > 200) compared to the tumor and other brain regions.

Hence, the image filter is used to separate the brain regions based on a chosen threshold value. Then by employing the solidity property, the skull is stripped from the brain MRI. In this paper, the skull stripping procedure discussed by Chaddad [10] and Tanougast is adopted.

2.1.3. Multi-level thresholding

In recent years, traditional and heuristic algorithm assisted multi-level image thresholding is adopted by most of the researchers due to its significance. During this process, a digital image frame is divided into multiple regions by grouping similar pixel values in order to locate and examine all the significant information available in the image. From the image processing literature, it can also be noted that, the implementation of multilevel thresholding is uncomplicated for gray scale image compared to the RGB images. In this work, all the MRI modality offers a gray scaled brain image; hence the implementation of the TLBO assisted multi-level thresholding is quite easy. From the literature, it can be observed that, entropy based approaches are widely adopted by the researchers to analyze the abnormality in medical images as well as signals. In this paper, TLBO and entropy function based multi-level thresholding process is chosen as the pre-processing stage.

3. Results and discussions

This section presents the experimental results of the proposed brain MRI segmentation and analysis work. The proposed procedure is initially implemented on 256 × 256 sized various brain MR images, such as coronal, sagittal and axial views obtained from Cerebrix and Brainix dataset. Later, the proposed method is validated using 216 × 160 sized MICCAI brain tumor segmentation (BRATS) challenge 2012 dataset images (a sum of 72 images of 6 patients recorded with Flair, T1C and T2 modalities). Fig. 1 depicts the proposed approach considered to segment the brain MRI dataset. The brain MRI images are initially recorded in a controller environment with a chosen modality. After choosing a test image, initially the pre-processing procedure is executed to enhance the image regions. This stage involves in the skull stripping procedure and a tri-level thresholding process. The reliability of pre-processing section is then analyzed based on the image quality measures. In the post-processing section a suitable segmentation approach is implemented to mine the tumor region from the pre-processed MRI. Finally the mined tumor section is compared against the ground truth offered by an expert member and the essential information like similarity measures and the statistical measures are computed. Fig. 2 shows the sample images of Cerebrix and Brainix dataset initially considered for the study.

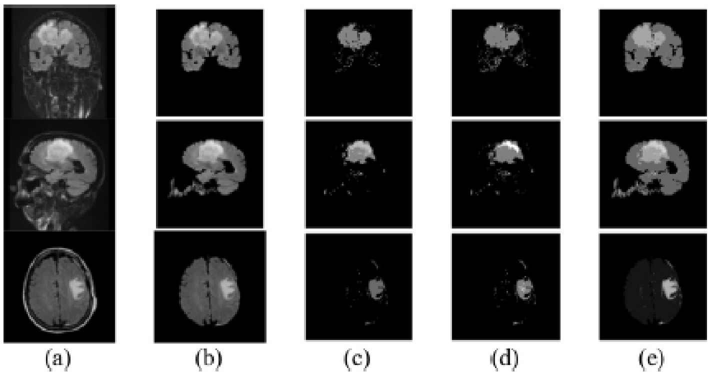

Fig. 2. Brain MRI dataset (a) Test image (Coronal, Sagittal and Axial), (b) Skull stripped image, (c) Kapur’s thresholding, (d) Tsallis thresholding, (e) Shannon’s thresholding.

During the implementation process, 10 slices of each test images are considered for the analysis. As shown in Figs. 1 and 2(b), initially the skull stripping is applied to remove the skull section from the rest image. The image pixels of the skull stripped image are then grouped using the TLBO algorithm assisted tri-level thresholding process with the maximization of entropy value. Each image is separately analyzed using the well-known entropy approaches, such as Kapur (Fig. 2(c)), Tsallis (Fig. 2(d)) and Shannon (Fig. 2(e)). In order to assess the superiority among the considered entropy based analysis, well known image quality measures, like PSNR, NCC, NAE and SSIM are computed. This can be observed that, average of image quality measures obtained with the Shannon's entropy is better than the alternatives considered in this work. This confirms that, Shannon entropy function can be considered during the preprocessing work in order to have the better segmentation of the tumor region from the brain MRI dataset.

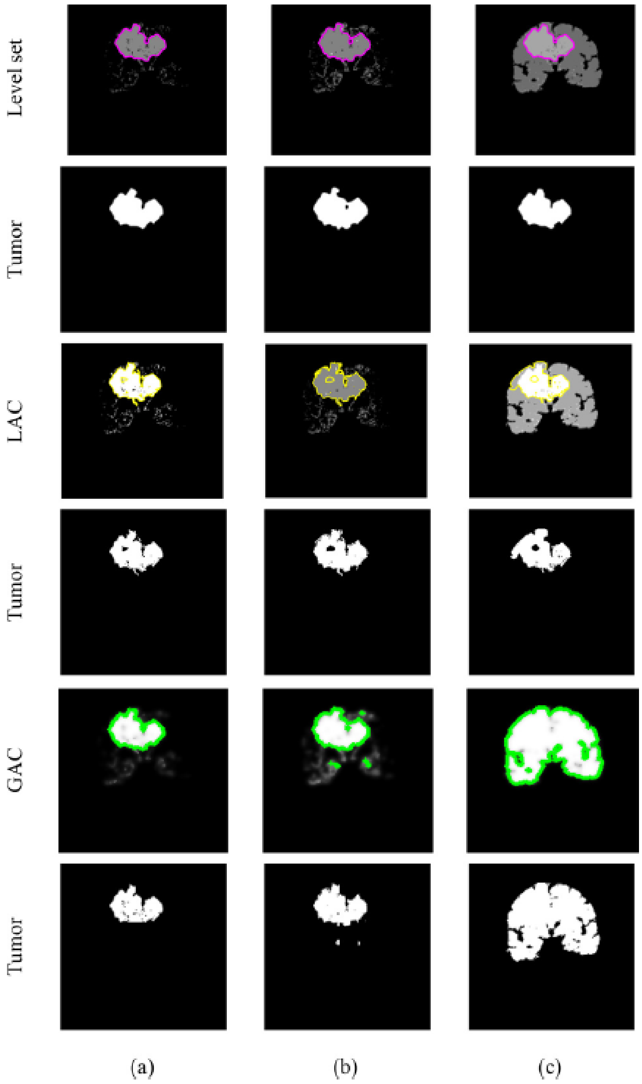

Fig. 3. Segmentation result of Level set and Active contour approaches: (a) Kapur, (b) Tsallis, (c) Shannon.

Fig. 3 shows the experimental result of the post-processing section of Coronal test image. From this result, it can be noted that, the brain MRI extracted using the Shannon entropy and level set offers better result compared with the localized AC (LAC) and global AC (GAC) considered in this work. Similar procedure is repeated for the other test images considered in this work and the results for the sagittal and axial test images. This confirms that, level set approach is superior to the active contour for the proposed segmentation work. Similar approach is then tested on the MICCAI brain tumor segmentation (BRATS) challenge 2012 dataset. During this study, brain MR images of fifteen patients are considered.. During this study, the MR images registered using the Flair, T1C and T2 are considered. This table also shows the ground truth region and the tumor core of the considered MRI slices. The considered dataset does not require the skull stripping section. The tumor extraction procedure is initially implemented for the Flair modality images and the outcome of the pre-processing section. This clearly shows the tri-level threshold images of various entropy values like Kapur, Tsallis and Shannon. During the post-processing operation, the tumor region is extracted from the pre-processed image using the level set approach as discussed earlier and its results, the vital

image metrics, such as the similarity measures and the statistical measures are then computed by comparing the extracted tumor with the ground truth image and the corresponding results.
Similar procedure is then adopted for the modalities T1C and T2 and its results are depicted. TheT1C modality offers only the tumor core and the rest of the modalities are efficient in offering the tumor core and edema sections. In this study, a novel two stage approach by integrating the meta heuristic multi-thresholding and the segmentation approach is presented to extract the tumor region from the well-known brain MRI dataset. This work also presented a detailed comparative study between the well-known entropy approaches such as Kapur, Tsallis and Shannon. This study confirmed that, Shannon's approach is efficient in providing better image quality measures for the considered dataset. Further, a detailed comparative study
among the level set, localized active contour and global active contour also presented. Finally, integration of Shannon entropy with level set segmentation (SE-LS) is validated against the FCM, PSOMRF and PSC using the BRATS dataset and using the images collected from Radiopaedia. From this work, it is confirmed that, the SE-LS offers the superior result compared with the other methods considered in this paper.

4. Conclusion

In this paper, Teaching Learning Based Optimization (TLBO) algorithm assisted segmentation and analysis of brain tumor is demonstrated by considering well known brain MR images. Proposed approach is an automated procedure and effectively extracts the tumor mass from the MRI dataset obtained using various modalities, such as T1, T2 and Flair. The proposed approach is grouped in to two sections, namely the pre-processing region and the post-processing region. The experimental result shows that, combination of Shannon's entropy based thresholding and level set segmentation offers better result for the considered dataset. The competence of the proposed segmentation procedure is validated using the BRATS 2012 dataset. Results of this study also exhibit that, the segmented tumor mass is approximately similar to the ground truth image and offers better values of Jaccard, Dice, FPR and FNR for the T1, T2 and Flair MRI dataset. The accuracy measure values, such as precision, F-measure, sensitivity, specificity, BCR, BER and accuracy are also better. Hence the proposed segmentation approach is clinically significant.

References

1.S. Bauer, R. Wiest, L.P. Nolte, M. Reyes, A survey of MRI-based medical image analysis for brain tumor studies, Phys. Med. Biol. 58 (13) (2013) R97–129,
doi:10.1088/0031-9155/58/13/R97.
2. M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal,
P.M. Jodoin, H. Larochelle, Brain tumor segmentation with deep neural networks, Med. Image Anal. 35 (2017) 18–31, doi:10.1016/j.media.2016.05.004.
3. A.A. Abdullah, B.S. Chize, Z. Zakaria, Design of cellular neural network (CNN)
simulator based on matlab for brain tumor detection, J. Med. Imaging Health
Inform. 2 (3) (2012) 296–306, doi:10.1166/jmihi.2012.1095
4. P. Shanthakumar, P.G. Kumar, Computer aided brain tumor detection system
using watershed segmentation techniques, Int. J. Imaging Syst. Technol. 25 (4)
(2015) 297–301, doi:10.1002/ima.22147.
5. I.D. Bolaño, A clustering-based method for brain tumor segmentation, Contemp. Eng. Sci. 9 (15) (2016) 743–754, doi:10.12988/ces.2016.6564
6. S.V.A. Kumar, B.S. Harish, A Modified intuitionistic fuzzy clustering algorithm for medical image segmentation, J. Intell. Syst. (2017), doi:10.1515/jisys-2016-0241.
7. E. Aslam, Khan, M.M.S. Beg, Improved edge detection algorithm for brain tumor segmentation, Procedia Comput. Sci. 58 (2015) 430–437, doi:10.1016/j.procs.2015.08.057.
8. P. Thirumurugan, P. Shanthakumar, Brain tumor detection and diagnosis using ANFIS classifier, Int. J. Imaging Syst. Tech. 26 (2) (2016) 157–162, doi:10.1002/ima.22170

9. C. Sompong, S. Wongthanavasu, An efficient brain tumor segmentation based on cellular automata and improved tumor-cut algorithm, Expert Syst. Appl. 72 (2016) 231–244, doi:10.1016/j.eswa.2016.10.064
10. Chaddad, Automated feature extraction in brain tumor by magnetic resonance imaging using gaussian mixture models, Int. J. Biomed. Imaging. (2015) 11 Article ID 868031, doi:10.1155/2015/868031
11. S.V.A. Kumar, B.S. Harish, D.S. Guru, Segmenting MRI brain images using evolutionary computation technique, International Conference Cognitive Computing and Information Processing (CCIP), IEEE, 2015, doi:10.1109/CCIP.2015.7100707.
12. B.Goossens Despotovic, W. Philips, MRI segmentation of the human brain: challenges, methods, and applications, Comput. Math. Methods Med. 23 (2015) (Article ID 450341), doi:10.1155/2015/450341
13. R.V. Rao, V.J. Savsani, D.P. Vakharia, Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems, Comput.-Aided Des. 43 (3) (2011) 303–315, doi:10.1016/j.cad.2010.12.015.
14. C. Li, C. Xu, M.D.Fox Gui, Distance regularized level set evolution and its application to image segmentation, IEEE Trans. Image Process. 19 (12) (2010) 3243–
3254, doi:10.1109/TIP.2010.2069690.
15. Abnormal Brain Images; Craniophryngioma, Hhigh gGrade Gglioma and Mmicroadenoma, https://radiopaedia.org. (Case courtesy of A.Prof Frank Gaillard, Radiopaedia.org, rID: 16812; rID: 2589; rID: 5277).