BREAST TUMOUR SEGMENTATION USING THRESHOLDING AND CANNY EDGE DETECTOR

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ABSTRACT

Mammogram acts as a screening tool is used to acquire images of the breast in order to detect early signs of breast cancer. However, the limitation of the mammogram images is it turn out to be too dark or too bright which endangers the loss of useful information. Numerous techniques have been introduced to improve the mammograms including quantitative evaluation. Unlike existing research that required additional hardware to be implemented in the segmentation process on the mammogram, this paper proposes an automated approach to segment breast tumours using image processing. The segmentation process is performed on the mammogram images using thresholding and canny edge detection algorithms. Thirty-three images are collected and tested. Qualitative evaluations showed that the proposed system outperformed segmented breast tumour at an acceptance rate of 52.09 percent, whereas quantitative evaluation using Area Overlap, False Positive Rate and False Negative Rate produced an acceptance rate 52.09 percent, 33.34 percent and 14.57 percent respectively. The findings could improve the quality of mammography images and help radiologists and doctors to detect breast tumours more accurate in a shorter period of time.

Keywords: Breast Tumour; Segmentation; Mammography Images; Thresholding and Canny Edge Detection.

1. INTRODUCTION

Mammograms can be used as a screening tool to detect tumours or early breast cancer in women experiencing no symptoms [1]. Over four decades, imaging systems such as breast ultrasound, mammograms and breast magnetic resonance imaging (MRI) have been used to screen for breast tumours. Mammograms are affordable and reliable with a recorded performance accuracy of 97 percent to 98 percent [2]. They are also used commonly than ultrasound and MRI in women more than 40 years old. Typically an image from mammography consists of two to four views. The two standard views are cranial caudal (CC) view from above and a mediolateral-oblique (MLO) view from the side. Figure 1 depicts an image of mammogram taken in mediolateral-oblique view.
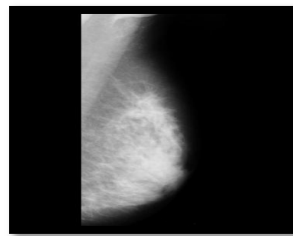

Fig. 1. Mammogram Image taken in mediolateral-oblque view

However, mammography images are noisy and produce a low-quality image that lacks in detail [3]. Therefore, it is important to improve the quality of mammogram images to prevent the loss of useful information [2]. One method to improve the quality of mammogram images is by using segmentation in the image processing [4]. Segmentation is used to obtain particular characteristics from an image.

Segmentation can be used in image processing to inspect and interpret images obtained from x-rays, MRIs and ultrasounds [5]. It can also detect abnormal masses in mammographic images [6]. Aside from that object and background of an image can also be distinguished [7].

Many researchers have sought to improve images using the segmentation method. Algorithm for fully automated gradient-based breast which limits recognition of mammograms, recorded a segmentation rate of 99 percent accuracy [8]. A vigorous algorithm for the automatic breast and pectoral muscle division from flash mammograms using k-means thresholding, achieved a segmentation rate at 89.69 percent [9]. Strategies for breast injury, whether recognition based or region growing strategies utilizing an area-based method or split and merge techniques achieved an effectiveness of 85 percent accuracy [10]. Meanwhile, isolated pre-processing and image segmentation by applying thresholding and canny edge detector [11]

successfully detected lesions in the breast parenchyma and retromammary area in more than 50 mammograms.

Although gradient-based techniques are recognized as an accurate method that produces a segmentation rate of 99 percent accuracy, thresholding and canny edge detector will be applied to segment the breast tumor. To implement this method it does not require additional hardware and it only uses MATHLAB software.

Mammograms are read and interpreted by radiologists. Radiologist diagnoses breast tumors manually based on mammography images provided. However, the problem of visual examination of a large volume of mammograms along with the shortage of experienced breast radiologists makes the process unsustainable [12]. This limitation can be overcome by using technological approaches such as applying thresholding and canny edge to assist in the detection of breast tumors. Mammography images will be improved, and the system can help doctors and radiologist to recognize a tumor and gives more accurate results in a shorter period of time.

This paper proposes an automatic approach that could improve the mammography images using thresholding method and canny edge detection algorithms. The performance of the proposed algorithms is measured using quantitative evaluation. Quantitative evaluation of the lesions detection methods is conducted by comparing the results obtained by the system with the gold standard that is obtained from a consultant radiologist [13].

2. METHODS

Figure 2 shows the process flow for the proposed algorithm to segment the breast tumour images from the mammogram images.
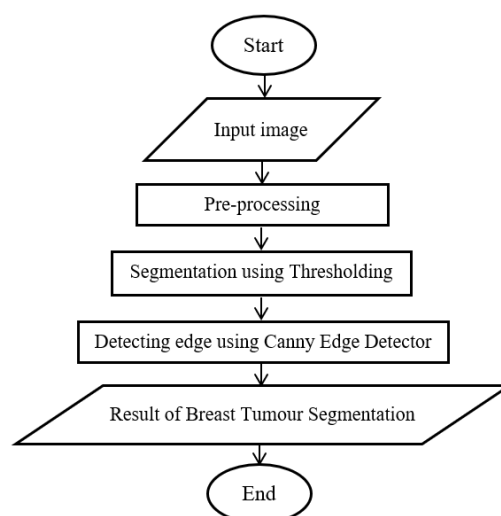

Fig. 2. A breast tumour segmentation process

2.1 Data Collection

In this study, 33 mammogram images were collected from the established Mammography Image Society Analysis (MIAS) database. All the retrieved images were available together with its ground truth. To validate the retrieved images further, a senior consultant radiologist from the Department of Radiology in a Medical Specialist Centre verified the results of the breast tumour segmentation.

2.2 Pre-Processing

Since all the images were downloaded from the MIAS database, they were all subjected to pre-processing. The aim of pre-processing is to further enhance the quality of the images. In this study, contrast enhancement and noise removal had been performed on all the images.
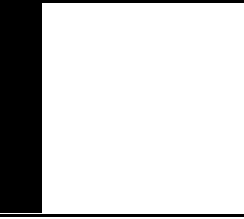
2.3 Thresholding
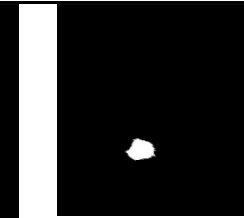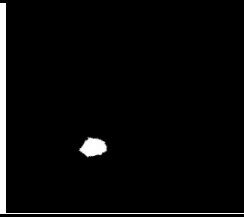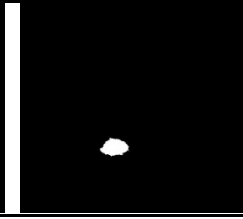
Fig. 2 shows the flowchart of the process used in this study. Thresholding is experimented with in this study as it is a well-known and widely used approach to segment images from the foreground and background. Thresholding will first convert the input image into a binary image based on the selection of the threshold (T) value from the histogram of the image using (1). From (1), f(x,y) is the input image and g(x,y) is the output image after the thresholding process is applied.

$$g(x,y) = \begin{cases} 1 \ \text{if} \ f(x,y) \geq T \\ 0 \ \text{if} \ f(x,y) < T \end{cases} \tag{1}$$

In this research, a preliminary study has been conducted in selecting the T value for the thresholding. A set of images had been tested with different T values. T value was chosen randomly and then observed by which of the T values that give more accurate result. Based on the experiments on these images, T = 70 yields the most accurate value to segment the breast tumour area from the input images. Table 1 shows the comparison of different values of T during the preliminary study. If the value of T is too small (i.e., T = 50, T = 60), unnecessary information will be included. However, if the value of T is too big (i.e., T = 110, T = 100, T = 90, T = 80), it will discard much necessary information. Hence, the selection of the T value is important to obtain a good segmentation result. The results show the difference of the segmented image that some image contain unnecessary information and some result missing the necessary information. The selected T value is chosen based on the intended result to be

obtained.

Table 1. Comparison in different T values

T = 50	T = 60	T = 70	T = 80

T = 90	T = 100	T = 110	

2.4 Canny Edge Detector

To detect the edges of the breast tumour area, the Canny edge detector is used. Canny edge detector works by isolating the noise from the image [14].

i. Convolving the image using a Gaussian function to obtain a smooth image. This works by smoothing the image with a Gaussian filter to eliminate noise and unwanted details on the images. Equation (2) shows the Gaussian function derivatives.

$$g(m,n) = G_\sigma(m,n) * f(m,n) \tag{2}$$

ii. Apply first gradient operator using the gradient operators. Equations (3) and (4) show the gradient operators of Sobel and Prewitt respectively.

$$M(n,m) = \sqrt{g_m^2(m,n) + g_m^2(m,n)} \tag{3}$$

$$\theta(n,m) = \tan^{-1}\left[g_n(m,n)/g_m(m,n)\right] \tag{4}$$

iii. Apply threshold to the image using Equation 1 as mentioned in section 2.3.

iv.   Apply non-maximal or critical suppression. This process will suppress edges obtained in M^T above to produce the edge ridges on the images.

3. RESULTS

A complete system to segment the breast tumour has been developed on the MATLAB platform using the proposed methodology in Fig. 2. The total numbers of 33 mammogram images were used to evaluate results of the proposed algorithm. A quantitative evaluation of the lesions detected is conducted by comparing the results obtained by the system with the gold standard which is obtained from area of overlap (AO) using (5). Table 2 shows the average accuracy of the AO for 33 images tested.

$$AO = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \times 100 \qquad (5)$$

Table 2. Results of average accuracy of the area of overlap (AO)

Measurement	Average Accuracy (%)
Area of Overlap (AO)	52.09

Next, the False Positive Rate (FPR) method is used to quantify the over-segmentation of the tumour area while the False Negative Rate (FNR) method measures the under-segmentation of the breast tumour within the images. Both evaluations using FPR and FNR are shown in (6) and (7) respectively.

$$FPR = 100 \times \frac{|S_1 \cap S_2'|}{|S_1 \cup S_2|} \qquad (6)$$
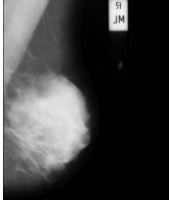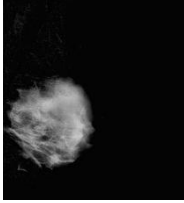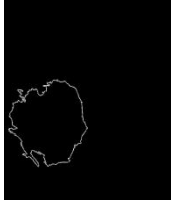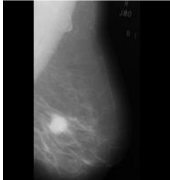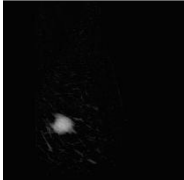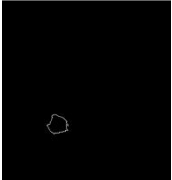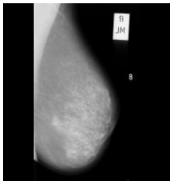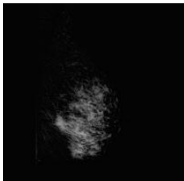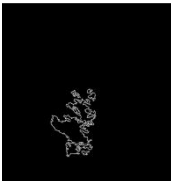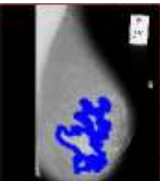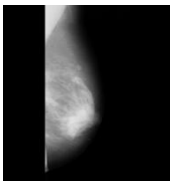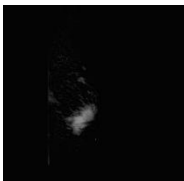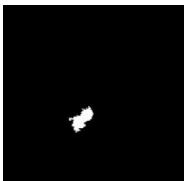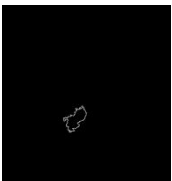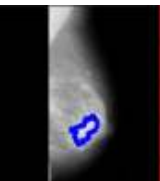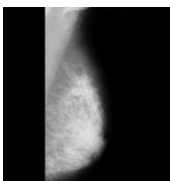
$$FNR = 100 \times \frac{|S_1' \cap S_2|}{|S_1 \cup S_2|} \qquad (7)$$

S_1 represents the area of the tumour image obtained by the proposed algorithms, S_1' is the complement of S_1, S_2 represents the area of the ground truth data and S_2' is the complement of S_2. Table 3 shows the average result of FPR and FNR from the proposed algorithm. Table 4 is a sample of output from the proposed algorithm.

Table 3. Results of average False Positive Rate (FPR) and False Negative Rate (FNR)

Measurement	Average Accuracy (%)
False Positive Rate (FPR)	33.34
False Negative Rate (FNR)	14.57

Table 4. Sample Results of the Breast Tumour Segmentation
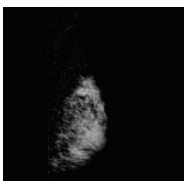
Original image	Pre-Processing	Segmented Image	Canny Edge	Tumour highlighted

4. CONCLUSION

The proposed algorithm of thresholding and Canny edge detector for segmenting breast tumour has utilized the percentage of AO, FPR and FNR from 33 test images. Table 2 shows the average accuracy of Area Overlap (AO) and Table 3 shows the average accuracy of FPR and PNR from the proposed algorithm. Overall, the performance of the proposed algorithm achieved 52.09 percent for AO and 33.34 percent and 14.57 percent for FPR and FNR respectively. Hence, the future work is to hybridize the proposed algorithm with optimization

techniques to increase the accuracy.

5. ACKNOWLEDGMENTS

6. REFERENCES

[1]   M. Sharma, R. Singh and M. Bhattacharya (2017, November*). Classification of breast tumors as benign and malignant using textural feature descriptor*. Paper Presented at 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). doi: 10.1109/BIBM.2017.8217811.

[2]   M. Yasmin, M. Sharif and S. Mohsin (2013). Survey paper on diagnosis of breast cancer using image processing techniques. *Research Journal of Recent Sciences*, 2(10), 88-98.

[3]   F. Shirazi, and E. Rashedi (2016, October 20). *Feature weighting for cancer tumor detection in mammography images using gravitational search algorithm*. Paper presented at 2016 6th International Conference on Computer and Knowledge Engineering (ICCKE). doi: 10.1109/ICCKE.2016.7802158.

[4]   J. M. Sharif, M. F. Miswan, M. A. Ngadi, M. S. H. Salam and M. M. Abdul Jamil (2012, February 27-28). *Red blood cell segmentation using masking and watershed algorithm: A preliminary study*. Paper presented at 2012 International Conference on Biomedical Engineering (ICoBE). doi: 10.1109/ICoBE.2012.6179016.

[5]   McAndrew, A. (2015). *A computational introduction to digital image processing*. Chapman and Hall/CRC.

[6]   B. Hela, M. Hela, H. Kamel, B. Sana and M. Najla (2013, March 18-21). Breast cancer detection: A review on mammograms analysis techniques. Paper presented at 10th International Multi-Conferences on Systems, Signals & Devices 2013 (SSD13). doi: 10.1109/SSD.2013.6563999.

[7]   M. Radha and D. S. Adaekalavan (2016). Mammogram of Breast Cancer Detection Based using Image Enhancement Algorithm. *International Journal of Emerging Technology and Advanced Engineering,* 5(7), 1-6.

[8]   P. Kus and I. Karagoz (2012). Fully automated gradient based breast boundary detection for digitized X-ray mammograms. *Computers in biology and medicine*, *42*(1), 75-82.

[9]   M. Mustra and M. Grgic (2013). Robust automatic breast and pectoral muscle segmentation from scanned mammograms. *Signal processing*, *93*(10), 2817-2827.

[10]   A. E. R. Duque, D. C. A. Gómez and J. K. A. Nieto (2014, September 17-19). *Breast lesions detection in digital mammography: An automated pre-diagnosis*. Paper presented at 2014 XIX Symposium on Image, Signal Processing and Artificial Vision. doi: 10.1109/STSIVA.2014.7010157.

[11]   N. N. Shah, T. V. Ratanpara and C. K. Bhensdadia (2014). Early Breast Cancer Tumor Detection on Mammogram Images. *International Journal of Computer Applications*, 87(14), 14-18.

[12]   Z. A. Jaffery and L. Singh (2013). Performance analysis of image segmentation methods for the detection of masses in mammograms. *International Journal of Computer Applications*, 82(2), 44-50.

[13]   R. Roslan, N. Jamil and R. Mahmud (2010, November 30). *Skull stripping of MRI brain images using mathematical morphology*. Paper presented at 2010 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES). doi: 10.1109/IECBES.2010.5742193.

[14]   S. S. Al-Amri, N. V. Kalyankar and S. D. Khamitkar (2010). Image segmentation by using edge detection. *International Journal on computer science and engineering*, 2(3), 804-807.