

# Adaptive Region Growing Image Segmentation Algorithms for Breast MRI



Joe Arun Raja, Nelson Kennedy Babu

**Abstract:** Early detection and characterization of breast lesion are important for a better and effective treatment of breast cancer. In this paper, four different adaptive region growing image segmentation algorithms are compared. In fact, seed selection was a vital step in the success of region growing methods, so, better schemes for seed selection methods are proposed, namely, joint probabilistic seed selection (JPSS) and Generalised simulated annealing (GSA) based seed selection. The proposed region growing methods namely Fuzzy Region Growing (FRG) and Neutrosophic Region Growing (NRG) are integrated as JPSS-FRG and GSA-NRG frameworks. Another two methods are Scale Invariant Region growing (SiRG) and Fuzzy Neutrosophic Confidence Region growing (FNCRG). The results showed that FNCRG algorithm increases breast cancer detection rate on MRI breast images with the maximum of 93% is achieved. SiRG algorithm improves the true positive rate by 13% compared to existing methods. Further, GSA-NRG makes better segmentation accuracy by 9% and true positive rate by 12%. Also, JPSS-FRG algorithm enhances segmentation accuracy by 24% and improving the true positive rate by 27% compared to Region Growing-Cellular Neural Network (RG-CNN) and Seeded Region Growing-Particle swarm optimization (SRG-PSO) methods respectively.

**Keywords:** Breast MRI, Fuzzy Logic, Neutrosophic logic, Region growing algorithm.

## I. INTRODUCTION

Breast Cancer tumour detection, based on Joint Probabilistic Seed Selection-Fuzzy Region Growing method is identifying probabilistic relevance factor of magnitude and structure features to get accurate seed point in region of interest, then segment solid tumour by aggregating neighbor pixel with fuzzy member functions and gradient vector applied to determine boundary criteria.

Generalised Simulated Annealing-Neutrosophic Region Growing algorithm is considering both perturbation factor and objective function of magnitude and structure features to obtain the seed pixel, then a seed pixel be a part of neutrosophic set where the degree of membership are

computing to identify nearest related pixels for region growing.

These proposed methods are compared with the existing tumor segmentation based on Region Growing and Cellular Neural Network segmentation (RG-CNN) algorithm [1] and modified automatic Seeded Region Growing based on Particle Swarm Optimization (SRG-PSO) image segmentation algorithm [2]. The experiment is conducted on different number of MRI breast images dataset with performance factors such as segmentation time, segmentation accuracy and true positive rate.

## PERFORMANCE FACTORS FOR IMAGE SEGMENTATION TECHNIQUES

### A. Segmentation time

In Medical Image processing, computational time efficiency is critical parameter because of emergency medical imaging modalities to save human life. Image segmentation time (i.e Computational Time) is higher in computer aided diagnosis systems nowadays. MATLAB image processing toolbox automatically calculates computational time in seconds. So, the efficacy of segmentation time of proposed methods studied as per benchmark in the literature.

### B. True Positive Rate

True Positive Rate (i.e Sensitivity) means acceptable rate of cancer detection through medical image information using computer algorithms. Statistical parameters like precision and recall along with F-measure are used to measure sensitivity.

### C. Segmentation Accuracy

Segmentation Accuracy means spot on volume measurement of cancerous part of ROI equivalence to manually identified volume measurement of breast lesion or malignant by medical radiologist.

## II. PERFORMANCE OF ADAPTIVE REGION GROWING ALGORITHMS BASED ON IMAGE SEGMENTATION TIME

In MRI based diagnosis system, as per DICOM (Digital Imaging and Communication in Medicine) standard size of the images are in Giga bytes. Image acquisitions are done in 2D and 3D modalities. This investigation studied on 2D-MRI modality so reducing MRI Image segmentation time gives prompt interventional radiology reports.

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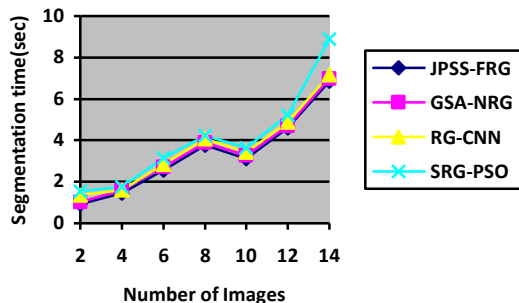
Image Segmentation time represents the time taken by different image segmentation methods for a given sample image. A lower segmentation time means faster computation and early detection of breast cancer. The comparison of segmentation time is presented in Table I with respect to the number of images (2-14) obtained from female cancer patients is provided.

The simulated results reveal that proposed JPSS-FRG framework [7] improves the performance in terms of segmentation time (seconds) than the state-of-the-art methods.

**Table- I: Performance analysis by Segmentation time**

No of Images	Segmentation time(sec)			
	JPSS-FRG	GSA-NRG	RG-CNN	SRG-PSO
2	0.93	1.01	1.35	1.55
4	1.45	1.59	1.62	1.75
6	2.55	2.71	2.85	3.15
8	3.78	3.89	4.08	4.22
10	3.12	3.28	3.42	3.65
12	4.59	4.68	4.89	5.23
14	6.85	6.97	7.15	8.89

Medical Image segmentation time of region growing methods is higher due to wrong seed selection. So, JPSS-FRG selecting seed pixel by probability measure and fuzzy measure to grow image region which are reduced segmentation time by 2 seconds as per Table I.



**Fig 1. Comparison of Segmentation time**

Moreover, with the aid of joint probabilistic seed selection and fuzzy measure that minimizes of the segmentation time by 2 seconds compared to existing region growing methods (Fig.1).

**III. PERFORMANCE ANALYSIS BY TRUE POSITIVE RATE**

If In evaluation of segmentation methods, Sensitivity (also called as True Positive (TP) rate or Recall) is the probability of correctly segmenting a target object (tumor region). In medical data analytics, sensitivity measure has assumed significance as it assesses the extent to which actual positives are not overlooked so that the false negatives are few. A comparative analysis of the JPSS-FRG framework [7] and GSA-NRG framework [8] with other state-of-the-art methods

available in the literature in terms of true positive rate is presented in Table-II. Artificial Neural network (ANN), Random forest, Multilayer Perceptron (MLP) and Support vector machine (SVM) are used to classify true positives [2].

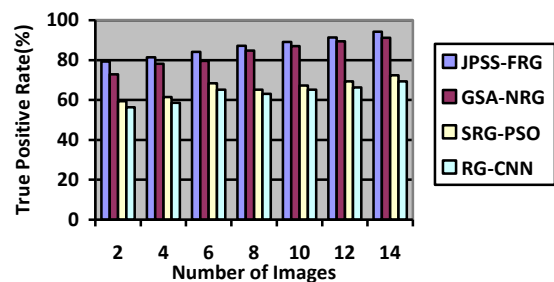
$$TPR = \frac{TP}{TP + FP} \tag{1}$$

Where in (1), TPR- True positive rate TP- True Positive and FP- False Positive.

**Table- II: Performance analysis by True Positive Rate**

No of Images	True Positive Rate (%)			
	JPSS-FRG	GSA-NRG	RG-CNN	SRG-PSO
2	79.32	72.83	59.37	56.33
4	81.45	78.11	61.5	58.56
6	84.15	79.67	68.37	65.13
8	87.10	84.81	65.15	63.10
10	89.13	86.92	67.18	65.13
12	91.35	89.43	69.40	66.35
14	94.28	91.13	72.33	69.28

From the Table II, it can be observed that the JPSS-FRG framework performs better when compared to all other methods.



**Fig 2. Comparison of True positive rate**

The Fig 2 illustrates that the true positive rate (TPR) of the proposed JPSS-FRG framework [7] and GSA-NRG framework [8] with other methods. The TPR is 21% higher than region growing and CNN [1] and 27% higher than SRG based on PSO [3] respectively. Further, the JPSS-FRG has merely 3% higher than GSA-NRG.

**IV. IMPACT OF SEGMENTATION ACCURACY**

Segmentation accuracy was computed to determine how accurately the proposed methods are able to detect malignancy from benign tumour cells.

$$Accuracy = \frac{TPR + TNR}{TPR + TNR + FNR + FPR} \tag{2}$$

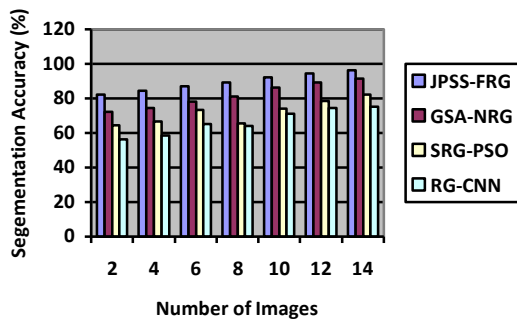
where in (2), TPR- True Positive Rate, TNR- True Negative Rate, FPR- False Positive Rate, FNR- False Negative Rate.

A comparative analysis of the JPSS-FRG framework and GSA-NRG framework with other state-of-the-art methods available in the literature in terms of Segmentation accuracy is presented in Table-III

**Table- III: Performance analysis by Accuracy**

No of Images	Segmentation Accuracy (%)			
	JPSS-FRG	GSA-NRG	RG-CNN	SRG-PSO
2	82.34	72.34	64.40	56.33
4	84.47	74.47	66.53	58.56
6	87.17	78.17	73.40	65.13
8	89.23	81.23	65.56	64.15
10	92.15	86.15	74.21	71.17
12	94.37	89.37	78.43	74.39
14	96.30	91.34	82.36	75.32

In this work, RIDER MRI (Magnetic Resonance Image) dataset [4] studied by executing codes of JPSS-FRG, GSA-NRG, SRG-PSO and RG-CNN in MATLAB environment. Later, the results are compared with proposed methods with Segmentation accuracy measured by DICE score.



**Fig.3. Segmentation Accuracy**

Fig 3. Illustrates that segmentation accuracy of the proposed JPSS-FRG framework and GSA-NRG framework. The graph shows linear growth of segmentation accuracy of JPSS-FRG framework is better than GSA-NRG framework. Further, which is higher than 16% compared to region growing and CNN [2] and 21% compared to SRG based on PSO [1] respectively

**V. MEASUREMENT OF QUANTITATIVE 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. Calculation of quantitative imaging biomarkers can be automated, which enables high-throughput analyses. Image biomarkers characterize the contents of an image, such as volume or mean intensity.

The radiomic feature mapping framework is presented to create radiomic MRI texture image representations [5] called the radiomic feature maps (RFM). They correlated the RFMs with image texture values, breast tissue using quantitative MRI and categorized benign from malignant tumors. They stated the tumor size between benign and malignant patient groups (Benign size=3.24 ± 2.67 cm<sup>2</sup>, Malignant size= 2.44 ± 0.31 cm<sup>2</sup>). The proposed FNCRG method detects solid tumour (i.e Image Biomarker) which are quantified in Table IV, these values are correlated to [5] [6] findings.

Let I be the set of computed segmented parts of proposed algorithms, and J the set of actual segmented parts, the DICE score calculated (3)

$$DICE(I, J) = \frac{2|I \cap J|}{|I| + |J|} \tag{3}$$

The quantitative Breast MRI biomarker is calculated using proposed FNCRG output metrics. Obviously, the similarity score of each set of images are studied using DICE score.

**Table- IV: Measurement of Breast MRI Biomarker**

Image Set	Image Biomarker(cm <sup>2</sup> )	DICE Score
BMR1	2.47±0.5	0.92
BMR2	1.82±0.5	0.74
BMR3	1.73±0.5	0.93
BMR4	0.92±0.5	0.72
BMR5	1.48±0.5	0.79

Each set of Breast MR(BMR) images have different set of noise so the similarity score is varied from 10% to 20%. The proposed method achieves average DICE scores of 82% ± 10% (range, 72%-93%) in testing. This shows promise for accurate breast masses segmentation, using adaptive region growing approach and compares favorably to state-of-the-art methods.

**VI. PERFORMANCE EVALUATIONS OF ADAPTIVE IMAGE SEGMENTATION METHODS**

Measuring image segmentation quality by average Precision-Recall (PR) statistics is also common in literature. The PR statistics are motivated by the image processing where segmented parts are first predicted in a binary manner for a set of test images and image set is then analyzed based on the predicted values. The precision and recall are defined as equation (4) and (5).

$$Pc = \frac{TP}{TP + FP} \tag{4}$$

$$Rc = \frac{TP}{TP + FN} \tag{5}$$

When different systems are compared in terms of precision (Pc) and recall (Rc), the performance measure is F-measure (6)

$$F = \frac{2}{(1/Pc + 1/Rc)} \tag{6}$$

**Table- V: List of Adaptive Image Segmentation Methods**

Method	Precision	Recall	F-measure
JPSS-FRG	74.44	68.42	78.82
GSA-NRG	74.64	69.23	70.19
SRG-PSO	80.23	65.14	72.65
RG-CNN	78.42	6.88	67.34
SiRG	81.57	69.23	79.48
FNCRG	92.08	64.56	87.12

The results of overall comparisons between different segmentation methods proposed in this work like JPSS-FRG[7], GSA-NRG[8], SiRG[9], FNCRG[10] and other methods available in the literature like SRG-PSO, RG-CNN are shown in Table V. The parameters of evaluation include measure like Precision, Recall and F-measure.



F-measure is measured based on the MRI breast images. If F-measure is high, then the method is said to be more efficient. From Table V, it can be observed that the FNCRG framework performs better in comparison to all other methods

### VII. CONCLUSION

The results show that JPSS-FRG framework offers better performance with an improvement of segmentation accuracy by 24% and improving the true positive rate by 27% compared to region growing and CNN and SRG based on PSO respectively.

A generalized simulated annealing based seed point selection was designed to select the seed point vector based on the perturbation factor and magnitude. Then, based on this measure, a Neutrosophic Region Growing algorithm is proposed that identifies the correct regions and finally obtains the segmented region improving the segmentation accuracy and breast cancer detection rate. 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 RG-CNN and SRG-PSO methods respectively. Through the experiments, observed that the GSA-NRG algorithm provided more accurate results compared to existing segmentation methods.

The results show that SiRG framework offers better performance with an improvement of accuracy by average of 8% and improving the true positive rate by 2% to 13% compared to RG-CNN, SRG-PSO, JPSS-FRG, and GSA-NRG respectively. It can be observed that the FNCRG framework performs better segmentation accuracy and time in comparison to all other methods.

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