Original Article

Effects of Enhancement Methods on Diagnostic Quality of Digital Mammogram Images

Langarizadeh M[1], Mahmud R[1], Ramli AR[2], Napis S[3], Beikzadeh MR[4], Wan Abdul Rahman WEZ[5]

Abstract

Background: Breast cancer is one of the most important diseases in females. Malaysian women have not excluded. According to the Malaysian Oncology Society [1], about 4% of women (who are 40 years old and above) have involved by breast cancer. Masses and microcalcifications are two important signs for breast cancer diagnosis on mammography. According to our estimation, radiologists could diagnose breast cancer on mammogram screening program, with approximately 75% accuracy. About 25% of breast cancers have missed on mammograms. This study aimed to explore the effects of enhancement methods on digital mammograms.

Methods: SPSS software have used for data analysis. Wilcox on ranked test and ROC have used to compare the original and manipulated images. In this study, 60 digital mammogram images which include 20 normal and 40 confirmed diagnosed cases of breast cancer (masses), have selected and manipulated by using histogram equation, histogram stretching and median filter.

Results: The results have shown that the histogram stretching and median filter methods could improve image quality for detection of masses with increased sensitivity and specificity by 5%.

Conclusion: The sensitivity and specificity have improved by using histogram stretching and median filter. The results of this study have shown results as below ; the histogram equation have improved the sensitivity up to 97.5% ,while the median filter could improve sensitivity (97.5%) and specificity (85.5%). It means that the median filter could be more effective than the other enhancement methods.

Key Words: Image Processing, Enhancement, Digital Mammogram, Sensitivity, Specificity

1. Faculty of Medicine and Health Science, University Putra Malaysia, Malaysia
2. Faculty of Engineering, University Putra Malaysia, Malaysia
3. Information and Communication Development Center, University Putra Malaysia, Malaysia
4. Malaysian Institute of Microelectronic Systems, Malaysia
5. Faculty of Mathematics and Quantitative Research, University Technology Mara, Malaysia

Corresponding Author:
Mostafa Langarizadeh,
PhD in Medical Informatics
Tel: (#6)0162949890
Email: langarizadeh2001@yahoo.com

Received: 23 Oct. 2009
Accepted: 30 Dec. 2009
IJCP 2010; 1: 36-41

Introduction

Cancer is one of the most important causes of death all over the world. In United States of America (USA), the second cause of death is cancer. Cancer is not limited to a specific gender or group of people. It can involve anybody and no one is spared. In US, 1 out of 2 men and 1 out of 3 women face to some kind of cancer [2, 3].

As World Health Organization have reported in 2005; 7.6 million deaths have occurred because of cancer, then more than 70% of them occurred in undeveloped countries. It is expected that death because of cancer will increase up to 9 million in 2015 and 11.4 million in 2030 [3].

In women population, breast cancer is one of the most important disease [4]. In USA 8% and in United Kingdom (UK) 5% of women population have involved with breast cancer [1, 4, 5]. According to the Malaysian Oncology Society, about 4% of women has breast cancer [1, 6]. This malignancy was the 10th cause of hospitalization and 3rd cause of death in Malaysia in 2006 [7].

Masses and microcalcifications are two important signs for breast cancer on mammograms. Mass detection is more difficult than micro calcification , because masses may have similar density as normal breast tissue and they have different shapes and possibly ill defined boundaries than micro calcifications [4, 8].

Currently, the most essential and important tool for" mass early detection" is mammography [9, 10]. Reading mammogram image for cancer detection could be challenged as the image occasionally show low contrast difference especially on dense breast. Furthermore, it will be a time consuming to train an expert person in this area [11].

The American Cancer Society, American Medical Association (AMA) and American College of Radiology (ACR) have recommended screening mammography for all above 40 which yearly mammogram is recommended. Mammograms should be done earlier in women who has breast cancer high risk [2, 12]. Screening mammography could be helpful for early detection of breast cancer and microcalcifications.

Since detection of mass and microcalcification is rather difficult in dense breast, the image quality thus, should contain high standards [4]. The main aim of study is to visualize the effect of different enhancement techniques, for increasing digital mammogram images quality, then providing the highest level of sensitivity and specificity to detect abnormalities by radiologists.

Histogram Stretching

Histogram stretch is an image processing technique that could make images more clear and improve quality [13]. In this technique, the picture gray scale may change from 0 (black) up to 255 (white) [14]. The histogram shows distribution of gray levels in an image. As a general rule, small spread in histogram is due to low contrast and wide spread histogram indicates image of high contrast.

Histogram stretching or contrast stretching is the simplest method to increase the contrast of an image. When this method is applied on mammogram images, a greater separation of contrast between background and foreground level distribution will be produced [15-17].

In this technique for each pixel will develop a new contrast based on the following equation:

$$I_{new} = \frac{G_{\min} + (I_{org} - I_{\min}) \times (G_{\max} - G_{\min})}{I_{\max} - I_{\min}}$$

(Eq. 1)

Where $I_{\min}, I_{\max}$ the range of the intensities of the original is image and $G_{\min}, G_{\max}$ is the range of intensities of the resulting image. The global histogram modification does not make any changes for texture enhancement since it cannot change the order of the gray levels of the original image. Therefore, it is not suitable for enhancing mammograms [4, 13, 14].

Histogram Equalization

Histogram equation is another method to change the histogram. Mammogram histogram is a probability distribution. Using histogram equation, changes the histogram and redistribute gray levels to obtain image contrast as uniform as possible. Each image may contain L different gray levels, 0, 1, 2, 3, L-1, and gray level I may occurs n_i times. The total number of pixels in this particular image is equal m which is summation of all gray levels frequencies [14, 16].

$$m = n_0 + n_1 + n_2 + \ldots + n_{L-1}$$

(Eq. 2)

To transform the gray levels to obtain better contrasted image, the gray level of each point could be changed according to the following equation:

$$\left(\frac{n_0 + n_1 + n_3 + \ldots + n_i}{m}\right)(L-1)$$

(Eq. 3)

Noise Removal Using Spatial Filtering

One of the most important methods is the noise removal. Based on the type of noise, there are different spatial filters which operate on small neighbourhoods for example 3x3. The most useful order filters is the median filter [17] and it is used to remove noise from mammogram images. It is a non-linear method to decrease blurring of edges [18]. When this method is employed to remove noise, current point value will be replaced by median of neighbourhoods. A 3 by 3 mask is applied and the output is equal to the median of values in the mask. In this process the lowest and the highest value will be detected at the top or bottom area and the values will change to the nearest value with its neighbour [18].

Background of the Study

A combined method suggested by Li et al. [19] which uses morphological operation, finite generalized Gaussian mixture (FGGM) and Bayesian relaxation labeling technique (CBRL) which have used to improve mammogram enhancement. They used 50 cancerous and 50 normal cases to train the system, then they tested the system on 23 normal cases and 23 confirmed cancerous cases. They mentioned that "FGGM model is better than the finite normal mixture model". They reported 84% sensitivity and 82% specificity.

Sun et al. [20] employed the tree-structured filter and wavelet transform techniques for image enhancement and adaptive fuzzy C-means algorithm for segmentation in their computer-aided detection (CAD) system. They developed an artificial neural network and combined it with Kalman filtering to train their suggested system. They employed a total of 100 images, which are including 50 normal and 50 abnormal cases. They stated that the detection of lesion was improved by using this method but there is no evidence that show how many percent.

According to Brice [21], CAD can show the edges to radiologists to diagnose cancer. He stated that since the CAD was adjusted to microcalcification detection it could not be useful for lesion detection in dense breasts. Researcher could not find any significant improvement in readers' ability to detect cancer in dense breast when they used CAD system. He mentioned that in fatty breasts, the sensitivity of mammography alone is 98% in comparison with 88% for mammography and CAD. This result is also supported by the other research which conducted by Brem and Schoonjans [22]. They collected both with and without CAD radiologists' interpretations on 84 mammogram images. They concluded that "no statistically significant changes in sensitivity were found when experienced radiologists were assisted by the CAD-system". The study also confirms that no significant compromise in specificity was shown.

The other researchers have published different results about commercial CAD systems' performance. Ciatto et al. [23], reported sensitivity of 42.1% for CAD and 46.1% for double reading (CAD and Radiologist).

Freer and Ulissey [24], however worked on 12860 screening cases and showed that proportion of early cancer detection increased from 73% to 78% .

Materials and Methods

Sixty digitized computed mammogram images including 40 confirmed cancerous cases (masses) and 20 normal cases are randomly selected from National Cancer Society of Malaysia. After cropping the unnecessary area from all original images and resize them to 1024 by 1024 pixels, different image processing methods including histogram equation (with gray level of 51, 102, 153, 204 and 255), histogram stretching, median filter and hybrid of median filter + histogram stretching were applied on the original images.

Manipulated images were scored by two expert radiologists from department of imaging, University Putra Malaysia. SPSS (version 15) is used to draw Receiver Operating Characteristic (ROC) curve and to calculate sensitivity and specificity of detecting of masses of different techniques.

Results

Table 1 shown fraction of True Positive and True Negative diagnosis of original images. The radiologists' sensitivity was 95% and their specificity was 80%. Histogram equation with gray level of 51, 102, 153, 255 and median filter + histogram stretching have not shown any improvement in sensitivity and specificity. There were the same sensitivity and specificity when images manipulated using histogram equation with gray scale of 204. As it shown in Tables 2 and 3 and also the ROC curve the histogram stretching and median filter methods could improve radiologists' sensitivity and specificity (Figure 1 and 2).

Regards to breast density, the images categorized to two groups: low density and dense groups. A total of 26 images were categorized in low density and 34 were dense. The fraction of sensitivity and specificity of original images according to breast density is shown in tables 4 and 5. Based on the results, the radiologists' sensitivity and specificity is higher in the case on low density cases than dense

Table 1. *Fractions of the original images*

		Confirmed diagnosis	
		Cancerous	Normal
Radiologist's Diagnosis	Cancerous	0.95	0.20
	Normal	0.05	0.80

Table 2. *Fractions of the manipulated images using histogram stretching*

		Confirmed diagnosis	
		Cancerous	Normal
Radiologist's Diagnosis	Cancerous	0.95	0.10
	Normal	0.05	0.90

Table 3. *Fractions of the manipulated images using median filter*

		Confirmed diagnosis	
		Cancerous	Normal
Radiologist's Diagnosis	Cancerous	0.975	0.15
	Normal	0.025	0.85

Table 4. *Fractions of the low density original images*

		Confirmed diagnosis	
		Cancerous	Normal
Radiologist's Diagnosis	Cancerous	0.938	0.10
	Normal	0.063	0.90

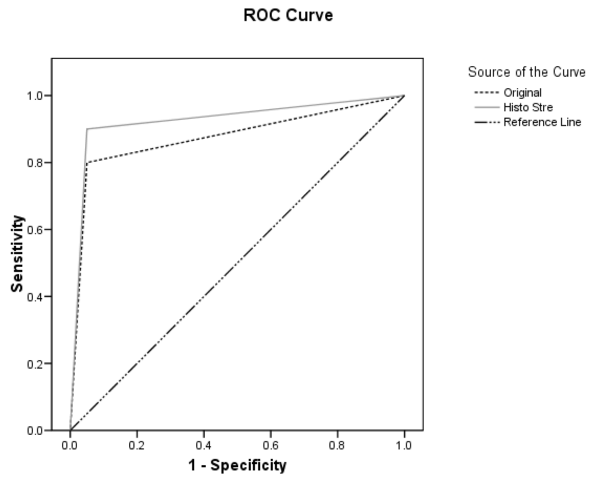

Figure1. *ROC curve for histogram stretching*

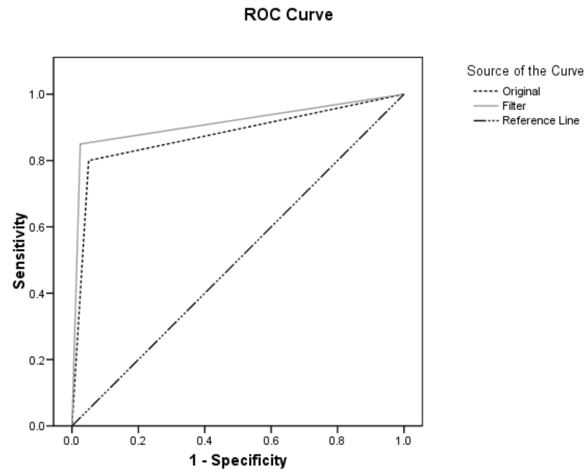

Figure 2. *ROC curve for Median Filter*

ones. It is happened since in the dense breasts the masses could hide behind dense areas and radiologists could not see masses as clear as in the low density cases.

After applying histogram stretching method the sensitivity and specificity of detection of masses in low density cases were the same as the original images. However, in the case on dense breasts, the sensitivity improved (95.8%) in comparison of the sensitivity of detection of masses in the original images (88.5%) while the specificity decreased (Table 6).

When the median filter method has applied in low density cases the sensitivity has improved up to 100% but the specificity reduced (80%) (Table7). Meanwhile, in dense category also the sensitivity improved (95.8%) however; the specificity has not changed in comparison with the original cases (Table 8).

Table 5. *Fractions of the dense original images*

		Confirmed diagnosis	
		Cancerous	Normal
Radiologist's Diagnosis	Cancerous	0.885	0.125
	Normal	0.115	0.875

Table 6. *Fractions of the manipulated dense images using histogram stretching*

		Confirmed diagnosis	
		Cancerous	Normal
Radiologist's Diagnosis	Cancerous	0.958	0.40
	Normal	0.042	0.60

Discussion

The results have shown that some of pre-processing techniques as median filter and histogram stretching are more effective on sensitivity and specificity. In addition median filter could improve both sensitivity and specificity. However, the histogram stretching could make improvement in just specificity. The histogram stretching method makes better visualization for radiologists, and then it causes better differentiation between normal tissue and mass area. The median filter specially removed noises, has caused better visualization for radiologists in order to diagnosis masses. Around 3% of diagnosis has been changed after using median filter.

These findings of current study are consistent with those of Tourassi et al. [25] who has found that the median filter could improve sensitivity from 78% to 82% in their study. They have examined 592 mammogram images and compared different filters. Furthermore, in comparison with previous studies results [26], the methods used in current study have made higher sensitivity and specificity improvement, which could be helpful to decrease number of biopsies and decrease cost of malignancy diagnosis. Using enhancement techniques could be more useful prior to use segmentation or classifying methods.

Table 7. *Fractions of the manipulated low density images using median filter*

		Confirmed diagnosis	
		Cancerous	Normal
Radiologist's Diagnosis	Cancerous	1	0.20
	Normal	0	0.80

Table 8. *Fractions of the manipulated dense images using histogram stretching*

		Confirmed diagnosis	
		Cancerous	Normal
Radiologist's Diagnosis	Cancerous	0.958	0.125
	Normal	0.042	0.875

Conclusion

Image processing methods have different effects on digital mammogram images and might make mammogram images more clear. The radiologists' interpretation could be improved by using image processing methods. The radiologist sensitivity and specificity are two important criteria in diagnosis of malignant changes on mammogram. These criteria have improved by using histogram stretching and median filter. The results of this study have shown, the histogram equation have just improved the sensitivity up to 0.975 while the median filter could improve both sensitivity (0.975) and specificity (0.855). It has shown that the median filter could be more effective than the other enhancement methods.

Acknowledgment

The authors would like to acknowledge Dr Suleiman Tamanang from National Cancer Society of Malaysia for his contributions.

Conflicts of Interest

The authors declared that this research is not supported by institutions' funding.

Author's Contribution

LM managed the project, wrote the paper, manipulated the images and concluded all parts. MR managed radiologists and did scoring procedure, RAR reviewed the literature, NS studied design and methods, BMR collected data, WARWEZ did the data entry and statistical procedures.

References

1.Wahid MI. Breast Cancer. 2007 [cited 06/02/2008]; Available from: www.malaysiaoncology.org.

2.American Cancer Society. What is Cancer? 2006 [cited06/02/2008]; Available from: http://www.cancer.org/docroot/CRI/content/CRI_2_4_1x_What_Is_Cancer.asp.

3.World Health Organization. Cancer. 2008 [cited 06/02/2008]; Available from: http://www.who.int/cancer/en/.

4.Cheng HD, Xu H. A novel fuzzy logic approach to mammogram contrast enhancement. Information Sciences. 2002; 148(1-4):167-84.

5.Cancer help. The Mammogram. 2002 [cited 06/02/2008]; Available from: www.cancerhelp.org.uk.

6.Elm H. Accreditation in Mammography – Pain or Gain? Bio med Imaging Interval J. 2005; 1(1):e6-18.

7.Ministry of Health. Health Facts 2006. 2006 [cited 06/02/2008]; Available from: http://www.moh.gov.my/MohPortal/index.jsp?lang=en.

8.Kang HK, Ro YM, Kim SM. A microcalcification detection using adaptive contrast enhancement on Wavelet transform and neural network. IEICE Trans Info System. 2006 March 1; E89-D (3):1280-7.

9.Wilson M, Hargrave R, Mitra S, Shieh YY, Roberson GH. Automated detection of microcalcifications in mammograms through application of image pixel remapping and statistical filter. 11th IEEE Symposium on Computer-Based Medical Systems; 1998 12-14 Jun;p. 270-4.

10.Breastcancer org. Mammograms. 2007 [cited 06/02/2008]; Available from: www.breastcancer.org.

11.Tucker AK: Text Book of Mammography, Introduction 2nd edition. Edited by : Tucker AK, Yin YN. Churchill Livingstone; 2001: 15.

12.Radiology Info. What is Mammography? 2006 [cited 06/02/2008]; Available from: www.radiologyinfo.org.

13.Baxes GA. Digital Image Processing: John Wiley and Sons; 1994.

14.Gonzalez RC, Woods RE. Digital Image Processing. 2nd edition.Prentice Hall; 2002.

15.Gonzalez RC, Woods RE, Eddins SL. Digital Image Processing Using Matlab: Prentice Hall; 2004.

16.McAndrew A. Introduction to Digital Image Processing with Matlab. Boston: Thomson, Course Technology; 2004.

17.Umbaugh SE. Computer Imaging: Digital Image Analysis and Processing. NewYork: CRC Press; 2005.

18.Tyan SG. Median Filtering, Deterministic Properties. In: Huang ITS, editor. Two Dimensional Digital Signal Processing. Berlin: Springer Verlag; 1981.

19.Li H, Liu KJ, Lo S. Fractal Modelling and Segmentation for the Enhancement of Microcalcifications in Digital Mammograms. Medical Imaging . Dec 1997; 16(6):785 - 98.

20.Sun X, Qian W, Song D. Ipsilateral-mammogram computer-aided detection of breast cancer. Computerized Medical Imaging and Graphics. 2004; 28(3):151-8.

21.Brice J. CAD uncovers more cancers in dense breast mammography. 2002 [cited 10/04/2008];Available from:http://www.diagnosticimaging.com/webcast02/showArticle.jhtml;jsessionid=YHFNH0FKIUGI4QSNDLPSKH0CJUNN2JVN?page=150.html

22.Brem RF, Schoonjans JM. Radiologist Detection of Microcalci®cations with and Without Computer-Aided Detection: A Comparative Study. Clinical Radiology 2001; 56:150-4.

23.Ciatto S, Turco MRD, Risso G, Catarzi S, Bonaldi R, Viterbo V, et al. Comparison of Standard Reading and Computer Aided Detection (CAD) on a National Proficiency Test of Screening Mammography. Eur J Radiol. 2003; 45:135-8.

24.Freer TW, Ulissey MJ. Screening Mammography with Computer-Aided Detection: Prospective Study of 12,860 Patients in a Community Breast Center. Radiology. 2001; 220: 781–6.

25.Tourassi GD, Ike R, Singh S, Harrawood B. Evaluating the Effect of Image Preprocessing on an Information-Theoretic CAD System in Mammography. Acad Radiol. 2008; 15(5):626–34.

26.Zheng L, Chan AK. An artificial intelligent algorithm for tumour detection in screening mammogram. IEEE Trans Med Imaging. 2001; 20(7):559-67.