Original Article

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Radiology Section

Characterisation of Breast Cancer Lesions using Image Processing Based Technique

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ABSTRACT

Introduction: Characterisation of mammographs deliberates as influential approaches in cataloguing of breast tissues and tumour. In breast, unravelling of nearby tissues in the mammographs is one of the tough processing procedures. The existence of speckle noise in these mammographs boundaries makes the pathology analysis more difficult.

Aim: To characterise breast cancer lesions using different image processing algorithms in order to improve the mammographs and increase their diagnostic value.

Materials and Methods: This retrospective study aims to locate structures and lesions in breast images. The algorithms use the noise speckles deletion, augmentation and subdivision of the breast tissue and the background in mammographs. More precisely, it aims to ascribe a label to pixels within the mammographs that have the same graphic characteristics. The segmented images were associated with the binary image mask to the original mammograph. The Root-Mean-Square Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR) were studied in images database. Both percentage match between ground truth and segmentation results were calculated.

Results: Percentage match measure of watershed algorithm was 96.60 ($p<0.05$) and Corresponding Ratio (CR) was 0.019 ($p<0.05$). The edge detection gave good and clear visualisation of the processed images that increased the diagnostic value of them.

Conclusion: The edge detection and water-marker technique are able to identify the breast lesions precisely and improves radiological analysis and diagnosis.

Keywords: Image enhancement, Image processing, Mammography, Segmentation

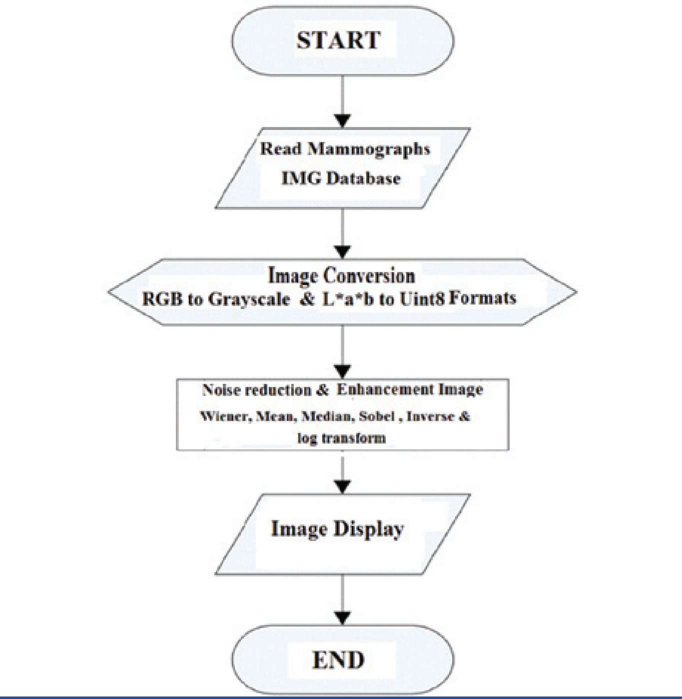
INTRODUCTION

Breast tissue Characterisation is most significant computerisation methods that are used to investigate the breast lesions [1-3]. It provides important dynamic and static data such as the outline, location and magnitude of the lesion. Those methods can increase the insight and interpretation rate. Breast cancer develops in both fatty and tubular tissues [4,5]. Breast cancer is most common malignant disease in occurrence and second most common cause of death among women globally. Mammography is a radiological procedure to visualise the whole breast tissues [6-8]. Recently, mammography is used in the detection of early breast cancer stages and treatment monitoring. Medical imaging is a process of producing visible images of inner structures of the body for scientific and medicinal study and treatment as well [9-11].

Medical imaging includes both organic and radiology which use electromagnetic energies (X-rays and gamma), sonography, magnetic, scopes, thermal and isotopes imaging. There are many other technologies which are used to record information about the location and function of the body. Those methods have many limitations compared with those modulates which produce images. Annually billions of images are done globally for different diagnostic purposes. About half of them use ionising and non-ionising radiation modulates [12]. Those images were produced using fast processors and due to conversion of the energies arithmetically and logically to signals [13-15]. Those signals later convert to digital images. They represent the different types of tissues inside the body. The clinical image analysis incorporates numerous kinds of strategies and tasks, for example, image pick-up, interpretation, archiving, viewing and transference. The advanced pictures have a few advantages, for example, quicker and shabby handling, simple archiving and transference, prompt quality evaluation, various duplicating and quick proliferation and versatile control. The disadvantage of computerised image is misapplication copyright, failure to resize with protecting the quality, need enormous limit memory and need quicker processor for control [16]. Image processing is the use of computer to manipulate on digital image. It has many benefits such as elasticity, adaptability, data storing and communication. With the growth of different image resizing techniques, the images can keep efficiently. It has many sets of rules to perform into the images synchronously. The 2D and 3D images can process in multiple dimensions. The image processing was founded in 1960s [17]. In the 1970s with the development of computer system, the cost of image processing becomes less and fast. In the 2000s, the image processing becomes quicker, inexpensive and simple [18-22].

MATERIALS AND METHODS

This retrospective study was conducted from November 2018 to January 2019. It aims to locate structures and lesions in breast images. More precisely, it aims to ascribe a label to pixels within the mammographs that have the same graphic characteristics. A sample of 100 mammographs was used in this study. Image processing program such as "MatLab" was used to perform both mathematical and logical operations in image scrutiny and characterisation. Mammography images comprise noise that makes the location and detection of suspicious tumour areas and breast tissue difficult. Consequently, the pre-processing operations are crucial to removing the noise and background in order to enhance the region of interest detection. Different resolution and contrast processes were used such as image modification, noise decline using Sobel, Canndy and Roberts's edge detection techniques. Noise and wiener adjustment techniques are used widely in contrast enhancement. Those techniques adjust the quality of the breast tissue in order to make the carcinoid areas diagnosis easier. Mammographs contain many noise speckles that result in wrong determination of the lesion. The [Table/Fig-1] showed the Gaussian technique that was performed in the study. The variance and mean of the images were measured using Wiener techniques [Table/Fig-1].



[Table/Fig-1]: Flowchart of Input, process and output of image enhancement techniques.

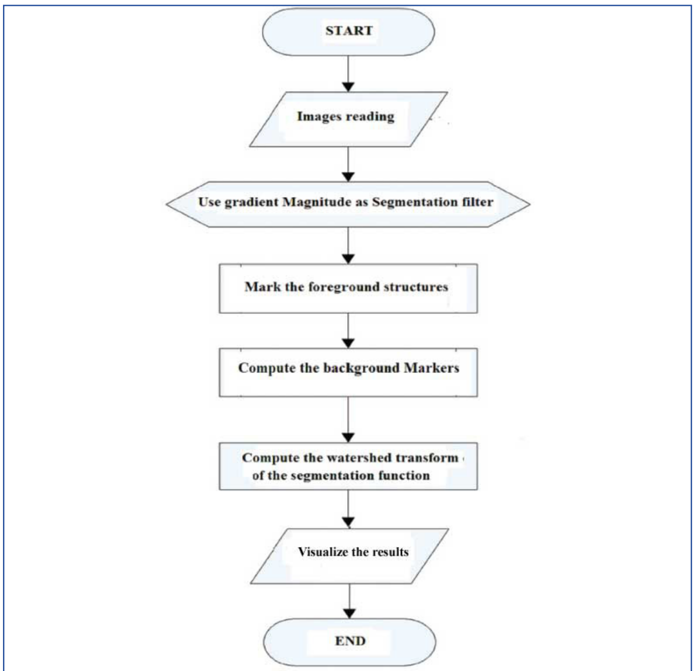
$$\mu = \frac{1}{NM}\sum_{n_1,n_2\in\eta} a(n_1,n_2) \text{ and } \sigma^2 = \frac{1}{NM}\sum_{n_1,n_2\in\eta} a^2(n_1,n_2) - \mu^2,$$

Where η is the *N*-by-*M* local region of respectively pixel in the mammograph.

$$b(n_1,n_2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}(a(n_1,n_2) - \mu),$$

v^2 represents the noise alteration.

Watershed segmentation can detect the breast tissue efficiently and precisely. This technique analyses the mammographs as a topographical grey image and it draw the gradient scenery of the mammograph and outline watersheds once the inundating of separate indicators appointment with one another. Henceforth, the documentation of markers is incredibly crucial in breakdown the over-segmentation tough. The recommended technique was a texture-based technique that selected the marker levels for the water-level involvement [Table/Fig-2]. The mammographs were divided into 10 groups.



[Table/Fig-2]: Input to, process, and output of Segmentation techniques.

The Forward Algorism

$$L^* = 116\left(Y/Y_n\right) - 16$$

$$a^* = 500\left[f\left(X/X_n\right) - f\left(Y/Y_n\right)\right]$$

$$b^* = 200\left[f\left(Y/Y_n\right) - f\left(Z/Z_n\right)\right]$$

Where, X_n,Y_n, and Z_n are the Tristiulus values of the white point.

The RMSE was used to measure the variances between values that foretold by a model and the values detected. The RMSE assists to aggregate the extents of the faults in estimation of numerous times into a single amount of predictive power. RMSE is a measure of accurateness, to compare estimating errors of dissimilar models for a specific dataset and not between datasets, as it is scale-dependent. The RMSE calculates as follows:

$$\text{RMSD } \theta) = \sqrt{MSE(\theta)} = \sqrt{E\left((\theta - \vartheta)^2\right.}$$

Where:

θ represents the estimator

ϑ represents the estimated parameter

The PSNR block calculates the signal-to-noise ratio, in decibels, between two different images. This ratio was used as a quality measurement tool between the original and a processed image.

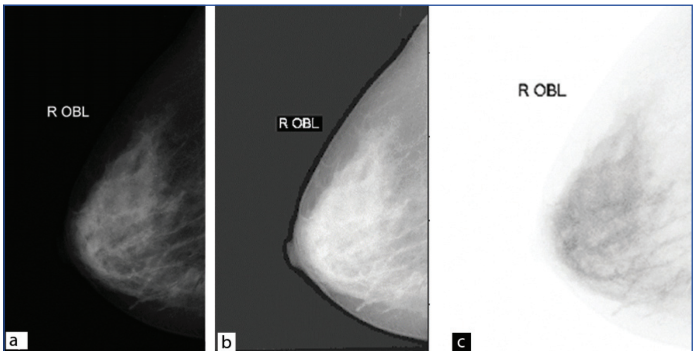
PSNR is calculated as follows:

$$PNSR = 10\log_{10}\left(\frac{R^2}{RMSE}\right)$$

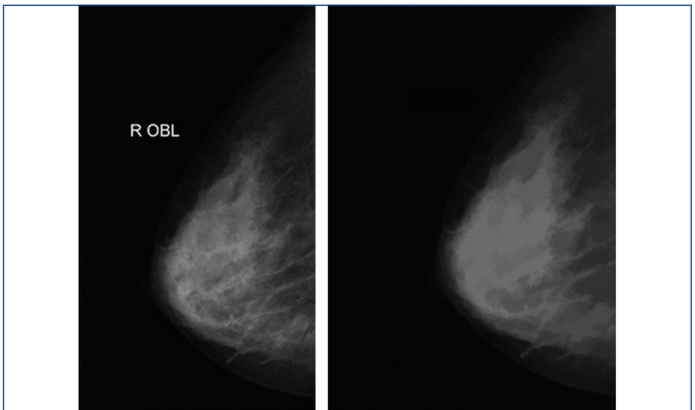
Where: R: represents the maximum fluctuation in the input image data.

RESULTS

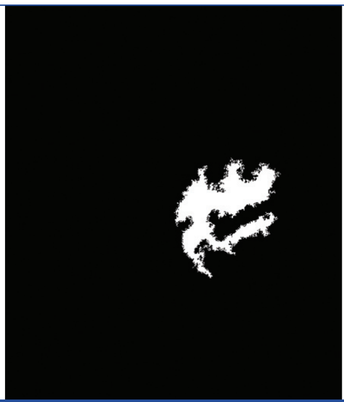
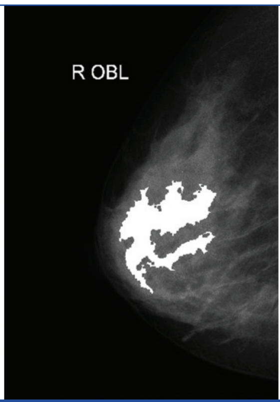
In pre-processing phase, the mammographs were read and stored as grey colored images. Then multiple algorithms were applied to binary converted images such as sharpen and log approaches. In this phase, the noise speckles were removed followed by median and log filter. Those techniques can give better results compared with the others. Those techniques work non-linearly to increased the quality of processed mammographs. The results got by the application scheme of detecting breast cancer as shown below in [Table/Fig-3-9].



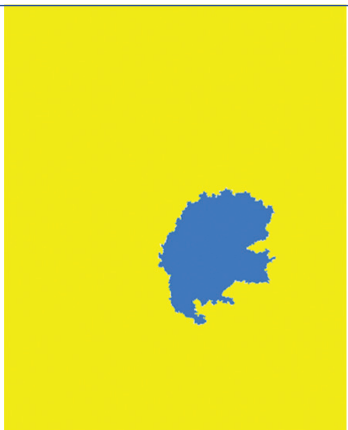
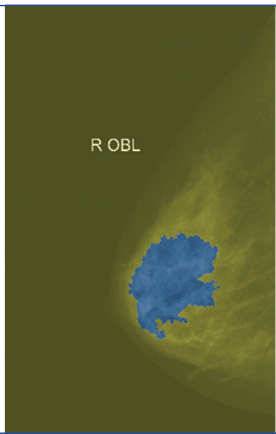
[Table/Fig-3]: Input to, process, and output of Image enhancement techniques: a) original image; b) Log transform; c) Inverse transform.



[Table/Fig-4]: The original mammography image.
[Table/Fig-5]: Opening close reconstruction algorithm. (Images from left to right)

[Table/Fig-6]: Opening close reconstruction algorithm. **[Table/Fig-7]:** Modified regional maxima superimposed on original image (fmg4). (Images from left to right)

[Table/Fig-8]: Coloured watershed label matrix (Lrgb). **[Table/Fig-9]:** Lrgb superimposed transparently on original image. (Images from left to right)

Quantitative Analysis of Segmentation Results

The [Table/Fig-10] showed the comparison segmentation results on images, time taken, number of clusters, numbers of iteration, RMSE and PSNR for the segmented images. Group 7 and Group 9 had highest number of iterations amongst the studied image groups. The RMSE ranged between 0.5055 and 0.6003 while the SNR ranged between 48.620 and 51.008. The [Table/Fig-11] showed the quantitative analysis of the segmented mammographs which were 96.60 and 0.19 for PM and CR respectively. The [Table/Fig-12] showed breast segmentation methods according to the approaches used in this study compared with other authors' methods and accuracy [23-29].

Image group	Time taken	Number of clusters	Numbers of iteration	RMSE	PSNR
Group 1	0.43 sec.	61	6	0.5431	48.623
Group 2	0.31 sec.	60	9	0.5951	49.012
Group 3	0.47 sec.	60	7	0.5763	48.961
Group 4	0.56 sec.	63	8	0.5102	48.620
Group 5	0.36 sec.	64	9	0.5055	48.751
Group 6	0.43 sec.	60	7	0.5310	49.521
Group 7	0.51 sec.	69	8	0.5642	50.123
Group 8	0.63 sec.	67	9	0.5341	51.008
Group 9	0.69 sec.	69	9	0.5961	48.753
Group10	0.59 sec.	68	8	0.6003	49.821

[Table/Fig-10]: Comparison of Outcomes of segmentation results on images.
RMSE: Root-mean-square error, PSNR: Peak signal-to-noise ratio

Case	GP1		GP2		Automated methods	
	PM	CR	PM	CR	PM	CR
Group1	94.43	0.75	96.28	0.35	98.77	0.87
Group 2	90.11	0.31	82.17	0.56	92.51	0.91
Group 3	82.53	0.63	91.08	0.12	95.01	0.58
Group 4	87.88	-1.01	96.36	-0.99	98.95	-1.21
Group 5	94.39	-2.15	91.87	-1.13	99.12	-1.99
Group 6	91.37	0.61	93.02	0.51	97.82	1.64
Group 7	90.43	-0.43	94.77	-0.45	98.32	-0.91
Group 8	85.07	0.32	95.60	0.65	94.99	2.04
Group 9	90.38	-0.92	98.62	-0.82	98.82	-0.98
Group 10	89.99	0.62	89.51	0.75	91.75	0.95
Mean					96.606	0.19

[Table/Fig-11]: The quantitative results of segmented mammograph.

Authors	Methods	Accuracy
Present study	• breast muscle segmentation • Noise removal	96.6%
Ma Y et al., [23]	• Label elimination • Image improvement	90.4%
Raba D et al., [24]	= breast muscle	98%
Zhang Z et al., [25]	segmentation	98.8%
Chen Z et al., [26]	Noise removal	
Wei K et al., [27]	Contrast improvement	95.7%
Raba D et al., [24]	Artifacts removal	88.2%
Mustra M et al., [28], Rahmati P et al., [29]	FCLAHE for image improvement	

[Table/Fig-12]: Breast segmentation methods according to the approaches used in this study compared with other authors' methods and accuracy [23-29].

DISCUSSION

The [Table/Fig-3-8] show the segmented images associate the binary image rough Mask to the original mammograph. Both of percentage match between ground truth and segmentation results were calculated. Those results were high compared by many other author results such as Abdallah Y, [19]. Breast tissues characterise using watershed segmentation methods. Those methods could delineate the breast lesions precisely. Noise speckles deletion and water-marker algorithms of the breast tissues those were used in this study gave high matching ratio with low amounts of SNR and high RMSE associating with other researchers such as Qin X et al., Abdallah Y, and Bushra M et al., [17,19,21]. Authors recommended in their study that the contrast using the FCLAHE technique would increase contrast and discernibility of the mammographs could upsurge using noise reduction by local contrast enhancement procedures [28]. The proposed techniques by this study showed high matching rates compared with the manual scrutiny of the images by physicians. Thus, utilisation of those algorithms would enhance the images precisely in short period. The combination of the image improvement techniques and segmentation would improve the Characterisation of the breast tissue and reduce the noise to lesser level. This method was precise, quiet and easy to be applied in large mammographs databases. In this paper, the proposed method is a combined method, which can be easily used to characterise the breast tissues and lesions. The results of this study were different than Loukas C et al., who evaluated the pattern of the breast tissue beneath high and low magnifications and Tomar RS et al., who used Neural network, wavelet, symbolic logic, biological process approach and eventually hybrid system, which employs integration of on top of technique [30,31]. This method was more precise, quieter and easier to be applied in large mammographs databases.

LIMITATION

Although the use of powerful image analysis tools and expert judgment is a common method of studying and characterising the breast tissues, this study does not provide a complete picture of other breast disorders and other breast imaging modalities which were not studied.

CONCLUSION

This study concluded that pre-processing procedures could improve the mammographs prior characterisation of breast structures using watershed approach. The future work should include large databases and multiple imaging modalities. This study discovered the k-means technique that can be beneficial for breast tissue characterisation. This study will help the researchers to uncover the critical areas of breast cancer automatic detection that many researchers were not able to explore.

Authors' Contribution

All authors conceived of the presented idea. YA developed the theory and performed the computations. YA and NHF verified the analytical methods. YA supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

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