

Novel MRI Image Biomarker Segmentation Using Fuzzy Neutrosophic Confidence Region Growing Algorithm

Joe Arun Raja P^{1*}, Dr. C.Nelson Kennedy Babu²

¹Assistant Professor, Department of Networking,
Subbalakshmi Lakshminpathy College of Science, Madurai, Tamilnadu, India.
¹Research Scholar, Manonmaniam Sundaranar University, Tirunelveli, India.
*Corresponding Author

²Professor and Dean, Department of Computer science & Engineering,
SMK Fomra Institute of Technology, Chennai, Tamilnadu, India.

Abstract

A new method to segment image biomarker in breast MRI is proposed. Early detection and characterization of image biomarker are needed for a better and effective treatment of radiotherapy to cancer. Hence with the inception of Image guided radiotherapy to breast lesion provides new arena for quantitative image biomarker segmentation. In this paper, a novel segmentation framework of image biomarker on MRI breast images by using improved region growing algorithm called Fuzzy-Neutrosophic Confidence connected Region Growing (FNCRG) algorithm. The FNCRG framework comprises of three parts designed with the objective of improving quantitative image biomarker segmentation. First, Breast anatomical structure detection using fuzzy rules to select candidate frame of ROI. Second, a seed point is detected by cover tree, which is initial seed derived from cover tree of nearest neighbour for reducing the breast segmentation time. Finally, from the collection of nearest neighbour pixel values, a Neutrosophic confidence interval is measured to detect similarity among pixels. Further, region growing algorithm based on Neutrosophic similarity measure is presented, ensuring true positive rate. The results show that the FNCRG framework improves the classification index of detection at an early stage, but also can effectively minimize the human intervention to certain extent.

Keywords: Neutrosophic Confidence, Fuzzy Rule, Image Biomarker, Region growing, Cover Tree.

1. INTRODUCTION

1.1. Quantitative Imaging

The image biomarker standardisation initiative (IBSI) is an independent international collaboration which works towards standardising the extraction of image biomarkers from acquired imaging for the purpose of high-throughput quantitative image analysis [1]. Quantitative imaging helps oncologist to measure the cancerous spot using image intensities. Further, patients undergone neo adjuvant chemotherapy with regular interval of period may have variance in malignancy so we are selecting RIDER data set, which would be useful to study breast lesion variance among female patients through quantitative imaging.

1.2. Image Biomarker

A Breast imaging biomarker is an image feature, or biomarker detectable in an image. In personalized medicine, breast imaging biomarker is relevant to cancer prognosis [2]. Many parameters of biomarkers are used to reveal risk of Breast cancer. First, a simple lesion in the Breast detected by Mammography or MRI can lead to the suspicion of a carcinoma. The lesion itself serves as a biomarker, but details of the lesion serve as biomarkers as well, and can collectively be used to assess the risk of cancer. Some of the imaging biomarkers used in breast cancer assessment includes size, Mammographic Spiculated Masses, calcification, location within the breast, rate of growth, and rate of metabolism. Breast imaging biomarkers can be measured using CT, Mammography, and MRI. So, the paper investigates on Breast MRI Biomarker in following sections.

2. RELATED WORKS

Breast cancer (BC) is the fourth leading cause of cancer deaths among women [3], being responsible for 6% of all cancer-related deaths and it is very difficult to diagnose in its early stages. At the time of diagnosis, 26% have survival rate, past 5 years only 21.5% of survival rate has been recorded [4].

Confidence connected region growing method used for automatic segmentation of liver and Alternative Fuzzy C-Mean clustering for lesion segmentation [5]. Joe et al [6] proposed segmentation framework with appropriate seed point selection using fuzzy region growing for MRI breast tumour segmentation is presented using Joint Probabilistic Seed Selection. Another segmentation method also developed by Joe et al [7] with Generalised simulated annealing for seed point selection, then Neutrosophic region growing to segment MRI breast tumour.

3. MATERIALS AND METHODS

3.1. MRI dataset

The Reference Image Database to Evaluate Therapy Response (RIDER) Breast MRI [8] is a targeted data collection neo adjuvant therapy treated female patient's breast MRI with

regular time interval, which is used to analyse of quantitative imaging methods applied to measure the response to drug or radiation therapy.

3.2. Fuzzy Neutrosophic Confidence Connected Region Growing Framework

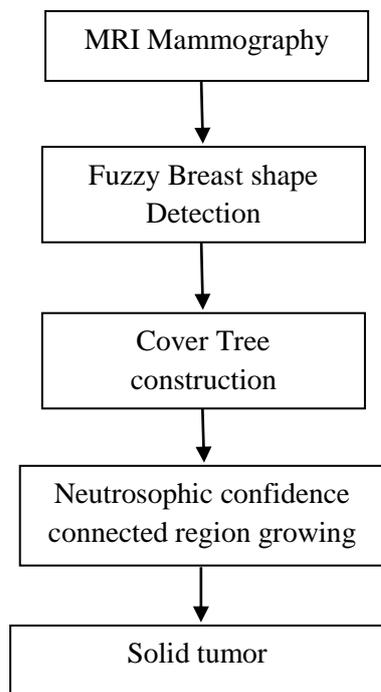


Figure 1. Fuzzy Neutrosophic Confidence connected Region growing framework

The FNCRG framework (Figure 1) comprises of three parts designed with the objective of improving the rate of detection of breast cancer at an early stage. First, Breast anatomical structure detection using fuzzy rules to select candidate frame of ROI. Second, a seed point is selected by human from the mass region based on intuition, which is used as the initial

index to construct cover tree of nearest neighbour for reducing the breast segmentation time. Finally, from the collection of nearest neighbour pixel values, a Neutrosophic confidence connected region growing algorithm based on scale key points is presented, ensuring breast cancer detection rate.

3.3. Fuzzy Rule for Breast Structure Detection

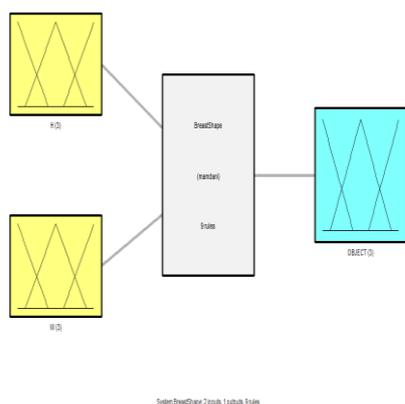
In DICOM, we need to select the candidate frame of full breast because DICOM sequences dynamically varied due to patient body structure and scanning factors. So we are using fuzzy rules to detect the full anatomical structure of breast [9], mean while the candidate frame with full breast can be identified. The following table 1 show intuitive fuzzy rule are based on mamdani fuzzy Rules systems [10].

Table 1. Fuzzy Rules for Full breast

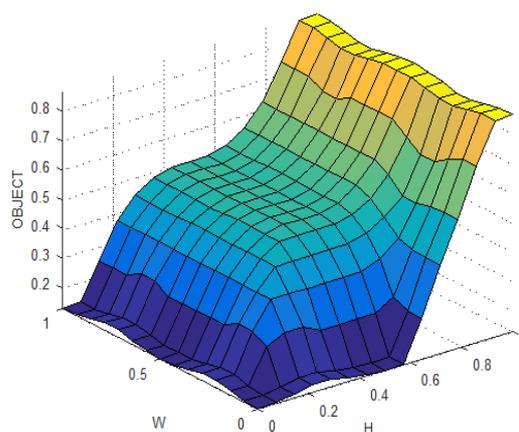
1. If (HTH is LOW) and (WTH is LOW) then (OBJECT is SMALL)
2. If (HTH Is LOW) and (WTH is MEDIUM) then (OBJECT is SMALL)
3. If (HTH is LOW) and (WTH is HIGH) then (OBJECT is SMALL)
4. If (HTH is MEDIUM) and (WTH is LOW) then (OBJECT is SMALL)
5. If (HTH is MEDIUM) and (WTH is MEDIUM) then (OBJECT is BREAST)
6. If (HTH is MEDIUM) and (WTH is HIGH) then (OBJECT is LARGE)
7. If (HTH is HIGH) and (WTH is LOW) then (OBJECT is LARGE)
8. If (HTH is HIGH) and (WTH is MEDIUM) then (OBJECT is LARGE)
9. If (HTH is HIGH) and (WTH is HIGH) then (OBJECT is LARGE)

Where WTH= width, HTH= height and OBJECT size in Micrometers.
 $20 \leq HTH \leq 60$ $20 \leq WTH \leq 80$ $-0.4 \leq O \leq 0.4$.

In Table 1, two fuzzy variables of object are declared as height and width. The parameters of HTH from 20 mm to 60 mm and WTH from 20 mm to 80 mm. Mamdani fuzzy rule inference is used to determine the Breast object. Where HTH and WTH are medium to select full breast object as well as candidate frame of MRI sequence.



a) Mamdani Fuzzy Inference System



b) Heat map of Fuzzy Inference

Figure 2. Fuzzy Rule based Breast Shape Detection

Breast shape detection is detected using fuzzy rule shown in figure 2a and Heat map of fuzzy inference in figure 2b. Parameters are medium to capture the candidate frame of full breast.

3.4. Cover Tree Construction

The cover tree can be a data structure to cover the children from root by distance 2^i . The level of cover tree C is descended by level of one [11]. It can be also used to approximate the nearest neighbour points as shown in figure 3. Each level of C in the cover tree has three important properties as follows

- $c_i \in c_{i-1}$
- For every point c_i in c_{i-1} , there exists a point in c_i in such that the distance from p to q is less than or equal to 2^i and exactly one such q is a parent of p .
- For all points $c_i \{p, q\}$, the distance from p to q is greater than 2^i .

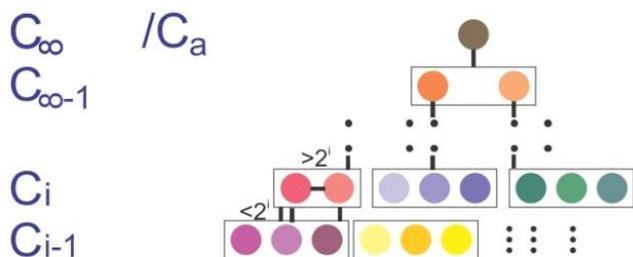


Figure 3. Cover Tree for nearest neighbours

Here, we are making multipoint cover tree with nearest neighbour by 2^i . The seed point is used as the initial index or root to construct cover tree of nearest neighbour for reducing the breast segmentation time. Further, Vector of seed pixels are parameters of proposed region growing algorithm.

3.5. Neutrosophic Confidence Connected Region Growing

In Neutrosophic confidence connected region growing algorithm, first MRI Image, Neutrosophic Confidence value, and Region of Interest are given as input. The following formula is used to compute Neutrosophic confidence interval value between image pixels in each voxel region.

$$\bar{x} \pm (z \text{ critical value}) \cdot \frac{\sigma}{\sqrt{n}}$$

Where \bar{x} is Neutrosophic mean and constant $z = 2.58$. The z critical value 1.645 corresponds to the confidence level of 90%, the z critical value 1.96 corresponds to the confidence level of 95%, and the z critical value 2.58 corresponds to the confidence level of 99%, similarly as in classical statistics [12].

First, compute Neutrosophic mean and Neutrosophic standard deviation between voxel points as shown in table 2, where the mean value is used to add more voxel region V_0 . V_0 is region of interest which is selected by the radiologist during the protocol. Secondly, Cover tree is used to select the initial seed from the seed vector which is from ROI. Finally, the iterative steps to grow the region from seed pixel until no more voxel to be added.

Table 2. Neutrosophic confidence connected region growing algorithm

<p>$C(f) = \text{NCRG}(I, z, \text{ROI})$</p> <p>Input:</p> <p>I: MRI image;</p> <p>z: Neutrosophic confidence value</p> <p>ROI: a rough rectangular region of interest manually drawn to enclose the tumor.</p> <p>Set parameters and number of iterations J;</p> <p>Initialization:</p> <p>Identify the seed point V_0 as the voxel with the maximum intensity in the ROI;</p> <p>Compute the initial Neutrosophic mean (m_0) and Neutrosophic standard deviation (s_0) of the intensity for all voxels in the window centred at V_0;</p> <p>Let current region $R = \{V_0\}$.</p> <p>Iteration:</p> <p>For $i = 1:J$</p> <p>$m_i = m_{i-1}$; $s_i = s_{i-1}$;</p> <p>Begin</p> <p>For each neighbour V of all voxels in R,</p> <p>If $V \in \text{ROI}$, $V \in R$ and $I(V) \leq [m_i - z \cdot s_i, m_i + z \cdot s_i]$, add V into R;</p> <p>If no more V can be added, break; End</p>

4. RESULTS

A comparative analysis of the FNCRG, JPSS-FRG framework and GSA-NRG framework is given below based on true positive rate. From Table 3, it can be observed that the JPSS-FRG framework performs better in comparison to all other methods.

Table 3. Comparative performance to measure true positive rate

Number of images	True positive rate (%)		
	FNCRG	GSA-NRG	JPSS-FRG
2	69.37	72.83	79.32
4	73.58	78.11	81.45
6	77.37	79.67	84.15
8	81.29	84.81	87.10
10	85.18	86.92	89.13
12	88.97	89.43	91.35
14	92.52	91.13	94.28

The true positive rate of Breast MR Image gradually improved from 69%, if we increase the sample images achieved maximum of 93%.

Our proposed method FNCRG is low positive rate compared to JPSS –FRG method. But segmentation time is improved to 12% compared to other state-of-the-art methods.

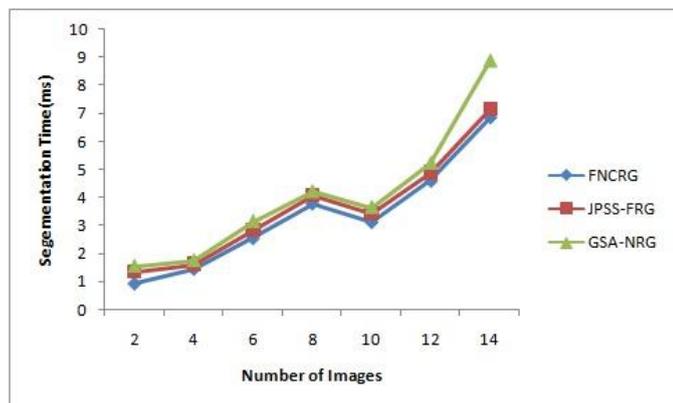


Figure 4. Segmentation time of FNCRG

Table 4. Quantitative Breast MRI Biomarker

Image Set	Image Biomarker (cm)	DICE score
BMR 1	2.47 ± 0.5	0.92
BMR 2	1.82 ± 0.5	0.74
BMR 3	1.73 ± 0.5	0.93
BMR 4	0.92 ± 0.5	0.72
BMR 5	1.48 ± 0.5	0.79

The quantitative Breast MRI biomarker is calculated using proposed FNCRG algorithm. Obviously, Table 4 shows the similarity score of each set of images are studied using DICE score. Each set of images have different set of noise so the similarity score is varied from 0.74 to 0.93.

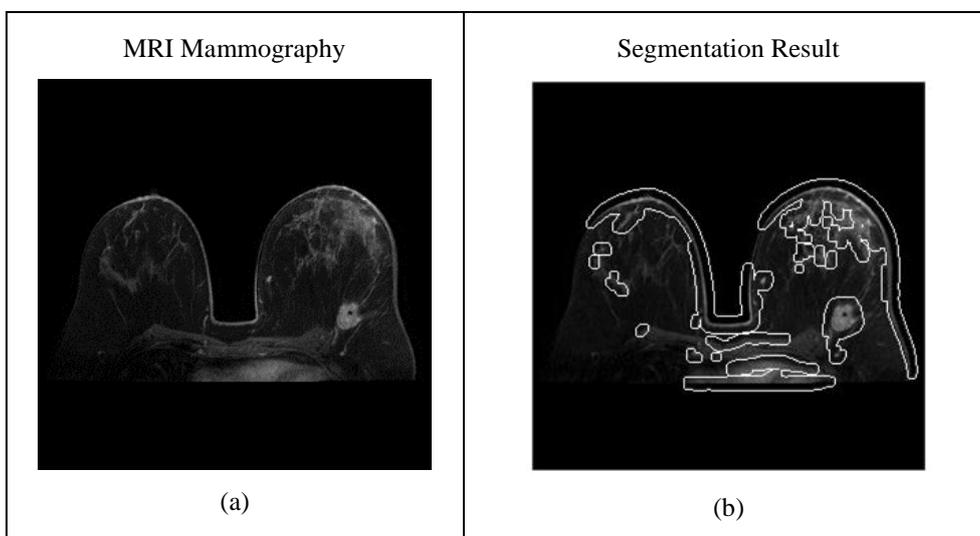


Figure 5 a) MRI Mammography b) FNCRG Segmentation Output

From Figure 5b, it can be observed that the FNCRG framework segmented the malignant from region of interest which is set by the radiologist. Due to same intensity of ROI threshold, the internal organ and outer skin area also segmented.

5. CONCLUSION

In this work, a novel segmentation framework using Fuzzy Neutrosophic confidence connected Region Growing (FNCRG) framework for breast tumor detection on MRI breast images is presented. The framework reduces the 12% of segmentation time during the seed selection and therefore breast cancer detection rate of disease on MRI breast images with the maximum of 93%. 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.

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Conflict of Interest

No conflict of interest between authors including honorarium, grants, membership, employment, ownership of stock or any other interest or non-financial interest such as personal or professional relation, affiliation and knowledge of the research topic.

REFERENCES

- [1] Zwanenburg, A., Leger, S., Vallières, M. and Löck, S., , 2016 “Image biomarker standardisation initiative”. arXiv preprint arXiv:1612.07003.
- [2] K. Ricketts, C. Guazzoni, A. Castoldi, V. L. Rosa, A. Gibson, M. Loizidou, and G. Royle, , 2013 “OC-0153: A quantitative technique for simultaneous imaging of multiple biomarkers,” *Radiotherapy and Oncology*, vol. 106.
- [3] C. Bright, D. Rea, A. Francis, and R. Feltbower, , 2016 ,“Comparison of quadrant-specific breast cancer incidence trends in the United States and England between 1975 and 2013,” *Cancer Epidemiology*, vol. 44, pp. 186–194.
- [4] N. M. Hylton, et al. 2016, “Neoadjuvant Chemotherapy for Breast Cancer: Functional Tumor Volume by MR Imaging Predicts Recurrence-free Survival—Results from the ACRIN 6657/CALGB 150007 I-SPY 1 TRIAL,” *Radiology*, vol. 279, no. 1, pp. 44–55.
- [5] S. S. Kumar, R. S. Moni, and J. Rajeesh, , 2011. “Automatic liver and lesion segmentation: a primary step in diagnosis of liver diseases,” *Signal, Image and Video Processing*, vol. 7, no. 1, pp. 163–172.
- [6] Joe Arun Raja , Nelson Kennedy Babu ,2016 ,“Joint Probabilistic seed selection based fuzzy region growing algorithm to segment tumour on breast MRI”, *International Journal of Printing, Packaging & Allied Sciences*, 2016, Vol. 4, No. 2, 1428-1437.
- [7] Joe Arun Raja , Nelson Kennedy Babu ,2016 “Breast Lesion Segmentation Using Generalised Simulated Annealing and Neutrosophic Region Growing Algorithm in Breast MRI”, *Academic Journal of Cancer Research*, 9(4):75-81.
- [8] Meyer, Charles R, Chenevert, Thomas L, Galbán, Craig J, Johnson, Timothy D, Hamstra, Daniel A, Rehemtulla, Alnawaz, & Ross, Brian D. , 2015 ,“Data From RIDER Breast MRI”, *The Cancer Imaging Archive*.
- [9] Selvi MC ., Muneeswarn K., 2015, “Neural Fuzzy based Human Object Detection Algorithm for Unconstrained Surveillance Videos” , *International Journal of Applied Engineering Research.*, Vol. No 20.18761-18769
- [10] AliKeles, AytürkKele saugur Yavuz, 2011, “Expert system based on neuro-fuzzy rules for diagnosis breast cancer, *Expert Systems with Applications*”, Volume 38, Issue 5, Pages 5719-5726
- [11] Izbicki M, Shelton C, 2015, "Faster cover trees" *International Conference on Machine Learning*.
- [12] Smarandache .F, , 2014, “Introduction to neutrosophic statistics”, Craiova, Romania: Sitech & Education Publishing.