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SITUATION OF BREAST MRI IN INDIA: CLASSIFICATION OF BREAST MR IMAGES USING FUZZY LOGIC AND RANDOM WALK SEGMENTATION

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***Abstract: Purpose**: Breast cancer is one of the leading causes of mortality in women due to cancer. We can find increase in breast cancer instances at the age of 35-40 in women. We could find a major age shift in the occurrence of the cancer and the percentage of morbidity is increased in younger women. This puts early diagnosis under a necessary category. Breast MRI is a challenging topic which plays an important role as adjunct to mammogram and ultrasound. An initiative to the early and accurate diagnosis will reduce the percentage of mastectomy. The aim is to show the benefits of fuzzy logic and random walk algorithm in segmenting and classifying the MR images.*

***Method:** In this study, fuzzy logic and random walk segmentation is applied on Breast MR Images. The results obtained from these are classified into affected and normal images using Naive Bayes classifier. These results are compared with available ground truth information collected by the radiologists.*

***Results:** The study resulted with 60% sensitivity, 75% specificity and with 66% of accuracy. The positive predictive value obtained is 75%, where as negative predictive value is 60%. The proposed combination of these two algorithms has shown an improved performance, which is an acceptable value with edge detection and classification.*

***Conclusion:** The research result defines the edge of the ROI, extracts it and classifies it into affected and normal MR images.*

***Keywords:** Breast Cancer, Computer Aided Diagnosis (CAD), Classification, Edge detection, Fuzzy Logic ,Magnetic Resonance Imaging (MRI), MATLAB, Tumor.*

INTRODUCTION

Breast cancer is one of the most common types of cancer causing morbidity and mortality in women. According to National Comprehensive Cancer Network,

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women more than 15% of lifetime risk must start screening at its very clinical instance[1]. We could find a major age shift in the occurrence of the cancer and the percentage of morbidity is increased in younger women. This puts early diagnosis under a necessary category.

Minimum age of screening for breast cancer is decreased when compared with the age for screening at present. According to the American cancer society guidelines, the annual mammogram screening starts at the age of 40-44. Mammogram being the basic screening modality, it may also miss the tumor identification in some cases. Younger the women, more chances of missing the diagnosis of tumor. This is due to the dense, fibrous breast and its benign appearance[2] [3]. Women with hereditary breast cancer are under high risk of breast cancer. According to *American cancer society guidelines*, MRI screening is recommended for women with 20-25% or greater lifetime risk of breast cancer[4][5][25]. Mammogram can miss the tumor identification in dense breast, but MRI assisted mammography and MRI adjunct to mammogram would complement in better diagnostic accuracy[6][7][8]. In few studies, it is identified that MRI is accurate than mammogram and ultrasound in detecting the actual pathologic size of the cancerous tumor and also the residual disease after neoadjuvant chemotherapy[9]. According to a study by Bassette et al. performance and interpretation of breast MRI in United states were investigated. According to radiology practices, the availability of breast MRI techniques and protocols provided reasonable approaches for the development of professional guidelines and the study also stated that contrast enhanced breast MRI is widely used in United States [8]. MRI could diagnose cancers that are missed by mammogram in particular cases where the lesions are not seen clearly by mammogram or ultrasound. As a screening routine, MRI is always considered only after mammogram and ultrasound, when these two screening modalities couldn't give the expected results MRI is considered. if the lesion is more clearly located by the basic screening, then the patient will be directly recommended for Biopsy [10]. In a study, [11] preoperative breast MRI had no significant statistical result in the locoregional recurrence or disease free survival. Invasive screening procedures can be opted further if results with mammogram, Ultra sound and MRI are true positive. MRI is very effective in certain cases where the lesions are difficult to be located and differentiated by other masses. If a patient is already with a problem of a lump which is clearly felt by observation and with pain, then the case is directly forwarded to biopsy. Breast MRI is a powerful screening tool as it gives lesser or no ionizing radiation effects on patients, hence considered safe for screening. It also provides good guidance for needle biopsy and pre surgical localization. MRI has a better sensitivity compared to other imaging modalities[12][13]. Women would prefer noninvasive diagnosis at their initial stage of screening, as the invasive pain, anxiety and psychological effects can be avoided[14]. Hence early, accurate and timely diagnosis plays an important role for the primary treatment and

prognosis of the lesion[15]. Breast MRI is regarded as most accurate breast imaging modality currently available for preoperative evaluation as it assesses accurate tumor diameter.[16]

Radiologist is a person who interprets the lesion as benign or malignant lesion through the images of mammogram or MRI. Generally the sensitivity of the breast MRI for the detection of cancer is considered greatest of all imaging techniques, making it very useful for the detection process in adjunct to Mammography and ultrasound[7][8]. Tumor can be different in every patient and its intensity also varies. An accurate CAD system would facilitate radiologist's workload. In a study by Birdwell *et al.* [2] 115 CAD marked 77% cancers missed at screening mammography. CAD can work as a second opinion while making decision. CAD has improved diagnosis[17].This will also reduce the anxiety rate in oncologists by giving a clear imaging result[18].

The other way around CAD system can also result in more number of false positive results[10]. Hence an accurate and reliable system is the need of the hour. The CAD supports the radiologist in the difficult task of differentiating benign and malignant breast lesions. Observing MRI images of patient manually per patient takes time and efficiency from the experts. In high volume centers, manual interpretation would be a reason for false diagnosis or missed diagnosis which may result in delay in treatment and finally which would lead to mastectomy. Mastectomy would be a traumatic experience for any woman. An initiative to the early and accurate diagnosis will reduce the percentage of mastectomy.

Diagnosis involves various levels of uncertainty and imprecision. There are many algorithms which are used in the segmentation and detection of the cancerous tumor. Fuzzy logic is one of the most efficient with improved accuracy in medical image segmentation. Brain MR Images also are segmented efficiently by fuzzy logic implementation. Many researches have been made to detect and identify the breast masses using CAD system. Neural networks also play an important role in unsupervised learning. In few studies fuzzy-C-means and neural-networks individually or in combination has improved classification of the images [19][20], [21] [2][22].

MRI machines come with basic default CAD system which differentiates the breast masses and locates the lesion. It defines whether the tumor is malignant or benign. Radiologist analyses these images with his gained knowledge to give the accurate results.

METHOD

Recent image segmentation approaches has provided many interactive methods that define the segmentation problem. In this study, the MRI images are acquired from real time and standard data bases. The main purpose is to locate the tumor

using MR images. Fuzzy logic and random walk segmentation is applied on Breast MR Images using MATLAB programming interface. The block diagram of the proposed technique defined in the Fig. 1 below. MATLAB has an advantage of customizing fuzzy membership functions and defuzzification techniques accordingly. The rule applied is shown in the Fig.1(a) below. The edge of the lesion is extracted from the region of interest and highlighted. The results obtained from these are classified into affected and normal images using Naive bayes classifier.

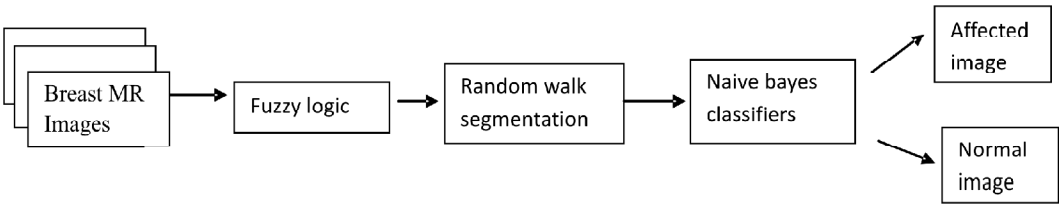
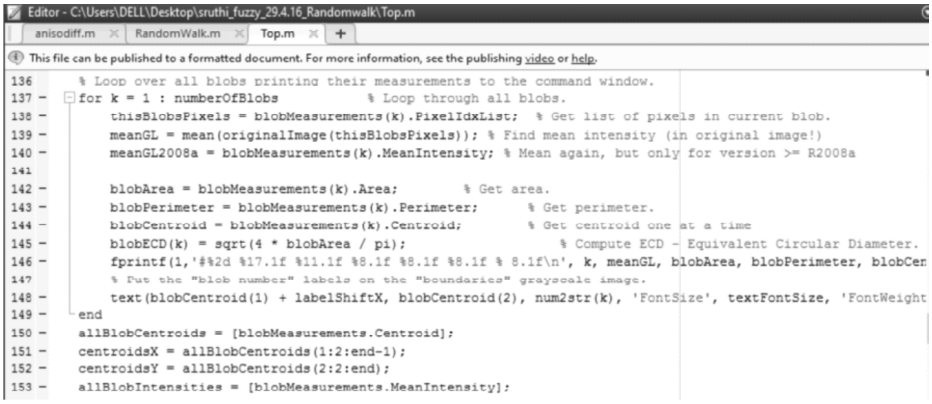


Figure 1: Block Diagram of the Proposed Technique



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136    % Loop over all blobs printing their measurements to the command window.
137 -  for k = 1 : numberOfBlobs           % Loop through all blobs.
138 -      thisBlobsPixels = blobMeasurements(k).PixelIdxList;  % Get list of pixels in current blob.
139 -      meanGL = mean(originalImage(thisBlobsPixels)); % Find mean intensity (in original image!)
140 -      meanGL2008a = blobMeasurements(k).MeanIntensity; % Mean again, but only for version >= R2008a
141
142 -      blobArea = blobMeasurements(k).Area;        % Get area.
143 -      blobPerimeter = blobMeasurements(k).Perimeter;      % Get perimeter.
144 -      blobCentroid = blobMeasurements(k).Centroid;        % Get centroid one at a time
145 -      blobECD(k) = sqrt(4 * blobArea / pi);               % Compute ECD - Equivalent Circular Diameter.
146 -      fprintf(1,'#%2d %17.1f %11.1f %8.1f %8.1f %8.1f %8.1f\n', k, meanGL, blobArea, blobPerimeter, blobCen
147      % Put the "blob number" labels on the "boundaries" grayscale image.
148 -      text(blobCentroid(1) + labelShiftX, blobCentroid(2), num2str(k), 'FontSize', textFontSize, 'FontWeight
149 -  end
150 -  allBlobCentroids = [blobMeasurements.Centroid];
151 -  centroidsX = allBlobCentroids(1:2:end-1);
152 -  centroidsY = allBlobCentroids(2:2:end);
153 -  allBlobIntensities = [blobMeasurements.MeanIntensity];
```

```
subplot(2,2,2); plotmf(edgeFIS,'input',2); title('Iy');
subplot(2,2,[3 4]); plotmf(edgeFIS,'output',1); title('Iout')
rules1 = 'If Ix is zero and Iy is zero then Iout is white';
rules2 = 'If Ix is not zero or Iy is not zero then Iout is black';
r = char(rules1,rules2);
edgeFIS = parsrule(edgeFIS,r);
```

Figure 1a: MATLAB Fuzzy rule

This method is a reliable way to guarantee accuracy, while making efficient use of an experts time. The affected area is been highlighted and edge of the affected area is identified. The images used in this analysis were collected from ***The Cancer Imaging Archive*** (TCIA) database [24]. The MR images consist of T1 weighted, T2 weighted, pre contrast, post contrast and sagittal view images. A set of 6 sagittal T2 weighted contrast enhanced MR breast images were selected for the analysis.

Results: The implementation of fuzzy logic and Random walk algorithm is based on the region of interest and edge detection. The edge of the tumor is been

identified and highlighted in fig 1(b). The highlighted area is extracted using the random walk segmentation. Naive Bayes classifiers are used to classify the MR images into affected and normal images. The fig 2(a) shows the edge of the tumor region which is classified as affected, where as in fig 2(b) the edge is not clear as the region is not prominent with tumor, hence classified as Normal image. The execution time of the technique is 8-10 seconds in MATLAB R2015a using 9 sagittal breast MR Images. The study resulted with 60% sensitivity, 75% specificity and with 66% of accuracy. The positive predictive value obtained is 75%, where as negative predictive value is 60%. The proposed combination of these two algorithms has shown an improved performance, which is an acceptable value with edge detection and classification. These results are compared with available ground truth information collected by the qualified radiologists.

DISCUSSION AND CONCLUSION

Fuzzy interface system succeeds in extracting the edge of the affected area and the region of interest is been located. Random walk segmentation plays an important element in locating the Region Of Interest (ROI). The Fig. 1(c) shown below is the initial gray image of a tumor affected Breast MR image and Fig. 2(a) is the gray

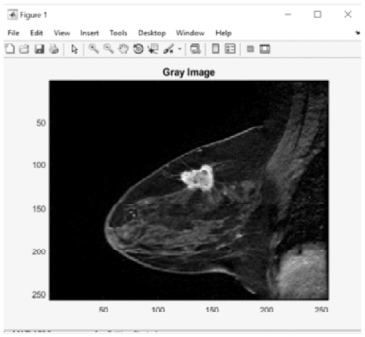

Fig. 1(c)

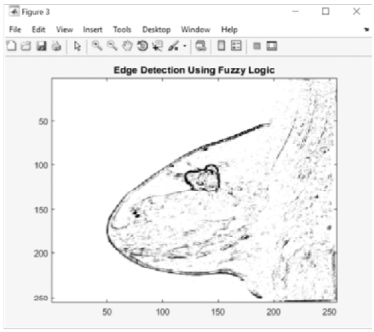

Fig. 1(d)

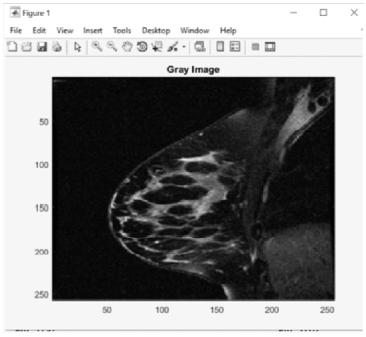

Fig. 2(a)

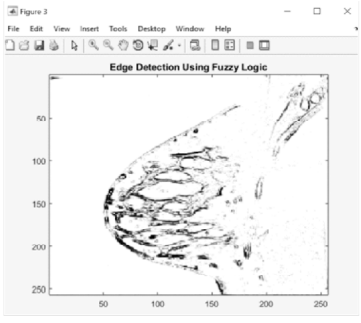

Fig. 2(b)

image of a normal breast MR image. Fig. 1(d) and Fig. 2(b) are the images obtained by fuzzy logic. In the tumor affected image Fig. 1(d), the edge of the tumor region is clearly highlighted.

In Fig. 3(a) and Fig. 3(b), we can see the initial image before segmentation, then the Random walk segmentation image with the tumor affected region and also the classification of the image into affected image or the normal image by Naive bayes classification.

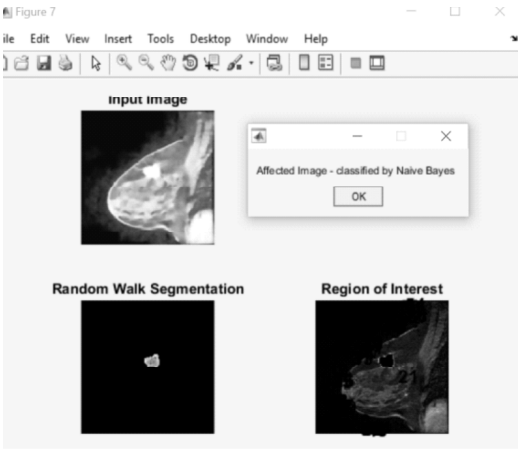

Figure 3(a)

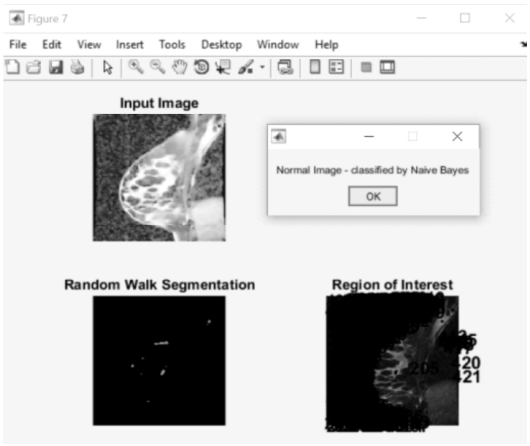

Figure 3(b)

In studies [17], [23] Mammogram images are used for segmentation and classification of breast tumor. Region based segmentation approach and fuzzy rules are applied to analyze and classify the tumor. Venkat Narayan Rao et al. proposed fuzzy enhanced mammogram segmentation using fuzzy rule[23]. In which method-1 outperformed with best results. Patricia Melin et al. presented an edge detection method based on the morphological gradient technique and generalized type-2 fuzzy logic which obtained better results. Though fuzzy logic is widely used in medical image segmentation, its application in classifying breast MRI is limited in the literature. Hence the research study is an effort towards this direction.

In this paper fuzzy logic and random walk segmentation is applied for better segmentation results in breast MRI. The research result defines the edge of the ROI, extracts it and classifies it. The performance of this method, its quality, its time strategy has been verified in several images and the best of 9 MR images is chosen. The purpose is to show the benefits of merging fuzzy logic and random walk algorithm. Other algorithm combination with fuzzy logic may give improved sensitivity. In future work, the features of the extracted tumor, texture can be analyzed to differentiate between benign and malignant tumor in the affected images. MRI gives visual clarity of the breast anatomy. MRI seems to be cost

effective in future years as it has more efficiency in detecting the smallest tumor in the dense breast. The false positive rate can be reduced by applying the different hybrid algorithm and improved software technique in future. CAD system is one of the cost effective way of tumor diagnosis.

References

N. Clinical, P. Guidelines, and N. Guidelines, "Breast Cancer Screening and Diagnosis The University of Texas," 2014.

R. L. Birdwell, D. M. Ikeda, K. F. O. Shaughnessy, and E. A. Sickles, "Abbreviations/ : Characteristics of 115 Missed Cancers Later Detected with Screening Mammography and," no. 1, 2001.

R. E. Bird, T. W. Wallace, and B. C. Yankaskas, "Analysis of cancers missed at screening mammography.," *Radiology*, vol. 184, no. 3, pp. 613–617, 1992.

D. Saslow, C. Boetes, W. Burke, S. Harms, M. O. Leach, C. D. Lehman, E. Morris, E. Pisano, M. Schnall, S. Sener, R. A. Smith, E. Warner, M. Yaffe, K. S. Andrews, and C. A. Russell, "American Cancer Society guidelines for breast screening with MRI as an adjunct to mammography," *CA Cancer J Clin*, vol. 57, no. 2, pp. 75–89, 2007.

P. van der Groep, E. van der Wall, and P. J. van Diest, "Pathology of hereditary breast cancer.," *Cell. Oncol. (Dordr).*, vol. 34, no. 2, pp. 71–88, 2011.

S. Diego, "MRI for breast cancer/ : Current indications," vol. 19, no. 2, pp. 161–169, 2009.

W. van Aalst, T. Twellmann, H. Buurman, F. A. Gerritsen, M. Bart, and H. Romeny, "Computer-aided Diagnosis in Breast MRI/ : Do Adjunct Features Derived from T2-weighted Images Improve Classification of Breast Masses?," *Bild. für die Medizin*, pp. 11–15, 2008.

L. W. Bassett, S. G. Dhaliwal, J. Eradat, O. Khan, D. F. Farria, R. J. Brenner, and J. W. Sayre, "National trends and practices in breast MRI," *Am. J. Roentgenol.*, vol. 191, no. 2, pp. 332–339, 2008.

M. Hamisa, N. Dabess, R. Yosef, and F. Zakeria, "Role of breast ultrasound , mammography , magnetic resonance imaging and diffusion weighted imaging in predicting pathologic response of breast cancer after neoadjuvant chemotherapy," *Egypt. Soc. Radiol. Nucl. Med.*, vol. 46, no. 1, pp. 245–257, 2015.

C. D. Lehman, C. Isaacs, M. D. Schnall, S. M. Ascher, P. T. Weatherall, D. J. Bowen, P. K. Marcom, D. K. Armstrong, S. M. Domchek, C. Gatsonis, E. D. Pisano, S. M. Ascher, P. T. Weatherall, D. A. Bluemke, D. J. Bowen, P. K. Marcom, D. K. Armstrong, S. M. Domchek, G. Tomlinson, S. J. Skates, and C. Gatsonis, "Cancer yield of mammography, MR, and US in high-risk women: prospective multi-institution breast cancer screening study.," *Radiology*, vol. 244, no. 2, pp. 381–8, 2007.

J. S. Sung, J. Li, G. Da Costa, S. Patil, K. J. Van Zee, D. D. Dershaw, and E. A. Morris, "Preoperative breast MRI for early-stage breast cancer: Effect on surgical and long-term outcomes," *Am. J. Roentgenol.*, vol. 202, no. 6, pp. 1376–1382, 2014.

M. V. Knopp, E. Weiss, H. P. Sinn, J. Mattern, H. Junkermann, J. Radeleff, A. Magener, G. Brix, S. Delorme, I. Zuna, and G. Van Kaick, "Pathophysiologic basis of contrast enhancement in breast tumors," *J. Magn. Reson. Imaging*, vol. 10, no. 3, pp. 260–266, 1999.

A. D., D. V.A., and T. T., "A new user-friendly visual environment for breast MRI data analysis," *Comput. Methods Programs Biomed.*, vol. 110, no. 3, pp. 411–423, 2013.

C. Abreu, A. Grilo, F. Lucena, and E. Carolino, "Oncological Patient Anxiety in Imaging Studies/ : the PET / CT Example," *J. Cancer Educ.*, 2016.

V. Gonzalez, K. Sandelin, A. Karlsson, W. ??berg, L. L??fgren, G. Iliescu, S. Eriksson, and B. Arver, "Preoperative MRI of the breast (POMB) influences primary treatment in breast cancer: A prospective, randomized, multicenter study," *World J. Surg.*, vol. 38, no. 7, pp. 1685–1693, 2014.

M. B. I. Lobbes, U. C. Lalji, P. J. Nelemans, I. Houben, M. L. Smidt, E. Heuts, B. de Vries, J. E. Wildberger, and R. G. Beets-Tan, "The quality of tumor size assessment by contrast-enhanced spectral mammography and the benefit of additional breast MRI," *J. Cancer*, vol. 6, no. 2, pp. 144–150, 2015.

T. Berber, A. Alpkocak, P. Balci, and O. Dicle, "Breast mass contour segmentation algorithm in digital mammograms," *Comput. Methods Programs Biomed.*, vol. 110, no. 2, pp. 150–159, 2013.

J. Nowakowski, G. Borowiec, I. Zwierz, W. Jagodzinski, and R. Tarkowski, "Stress In An Oncologist ' s Life/ : Present But Not Insurmountable," 2015.

S. Anand, V. Vinod, and A. Rampure, "Application of Fuzzy c-means and Neural networks to categorize tumor affected breast MR Images," *Int. J. Appl. Eng. Res.*, vol. 10, no. 64, p. 2015, 2015.

A. Ortiz, J. M. Gorriz, J. Ramirez, and D. Salas-gonzalez, "Improving MR brain image segmentation using self-organising maps and entropy-gradient clustering," *Inf. Sci. (Ny).*, vol. 262, pp. 117–136, 2014.

A. Ortiz, J. M. Górriz, J. Ramírez, D. Salas-González, and J. M. Llamas-elvira, "Two fully-unsupervised methods for MR brain image segmentation using SOM-based strategies," *Appl. Soft Comput. J.*, vol. 13, no. 5, pp. 2668–2682, 2013.

H. D. Cheng and M. Cui, "Mass lesion detection with a fuzzy neural network," *Pattern Recognit.*, vol. 37, no. 6, pp. 1189–1200, 2004.

T. Venkat Narayana Rao and A. Govardhan, "Efficient segmentation and classification of mammogram images with fuzzy filtering," *Indian J. Sci. Technol.*, vol. 8, no. 15, 2015.

The Cancer Imaging Archive, viewed March 2015, *http://www.cancerimagingarchive.net/*

American cancer society- Guidelines for early detection, viewed March 2015, *http://www.cancer.org/healthy/findcancerearly/cancerscreeningguidelines/american-cancer- society-guidelines-for-the-early-detection-of-cancer*