ISSN 2229-5518

Pixel-Based Morphological Technique for Breast Tumour Detection

Adepoju T. M., Ojo J. A., Omidiora E. O., and Olabiyisi O. S.

Abstract— Breast region segmentation is the process of splitting mammogram image into breast region and background to focus and limit the search for abnormality on the breast region without the effect of the background on the results. In addition, performance of existing Computer Aided Detection (CAD) systems for detection of malignant tumours in breast tissue have been limited by the methods of segmentation. Image segmentation is a multi-objective problem where multiple criteria must be considered for extraction of breast region. The developed segmentation technique in this paper considered intensity of pixel for image binarization (using Otsu thresholding) and shape for image boundary refinement (using mathematical morphological processes), to detect exact location of tumour in breast tissue. The developed technique was evaluated using Kappa agreement scale (Hit, Miss and Over-hit). A moderate value of 0.59 in Kappa agreement scale was achieved for the segmentation. The Two-stage Segmentation Technique is efficient to extract the locations of breast tumour with low level of false positive.

Key words— Segmentation, pixel, morphology, tumour, Hit, Kappa, benign and malignant.

1 INTRODUCTION

The World Health Organization's International Agency for Research on Cancer estimated that more than 150,000 women worldwide die of breast cancer each year [15]. Mammography screening is the golden standard method for early detection of tumour in breast, but 10-30% of the tumour are missed by mammography because tumour are obscured by radiographically dense breast tissue [12]. Mammography is one of the commonly used methods to detect breast tumour but radiologist show variation in interpreting mammograms [6]. Mammography is a non-invasive screening tool recommended for young women who have symptoms of breast cancer or have a high risk of breast cancer, as well as for women older than 40 years even if there is no sign of the disease [2].

Current research works conducted in the area of breast cancer detection and classification focused on segmentation because of the fact that breast cancer is becoming the most common form of cancer disease of today's female population.

Segmentation refers to the process of partitioning a digital image into multiple segments [13], to simplify and change the representation of an image into something that is more meaningful and easier to analyze. Accuracy of breast cancer in mammograms depend on the segmentation of images [10]. Since there is no general solution to the image segmentation problem; different algorithms often have to be combined in order to effectively solve an image segmentation problem[7].

Image segmentation is a multi-objective problem (multiple criteria must be considered for image segmentation such as intensity of pixels, texture, shape and colour) [7]. The most significant feature that indicates whether a mass is benign or malignant is its shape[9]. The shape can be round, oval, lobular, or irregular as indicated in Figure 1. Masses that are sharply defied (circumscribed oval and round masses) are usually benign. Masses with irregular shapes (faint jagged edge) and indistinct or spiculated margins have a higher likelihood of malignancy.

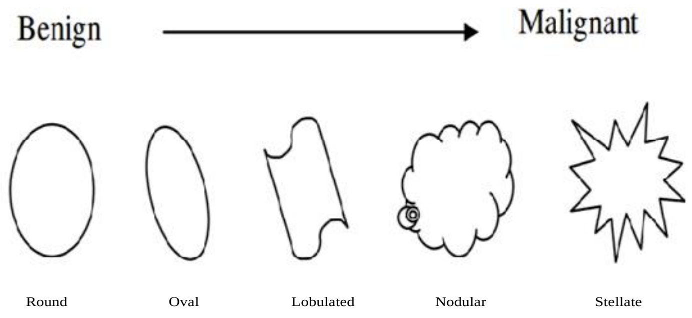

Fig. 1: Morphology of masses [9]

All authours are corresponding authour

- T. M. Adepoju has completed her Doctor of Philosophy degree program in computer science and engineering, LAUTECH, Ogbomoso. E-mail: atemilola@gmail.com
- J. A. Ojo is an associate professor in the department of Electronic and Electrical Engineering, LAUTECH, Ogbomoso. E-mail: jaojo@lautech.edu.ng
- E. O. Omidiora is a professor in the department of computer sciences and engineering, engineering, LAUTECH, Ogbomoso Email: omidiorasayo@yahoo.co.uk
- S. O. Olabiyisi is a professor in the department of computer sciences and engineering, engineering, LAUTECH, Ogbomoso Email: tundeolabiyisi@hotmail.com

2 RELATED WORKS

Recently, several researchers have developed breast cancer segmentation model that involved combination of technique to locate breast cancer. [5] developed an algorithm for segmenting speculated masses based on pulse coupled neural networks (PCNN) in conjunction with fuzzy set theory. [4] used active contour model (ACM) based on self-organizing network (SON) to segment the ROI. This model explores the principle of isomorphism and self-organization to create flexible contours that characterizes the shapes in the image.

[1] segmented suspicious masses in polar domain. They used adaptive level set segmentation method (ALSSM) to adaptively adjust the border threshold at each angle in order to provide high-quality segmentation results. They extended their work in [1] using speculation segmentation with level sets (SSLS) to detect and segment spiculated masses. In conjunction with level set segmentation they used Dixon and Taylor line operator (DTLO) and a generalized version of DTLO (GDTLO).

[16] employed a dual-stage method to extract masses from the surrounding tissues. Radial gradient index (RGI) based segmentation was used to yield an initial contour close to the lesion boundary location and a region-based active contour model wass utilized to evolve the contour further to the lesion boundary.

[3] applied active contours to segmenting the pectoral muscle and localized dense tissues by using the maxima method. The textures of the located zones are analyzed through the co-occurrence matrix and the Haralick features to classify them in normal or abnormal tissues using the SVM.

[10] developed a multistage segmentation method to segment the mammograms based on watershed algorithm and level set method. They used watershed transform to provide a coarse and fast pre-segmentation, and used the resultant segmentation as the initial contour for the level set segmentation. In the combined algorithm, the segmentation results from the watershed were used as the input of the level set segmentation and the level set algorithm is used to refine the boundary of the segmented image.

3 TWO-STAGE SEGMENTATION TECHNIQUE

The developed algorithm considered intensity of pixels and shape as criteria for the two-stage segmentation. The acquired images from Mammographic Image Analysis Society (MIAS) were pre-processed using polygon approximation method. The pre-processed mammograms were pre-sorted into low density (fatty) and high density breast tissue images, following medical procedural approach. The flow chart in Figure 2 presents the two-stage segmentation technique based on Otsu thresholding for the image binarization and morphological erosion to refine the image shape.

Otsu threshold is a pixel based algorithm in which a threshold T was set to maximum intensity value of initial point of interest. The gray scale images were converted to binary images (background and object) by estimating the class probability as shown in Figure 2. The class mean of both the background and object is computed according to expression in Figure 2. The average of the class mean as shown in the Figure determined the calculated threshold T_c for the images. The binary images were obtained by comparing the calculated threshold with set threshold as presented in the flow chart. The shape of the object in the binary images were obtained by image erosion according to the expression in the flow chart. The irregularities or false lines connected to the boundary of the segmented images are eliminated by erosion process of mathematical morphology as stated in equation 1.

$$\beta(A) = (A \oplus B) - ((A \oplus B) \otimes B) \qquad (1)$$

The segmentation algorithm stepped through different threshold to ascertain the threshold value with better binary image. The performance of the segmentation algorithm was evaluated by calculating and analysing, Kappa scale of agreements (Hit, Miss and Overhit) while confusion matrix is used to determine the accuracy of classifying the segmented mammograms into normal benign and malignant tumour. These are defined as follows:

i. Hit: denotes the ratio of correct segmentation.

$$Hit = \frac{TP}{TP + FN}$$

ii. Miss: denotes the ratio of missing segmentation.

$$Miss = \frac{FN}{TP + FN}$$

iii. Over Hit: denotes the ratio of false segmentation.

$$Over\ Hit = \frac{FP}{TP + FN}$$

iv. Kappa: is a measure of inter-observer agreement.

$$Kappa = \frac{2 \times Hit}{2 \times Hit + Miss + OverHit}$$

v. Accuracy: it is the fraction of correctly classified image with regard to all images of that ground truth class.

$$Accuracy = \frac{no\ of\ diagonal\ mammogram\ in\ the\ matrix}{Total\ number\ of\ mammogram}$$

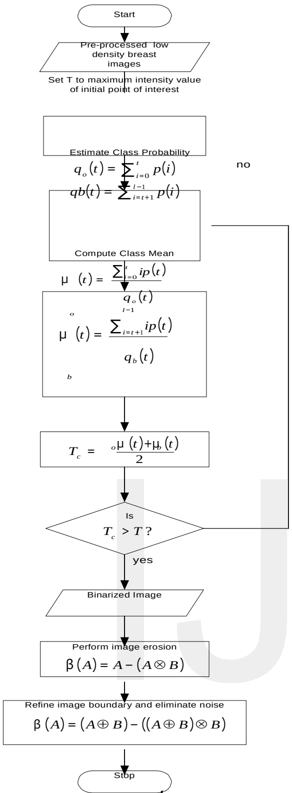

Fig. 2. Flow chart of the two-stage segmentation technique

4 RESULTS AND DISCUSSION

The images obtained from pre-processing stage aids identification of low density (fatty) breast tissue images that were used in the two-stage segmentation analysis. The results obtained at the segmentation stage is presented in Table 1. The metrices used to obtain these results are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The two-stage segmentation algorithm stepped through different threshold values starting from 0.900. It was observed that at 0.900, 0.517 of the mammograms were segmented correctly, 0.429 of the images missed the exact location of abnormality while 0.381 of the images include other pixels asides the abnormality pixels. It was observed that the segmentation accuracy of the mammogram at threshold value of 0.900 with false positive (8), was 0.590 which fall into moderate segmentation in kappa agreement scale. The segmentation accuracy (0.500, 0.470 and 0.390) obtained at the other threshold values are lower than the segmentation accuracy at threshold value 0.900. The segmentation accuracy (0.59) at threshold value 0.900 is preferred because when a threshold value is reduced, more abnormality are usually located (sample, 2003). The moderate segmentation accuracy (0.590) was considered as better Kappa agreement result when compare with other result in the table, since the objective at this stage is to locate abnormality.

Some of the segmented abnormal and normal images are shown in Figure 3 and Figure 4 respectively. It was observed that the images in Figure 3 contain abnormality, showing that the mammograms are affected while the images in Figure 4 appeared blank, showing that algorithm for segmentation could not find any abnormality in the mammograms. It was observed that the shape of the segmented objects in Figure 3(a) and 3(b) is the exact shape of the tumour in the acquired gray scale image when benchmark with golden standard in the MIAS images.

Also, the images in the Figure 3(a) and 3(b) were classified correctly into benign and malignant tumour base on the shape appearance.

Fig. 3(a). Matlab GUI for Two-stage segmentation of a normal mammogram

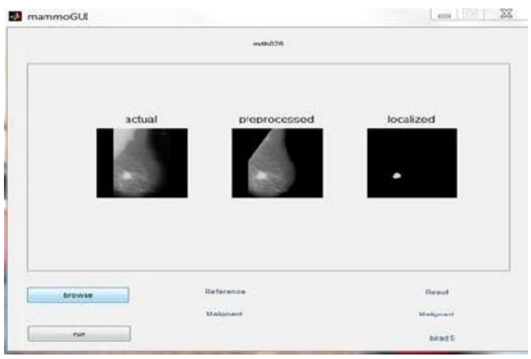

Fig. 3(b). Matlab GUI for Two-stage segmentation of a benign mammogram

Metrices	Results	Threshold values	Hit	Miss	Overhit	Kappa Value	Actual Class	Normal	Malignant	Benign	Accuracy
T P	12										
F P	8	0.900	0.571	0.429	0.381	0.590	N	27	2	4	
T N	9										
F N	20						M	1	10	0	85.71%
							B	0	0	5	
T P	9										
F P	6	0.915	0.429	0.571	0.286	0.500	N	25	2	5	
T N	12										
F N	22						M	2	10	0	79.59%
							B	1	0	4	
T P	9										
F P	6	0.925	0.429	0.571	0.286	0.500	N	25	2	6	
T N	12										
F N	22						M	3	10	1	75.51%
							B	0	0	2	
T P	8										
F P	5	0.935	0.381	0.619	0.238	0.470	N	25	3	6	
T N	13										
F N	23						M	3	9	0	75.51%
		0.945	0.286	0.714		0.390	B	0	0	3	
T P	6										
F P	4				0.191		M	1	7	0	69.39%
T N	15						N	27	5	9	
F N	24										
							B	0	0	0	
T P	6										69.39%
F P	4	0.950	0.286	0.714	0.191	0.390	N	27	6	6	
T N	15										
F N	24						M	1	5	1	
							B	0	1	2	

Table 1
Two-stage segmentation results

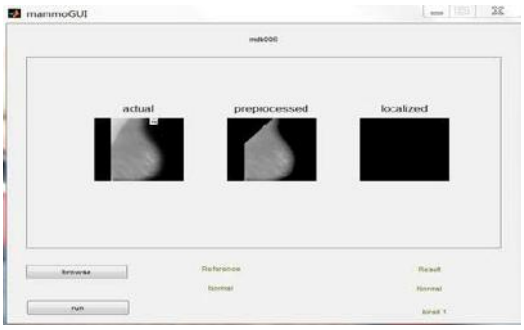

Fig. 4. Matlab GUI for Two-stage segmentation and classification of a normal mammogram

5 CONCLUSION

In conclusion, The inter-observer agreement between the radiologist and the proposed segmentation algorithm, at a given threshold of 0.9 was at moderate level (0.59) of the kappa scale, has in effect improved the detection of abnormality at exact location.

References

[1] Ball, J.E., Bruce, L.M. (2007). "Digital Mammogram Spiculated Mass Detection and Spicule Segmentation using Level Sets", *Proceedings of the 29th Annual International Conference of the IEEE EMBS*, Cité Internationale, Lyon, France, pp.4979–4984.

[2] Eden, A. A., Jose, L. H., Jesus, S. C., Camila, C., Hugo, T., Santiago, E. C. (2012). "Analysis of Machine Learning Techniques Applied to the Classification of masses and Microcalcification Clusters in Breast Cancer Computer-Aided Detection", *Journal of Cancer Therapy, Scientific Research*, pp. 1020-1028.

[3] Eddaoudi, Fatima, Regragui, Fakhita Mahmoudi, Abdelhak Lamouri, and Najib (2011). "Masses Detection Using SVM Classifier Based on Textures Analysis", *"Applied Mathematical Sciences"*, Vol. 5, No. 8, pp. 367 – 379.

[4] Ferreira, A. A., Nascimento J., F., Tsang, I. R., Cavalcanti, G. D. C., Ludermir, T. B., de Aquino, R. R. B.(2007). "Analysis of Mammogram Using Self-Organizing Neural Networks Based on Spatial Isomorphism", *Proceedings of International Joint Conference on Neural Networks (IJCNN)*, Orlando, Florida, USA, pp. 1796–1801.

[5] Hassanien, A. E., Ali, J. M.(2004) "Digital Mammogram Segmentation Algorithm Using Pulse Coupled Neural Networks", *Proceedings of the Third International Conference on Image and Graphics*, ICIG.

[6] Hussain, M., Wajid, S. K., Elzaart, A. and Berbar, M. (2011). " A Comparison of SVM Kernel Functions for Breast Cancer Detection'", International Conference Computer Graphic, Imaging and Visualization, IEEE Computer Society, Vol. 31, p. 145.

[7] Ojo J. A., Adepoju T. M., Omdiora E. O., Olabiyisi O. S. and Bello O. T, (2014) "Survey of Multi-Level Segmentation Techniques for Detection of Breast cancer" *European Journal of Scientific Research*, Vol. 123, No 4, pp.430-434. ISBN 1450-216X/1450-202X.

[8] Liu, J., Chen, J., Liu, X., Chun, L., Tang, J., and Deng, Y. (2011). "Mass segmentation using a combined method for cancer detection", *BMC Systems Biology*, Vol. 5, No. 3, p. 6.

[9] Nawazish N., Tae-Sun C. M. and ArfanJaffar (2011). "Malignancy and abnormality detection of mammograms using DWT features and ensembling of classifiers", *International Journal of the Physical Sciences*, Vol. 6, No 8, pp. 2107-2116.

[10] Ramani, R. Suthanthiravanitha, S. and Valarmathy, S. (2012). "A Survey of Current Image Segmentation Techniques For Detection Of Breast Cancer", *International Journal of Engineering Research and Applications (IJERA)*, ISSN: 2248-9622 Vol. 2, No 5, pp. 1124-1129.

[11] Ricardo, J. F., Kimberley, A. H., Donald, B. P. and Anne, L. M. (2008). "Can bilateral asymmetry analysis of breast MR images provide additional information for detection of breast disease", Brazilian Symposium on Computer Graphics and Image Processing, IEEE Computer Society, Vol.10, p. 113.

[12] Sample , J. T. (2003). *"Computer Assisted Screening of Digital Mammogram Images"*, A Dissertation Submitted to the Department of Computer Science, the Graduate Faculty of the Louisiana State University.

[13] Senthilkumar, B., and Umamaheswari, G. (2011). "A Review on Computer Aided Detection and Diagnosis - Towards the Treatment of Breast Cancer", *European Journal of Scientific Research,* Vol. 52 No. 4, pp. 437-452.

[14] Strauss, A., Sebbar, A., Désarnaud, S., Mouillard, P., and Le Gal, M. (1992). "Cancer du sein: des progrès en détection automatique des microcalcifications", *Nouvelles Méthodes de Traitement de l'Information en Médecine*, Paris, Springer-Verlag, France, Vol. 5.

[15] Suri, S. J., and Rangayyan, R. M. M. (2006). "Recent Advances in Breast Imaging", Mammography and Computer-Aided Diagnosis of Breast Cancer, *Spie Press*, Belligham, Washington USA, ISBN: 9780819460813.

[16] Yuan, Y., Giger, M.L., Li, H., Sennett, C. (2008). "Correlative Feature Analysis of FFDM Images", *Proceedings of SPIE Medical Imaging, Computer-Aided Diagnosis,* Vol. 69, No. 15.