Academic Journal of Cancer Research 9 (4): 75-81, 2016
ISSN 1995-8943

DOI: 10.5829/idosi.ajcr.2016.

Breast Lesion Segmentation Using Generalised Simulated Annealing and Neutrosophic Region Growing Algorithm in Breast MRI

[1]Joe Arun Raja Ponnusamy and [2]C. Nelson Kennedy Babu

[1]ACT College of Engineering and Technology, Nelvoy, Tamilnadu, India
[2]Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamilnadu, India

Abstract: A new method to segment breast lesion in breast MRI was proposed. Early detection and characterization of breast lesion are needed for a better and effective treatment of breast cancer. Hence with the inception of computer-aided detection of breast lesion provides automatic detection of cancer affected breast region. In this paper, a novel segmentation framework of masses on MRI breast images by using improved region growing algorithm called Generalised Simulated Annealing and Neutrosophic Region Growing (GSA-NRG) framework was proposed for breast tumor detection. The GSA-NRG framework comprised of two parts designed with the objective of improving the rate of detection of breast cancer at an early stage. First, a seed point vector was selected automatically from the region of interest based on Generalised Simulated annealing for reducing the breast segmentation time. Finally, the selected seed point vector used in a region growing algorithm based on Neutrosophic logic was presented, ensuring true positive rate or breast cancer detection rate and segmentation accuracy. The results showed that the GSA-NRG framework improves the true positive rate and segmentation accuracy, but also can effectively minimizes processing time.

Key words: Breast Cancer · Breast MRI · Generalised Simulated Annealing · Neutrosophic Logic · Neutrosophic Region Growing · Seed vector

INTRODUCTION

In recent years, technological developments in MRI images have contributed significantly to screening for breast cancer defects in women. It is the second most common reason of deaths in women after lung cancer. Studying how these abnormalities manifest themselves, will require real-time imaging modalities and automated image-processing tools. Two automated methods were presented in Ponnusamy [1] using Region Growing based on Cellular Neural Network (RG-CNN) and Joint Probabilistic seed selection based Fuzzy Region Growing (JPSS-FRG) to diagnose benign and malignant tumors in Breast MRI. Segmentation was performed using Seeded Region growing algorithm. On the other hand, segmentation was performed by Fuzzy region growing algorithm using Joint probabilistic relevance factor.

Modified Automated Seeded Region Growing based on Particle Swarm Optimization (PSO) was presented in Al-Faris *et al*. [2] to perform MRI breast tumour segmentation. A pre-processing stage was involved using level set active contour and morphological thinning. Followed by it, automated thresholding was involved to perform efficient segmentation resulting in the improvement in the detection.

The main aim of this paper was to design and develop a framework for segmenting and improving the segmentation accuracy and breast cancer detection rate using MRI breast images using the above mentioned Generalised Simulated Annealing and Neutrosophic Region growing (GSA-NRG). This paper focused on selecting an appropriate method for each design stage after performing a comparative analysis of the various commonly used methods in each category. The various stages involved in the proposed framework include acquisition of MRI breast images, seed point selection based on Generalised Simulated annealing, followed by a region growing method was designed using Neutrosophic logic for segmentation of MRI breast images.

In this study a new framework for automatic segmentation of MRI breast images for improving the abnormality detection at an early stage was presented.

Corresponding Author: Joe Arun Raja Ponnusamy, ACT College of Engineering and Technology, Nelvoy, Tamilnadu, India.
E-mail: joearunraja@gmail.com.

The proposed GSA-NRG framework for efficient segmentation of MRI breast images is summarized as follows. First of all, correct identification of seeds is made through seed point evaluation reducing the noise present in the images and therefore reducing the segmentation time. Followed by this, a region growing Neutrosophic logic is applied that not only considers the degree of membership and non-membership but also the indeterminacy which in turn resulting in the improvement of breast cancer detection rate and segmentation accuracy. Finally, the proposed method is tested on MRI breast images and the experimental results indicate that the performance of proposed framework is good.

In recent years, several works have reported in the literature for the design and development of methods for segmentation of breast tumour in MRI breast images for early detection. In Melouah [3], a comparison analysis using region growing technique was presented for breast tumour detection, based on thresholding and features similarity. Recently, low level tasks such as edge detection or line detection, energy minimizing approach have an affluent history. An active snake contour model [4] identified salient image contours that greatly enlarge the capture region around features of interest. The combined region growing approach with deformable models proposed by Balakumar [5] to segment brain structure effectively.

Breast cancer has major influential impact on women all over the world. Breast cancer stands next to lung cancer in mortality among women. Various efforts have been made to minimize the false positive and enhance the classification accuracy between benign and malignancy. In Koundal *et al*.[6], LEE and KUAN filters were implemented in Neutrosophic domain for the reduction of speckle noise. PSO and incremental clustering [7] optimized the classification rate by introducing a Gabor filter bank on multi-scale and multi-orientation texture micro-patterns in a mammogram. Yet another method to reduce the false positive rate using circular Hough transform [8] and applying four classification models namely, back propagation algorithm, probabilistic neural network (PNN), learning vector quantization and support vector machine (SVM). Gene expression data were also used as a means for abnormality detection in Mandal *et al.* [9].

Though the rate of breast cancer is exponentially increasing, early detection is highly required for the chance of cure. In Karabtak *et al.* [10], a Color image segmentation method in Neutrosophic domain (NS) was used. Firstly, the image was transformed into NS domain by defining three memberships then alpha mean and beta enhancement operations were used to reduce the indeterminacy. The method suffered from over segmentation and fixed parameters. A watershed segmentation method was employed in Zhang *et al*. [11]. In the first phase image was mapped to NS domain and then Neutrosophic logic and thresholding was used to get binary image. Final segmentation result was obtained from watershed method. The Neutrosophic watershed method had better performance on blurry as well as noisy image.

In Casti *et al*. [12], bilateral masking procedures were adopted for the automatic detection of anatomical landmarks using correlation-based structural similarity indices. The method also used spatial and complex wavelet domains with multidirectional gabor filter to detect the abnormality at an early period. Also, PSO clustering algorithm in Ben Ali [13] resulted in the improvement of classification rate. A multi-threshold model based on co-occurrence matrix was presented in Kaur *et al*. [14] on brain tumour images to reduce the error rate in identifying the detection rate.

Early detection of breast cancer not only helps in providing accurate and timely treatments to the patients but also helps in increasing their life expectancy through efforts. In Li *et al.* [15], tumor detection based on Ensemble Empirical Mode Decomposition (EEMD) method was constructed to provide correct tumor information at an early stage. A region growing method on the basis of frequency occurrence in the image was presented in Kansal and Jain [16] using automated seed selection not only eliminated the problem of over segmentation but also provided solution towards under segmentation.

Accurate and automatic location of region of interests plays a major role in early detection. In Xian *et al.* [17], adaptive reference point generation algorithm was designed in which the cost function was defined in terms of tumor's boundary and region information in both frequency and space which was proven to be more accurate and robust in segmenting Breast Ultra Sound (BUS) images. An automatic segmentation method to extract breast portion including tumor or abnormalities was presented in Rajkumar and Raju [18]. Max-Min and Least Variance [19] technique were introduced to detect the tumor cells for the detection of breast cancer. A Neutrosophic L-means Clustering method was designed in Shan *et al.* [20] to detect tumour in breast ultrasound images.

In this proposed work, a segmentation framework with appropriate seed point selection using Generalised Simulated Annealing for MRI breast tumor segmentation was presented using Neutrosophic region growing algorithm.

MATERIALS AND METHODS

The Generalised Simulated Annealing and Neutrosophic Region Growing (GSA-NRG) starts with a seed point selection using Generalised Simulated Annealing that is followed by the Neutrosophic Region Growing method for Breast MRI image segmentation. Then the threshold selection processes based on K-means algorithm before the Neutrosophic Region growing algorithm were applied. The whole perspective of GSA-NRG framework is shown in Fig. 1.

The elaborate description of GSA-NRG framework was divided into two parts namely, seed point selection using Generalised Simulated Annealing, Secondly, region growing with the aid of Neutrosophic Logic. The Breast MRI images selected from RIDER MRI dataset [21] to evaluate the proposed algorithm. The detailed description was provided in the forthcoming sections.

GSA-NRG Framework

Generalised Simulated Annealing: A seed point being the pivotal element for region growing and its accurate selection is highly necessary for efficient segmentation. If a seed point is either selected outside the region of interests (ROI) or inside the ROI, the resultant final segmentation may not give appropriate results. Due to the minimum quality of MRI images, most of the region growing mechanisms require the accurate seed point selection. In this work, a seed point selection mechanism was developed for MRI breast images.

A novel seed selection method was designed on the basis of probabilistic relevance factor that ensures region growing stability, while extensively minimizing the human interference. Some researchers used center of the region of interest [3] to select seeds. As a result, the seed presented was beside the edge. But in order to obtain accurate and good segmentation result, the GSA-NRG considers both the magnitude and structure features from the entire image.

Let us considered image vector in order to obtain the seed point, where each cluster was considered as initial seeds of vector were obtained as given below.

$$V(l) = \frac{S((i-1)*d+l}{M}*(R(q)-L(q))+L(q) \quad (1)$$

$$\min p(x(q)) = L(q) \quad (2)$$

$$\max p(n(q)) = R(q) \quad (3)$$

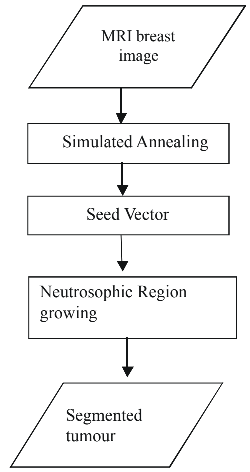


Fig. 1: GSA-NRG framework

From (1), (2) and (3), the initial seeds of image vector were obtained. Perturbation function was performed unit perturbation function over solution vector S for perturb factor (P-Factor) timed.

$$P-Factor = \left[\frac{NIP}{NI}*(NIP-1)+0.5\right] \quad (4)$$

With the initial values of T_0 be the number of perturbations for the objective function value and increase in objective function value was observed respectively with acceptance probability.

As illustrated in Fig. 2, for each image and pixels, the Generalised Simulated Annealing considered both the perturbation factor and objective function to obtain the seed point selection. With this consideration of perturbation factor, the breast tumour segmentation is performed at an early stage, therefore improving the segmentation time.

Neutrosophic Region Growing Method: With the obtained seed points, the next step in the GSA-NRG is the design of Neutrosophic Region Growing method for mammogram image segmentation to detect breast cancer. In Shan *et al.* [20], a seed point be at its subset, a degree of membership as true ‘TS’, a degree of indeterminacy ‘IS’ and a degree of non-membership as false ‘FS’ respectively method for segmentation of MRI images.

Let us consider the image in Neutrosophic domain as P_{ns}(TS, IS, FS). Then, the degree of true membership D(TS), degree of Indeterminate D(IS), degree of false membership is as given D(F) below.

$$TS(i,j) = \frac{LM(i,j)-LM\min}{LM\max-LM\min} \quad (5)$$

Input: Image vector , S_0 , E_0 ,S_f ,E_f ,T_0 ,T_f , MI, NI
Output: seed points
Begin
Initialize S_0, E_0= NL-Means(S), p= NI
While(T_0>T_f)
Begin
S_1=perturb(S_0, p)
E_1=NL-means(S_1)
Iff(e_1<e_0)v(exp(-(E_1-E_0)/T_0) >random(0, 1))
S_0=S_1, E_0=E_1;
K=k+1
End
P=p+1
T_0=δ*T_0;
End
Output S_0

Fig. 2: Generalised Simulated Annealing.

$$IS(i,j) = \frac{AD(i,j) - AD\min}{AD\max - AD\min} \quad (6)$$

$$FS(i,j) = 1 - TS(i,j) \quad (7)$$

From (6), (7) and (8), with the true membership, Indeterminate membership and false membership is evolved. With this value, the mean difference between the current pixel and the current lesion region's mean, ensures as a means for region growing. This in turn helps in arriving at if the current pixel should be included into the region or not.

Input: Image vector, seed point
Output: region detection
Begin
For each obtained seed from generalised simulated annealing
Initialize membership matrix U_k= u_{xy} ;K=0.
Here x is pixel index, y is the region index and k is the iteration number
K=k+1 at the kth iteration ,
calculate TS, IS and FS for image P_{ns} by using Eq. (5), (6), (7) and
transform TS and IS into vector VT and VI
Calculate the center vector lk=lq using Uk , VT and VI
Update the membership matrix Uk+1 =Uxy
Where L is the number of regions and Update Image
If Uk< E stop: otherwise goto step 2
End for
End

Fig. 3: Neutrosophic Region Growing Algorithm

As illustrated in Fig. 3, for each seed measured through seed point, degree of true, false and indeterminacy membership value is evaluated. With this resultant value obtained, the region growing is ensured using Neutrosophic logic that separates theregion correctly, ensuring true positive rate and segmentation accuracy.

RESULTS AND DISCUSSION

The segmentation accuracy depends upon the number of correctly segmented samples (i.e., true negative and true positive) [6] and is calculated as follows:

$$Accuracy = \left(\frac{TP + TN}{N}\right) * 100 \quad (8)$$

From (8), the segmentation accuracy 'Accuracy' was measured using the true positive rate 'TP', true negative rate 'TN' with respect to total number of images 'N' respectively.

The comparison of segmentation accuracy is presented in Table1 with respect to the differing MRI breast images in the size of 2 to 14. While increasing the number of images, the segmentation accuracy also gets increased. The table shows that the comparison results of three different methods RG-CNN [1], SRG based on PSO [2] and GSA-NRG framework. From the result, the proposed GSA-NRG framework increased the performance result than the existing methods.

Fig. 4 shows while increasing the image size, the segmentation accuracy are also increased, though node linearly in all the methods. But comparatively, it is increased in the proposed GSA-NRG framework. Fig.5 illustrates that the segmentation accuracy based on the different number of images. From the results, it is clearly reported that the proposed GSA-NRG framework improves the performance results in terms of segmentation accuracy than the state- of- the- art methods [1, 2].

Furthermore, with the ability to capture both the internal and external factors during the segmentation enhanced further the segmentation accuracy. Also, by applying seed vector and image map obtained, Neutrosophic Region growing method separated the region in a correct manner thereby ensuring the original MRI breast images possessing precise edges with good segmentation results. Therefore, the proposed GSA-NRG framework improved breast lesion segmentation accuracy and reduced the noise. This helps to improve the segmentation accuracy in GSA-NRG framework by 9% compared to RG-CNN [1] and 12% compared to SRG based on PSO [2] respectively.

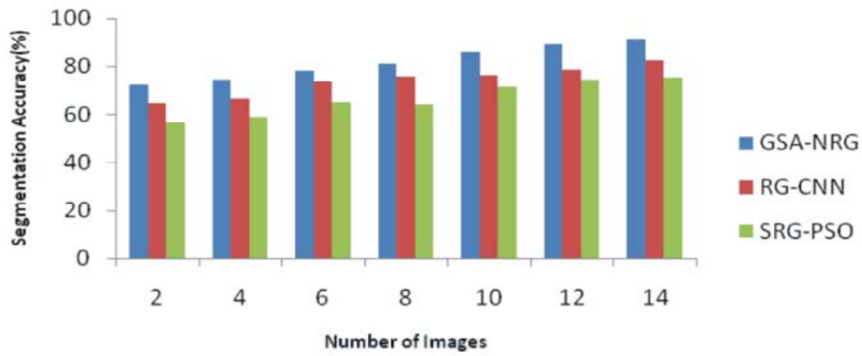
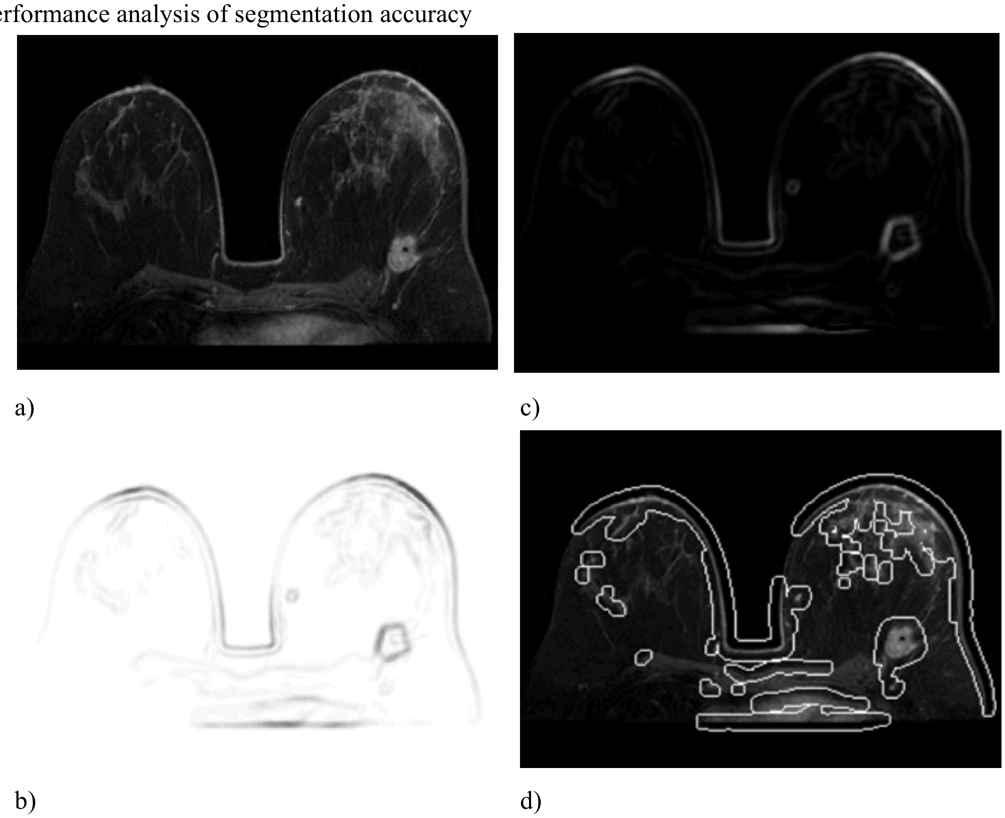


Fig. 4: Performance analysis of segmentation accuracy



a) Original MRI b) Indeterminate Image c) Homogenity Image d) Segmented Image

Fig. 5: Illustrated Neutrosophic Region Growing Algorithm

Table 1: Comparative performance of segmentation accuracy

	Segmentation accuracy (%)		
Number of images	GSA-NRG	RG-CNN	SRG -PSO
2	72.34	64.4	56.33
4	74.47	66.53	58.56
6	78.17	73.4	65.13
8	81.23	75.56	64.15
10	86.15	76.21	71.17
12	89.37	78.43	74.39
14	91.34	82.36	75.32

CONCLUSIONS

In this paper, a novel segmentation framework using Generalised Simulated annealing and Neutrosophic Region Growing (GSA-NRG) framework for breast tumor detection on MRI breast images was presented. This framework reduced the segmentation time by the optimal seed selection and therefore provided abnormality detection of disease on MRI breast images at an early stage. The goal of MRI breast image segmentation is to improve the true positive rate using the training and test images which significantly contribute to the relevance. To do this, a generalised simulated annealing based seed point selection was designed to select the seed point vector based on the perturbation factor and magnitude to reduce the noise. Then, based on this measure, a Neutrosophic Region Growing algorithm was proposed that identifies the correct regions and finally obtains the segmented region improving the segmentation accuracy and breast cancer detection rate. Through the experiments, observed that the GSA-NRG algorithm provided more accurate results compared to existing segmentation methods. The results showed that GSA-NRG framework offers better performance with an improvement of segmentation accuracy by 9% and improving the true positive rate by 12% compared to existing methods respectively.

REFERENCES

1. Ponnusamy, J.A.R. and N.K. Babu, 2016. Joint Probabilistic seed selection based fuzzy region growing algorithm to segment tumour on breast MRI, International Journal of Printing, Packaging and Allied Sciences, 4(2): 1428-1437.
2. Al-Faris A.Q., U.K. Ngah, N.A.M. Isa and I.L. Shuaib, 2014. Computer Aided segmentation system for Breast MRI tumour using modified automatic seeded region growing, J. Digital Imaging, 27(1): 133-144.
3. Ahlem Melouah, 2015. Comparison of Automatic Seed Generation Methods for Breast Tumor Detection Using Region Growing Technique, Computer Science and Its Applications, Springer, 456: 119-128.
4. Kass, M.A., 1988. Snakes: active contour models, International Journal of Computer Vision, 1(4): 321-331.
5. Balakumar, B. and P. Raviraj, 2015. Automated Detection of Gray Matter in MRI Brain Tumor Segmentation and Deep Brain Structures Based Segmentation Methodology, Middle-East Journal of Scientific Research, 23(6): 1023-1029.
6. Koundal, D., S. Gupta and S. Singh, 2016. Speckle reduction method for thyroid ultrasound images in Neutrosophic domain, IET Image Processing, 10(2): 167-75.
7. Salabat Khana Hussain M., H. Aboalsamh, H. Mathkour, G. Bebisc and M. Zakariah, 2016. Optimized Gabor features for mass classification in mammography, Applied Soft Computing, Elsevier, 44: 267-280.
8. Yasmeen, M.G. *et al*., 2014. Remote Computer-Aided Breast Cancer Detection and Diagnosis System Based on Cytological Images, IEEE Systems Journal, 8(3): 949-964.
9. Monalisa, M., M. Jyotirmay and A. Mukhopadhyay, 2015. A PSO-based Approach for Pathway Marker Identification from Gene Expression Data, IEEE Transactions on NanoBioscience, 14(6): 591-597.
10. Karabtak, E., Y. Guo and A. Sengur, 2013. A Modified Neutrosophic Approach to color image segmentation, Journal of Electronic Imaging, 22(1): 1-11.
11. Zhang, M., L. Zhang and H.D. Cheng, 2010. A Neturosophic approach to image segmentation based on watershed method, Signal Processing, 90(5): 1510-1517.
12. Casti, P., A. Mencattini, M. Salmeri and M.R. Rangayyan, 2015. Analysis of Structural Similarity in Mammograms for Detection of Bilateral Asymmetry, IEEE Transactions on Medical Imaging, 34(2): 662-671.
13. Ben Ali, Y.M., 2015. Unsupervised Clustering Based an Adaptive Particle Swarm Optimization Algorithm, Neural Processing Letters, Springer, 44(1): 221-244.
14. Kaur, T., S. Saini and S. Gupta, 2016. Optimized Multi Threshold Brain Tumor Image Segmentation Using Two Dimensional Minimum Cross Entropy Based on Co-occurrence Matrix, Studies in Computational Intelligence, Springer, 651: 461-486.
15. Qinwei Li, X. Xiao, L. Wang, H. Song, H. Kono, P. Liu, H. Lu and T. Kikkawa, 2015. Direct Extraction of Tumor Response Based on Ensemble Empirical Mode Decomposition for Image Reconstruction of Early Breast Cancer Detection by UWB, IEEE Transactions on Biomedical Circuits And Systems, 9(5): 710-724.
16. Kansal, S. and P. Jain, 2015. Automatic Seed Selection Algorithm For Image Segmentation Using Region Growing, International Journal of Advances in Engineering & Technology, 8(3): 362-367.
17. Min Xian, Zhang Y. and H.D. Cheng, 2014. Fully automatic segmentation of breast ultrasound images based on breast characteristics in space and frequency domains, Pattern Recognition, Elsevier, 48(2) :485-497.
18. Rajkumar, K.K. and G. Raju, 2015. Automated Mammogram Segmentation Using Seed Point Identification and Modified Region Growing Algorithm, British Journal of Applied Science & Technology, 6(4): 378-385.

19. Singh, A.K. and B. Gupta, 2015. A Novel Approach for Breast Cancer Detection and Segmentation in a Mammogram, Elsevier, Procedia of Computer Science, 54: 676-682.
20. Shan, J., H.D. Cheng and Y. Wang, 2012. A novel segmentation method for breast ultrasound images based on neutrosophic l-means clustering, Medical Physics, 39(9): 5669-5682.
21. The Reference Image Database to Evaluate Therapy Response(RIDER) downloaded from https://wiki.cancerimagingarchive.net/display/Public/RIDER+Breast+MRI.