FUZZY WEIGHTED MEDIAN FILTER WITH UNSHARP MASKING FOR ENHANCEMENT OF DBT IMAGES IN BREAST CANCER DETECTION

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Abstract

Breast cancer survival rates can be increased by providing early treatment to patients; thereby, microcalcification detection is critical because microcalcifications are an early sign of breast cancer. The visibility of microcalcifications can be improved by using Digital Breast Tomosynthesis (DBT) images, which have been shown to improve the overlapping issue in mammograms. However, since DBT screening techniques generate blurry artefacts and noise, this study proposes a DBT image enhancement procedure. As a result, this study indicated an enhancement method based on Non-Linear Unsharp Masking filters (NLUM). A filter, such as the Median Filter in conventional NLUM, is required to complete the non-linear element in the algorithm. Other researchers have previously proposed and demonstrated the Fuzzy Weighted Median Filter (FWMF) to improve medical images; thus, these filters can be adapted to the NLUM and replaced with the conventional filter. Following that, the enhancement process's performance will be evaluated using Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). When compared to the Median Filter, the results show that the FWMF is the best filter to use in NLUM and successfully enhances DBT images with MSE and PSNR averages of 0.0171 and 67.0574, respectively.

Keywords: DBT enhancement, Digital Breast Tomosynthesis, Fuzzy Weighed Median Filter, Non-linear Unsharp Masking

Introduction

Breast cancer is a type of cancer that women all over the world fear as it is the most popular disease that attacks women. This disease has become the leading cause of death for women aged 35 to 55, especially considering the fact that 66% of women with breast cancer are diagnosed after the age of 55 (1). These tumours initiate with microcalcifications, which are small clusters of calcium deposits that develop in breast tissues and can be seen as white spots inside the breast area on mammograms and Digital Breast Tomosynthesis (DBT) images (2). These microcalcifications necessitate further screening though since they can be a sign of cancer (1). Due to the fact that microcalcifications are an early sign of breast cancer, early detection affects a patient's survival rate, as 99 percent of cases survive within 5 years (1, 3).

As a result, previous researchers discovered methods to develop models capable of detecting microcalcifications in DBT images. DBT is a new technology that generates 3D screening images of the breast area that can be viewed from any angle or location (4). In order to produce DBT images and the complete dimension of a breast area, 10 to 30 projection images at a limited angle range of about 11° to 60° are required (5). Moreover, DBT images can reduce false positive rates by 6 to 67 percent compared to mammogram images due to improvements in overlapping tissue that occur on mammogram images due to superimposing breast tissue, which causes the normal tissue to appear abnormal or suspicious (5–7).

However, the great DBT screening technology in producing 3D images had drawbacks such as the presence of blurry artifacts. The noise produced by the DBT images during screening is referred to as blurry artifacts. Despite advancements in technology, this new technology cannot avoid the presence of blurry artifacts, which can result from poor positioning, patient movements during screening, and excessive radiation exposure (8). These factors can reduce the visibility of microcalcifications in DBT images, necessitating an enhancement stage to deblur some blurry objects and remove noise from DBT images in order to see microcalcifications in the breast region more clearly (8).

Algorithms or methods will be used to remove noise from DBT images. Some noise filtering techniques will be used, while thresholding methods will be used to enhance the DBT images (9–16). Many researchers, however, use unsharp masking to aid their proposed model, such as a deep learning model, and use it as the main proposed enhancement algorithm. Moreover, other researchers used the unsharp masking algorithm in conjunction with a weighted guided filter to improve the vessel details of mallendoscopic images, while another researcher proposed using unsharp masking to improve their proposed deep learning models, ChampNet (17,18).

Many studies have already proposed a non-linear element into the unsharp masking algorithm where they insert the non-linear element with a non-linear filter such as Median Filter (19). As a result, the conventional non-linear unsharp masking (NLUM) technique used the Median Filter to form NLUM. NLUM is a method of image enhancement that has been shown to produce clear images of breast scans as well as other types of medical images such as hand, leg, breast, and body scan images (18,19). Panetta et al. proposed a traditional NLUM in 2011 for enhancing mammogram images using the Median Filter for non-linear elements in the NLUM algorithm. On the other hand, a study that used NLUM to enhance an image while using a modified Hybrid Median Filter in the NLUM algorithm was proposed (20). By using a modified Hybrid Median Filter instead of a conventional NLUM, this method reduced halo artifacts in images and produced satisfactory visuals (20).

As the NLUM need a filter in the algorithm, some filters had been studied for their effectiveness in enhancing medical images. Based on the previous study, Fuzzy Weighted Median Filter (FWMF) was proposed to enhance images that had been contaminated by the salt and pepper noise in it, and this method also used to combine with Denoising Based (DB) clustering method to produce more effective enhancement techniques (21). These filters produce promising results in enhancing and filtering the targeted image competing with the other filters in the prospective studies. This filter had more strict conditions in determining the pixel value to replace the existing pixel value in the enhancement process instead only finding the median of all the pixel in 3-by3 window as a conventional median filter (21).

However, these methods are still not sufficient as there exist studies that implement image filtering for breast cancer detection, but most of them focused on MRI images and non-medical images. To the best of our knowledge, there was lack of study conducted on DBT images using this filtering technique. The original unsharp masking method is inconvenient to use on DBT images as the method filters the images basically and generally to all pixels in the image without applying any conditions to particularly choose the pixel value. Hence, the presence of the non-linear element in the algorithm of unsharp masking makes the filtering technique can be altered for flexibility and specificity in enhancing the images. Moreover, this is more reason for this method is suitable for DBT images. Therefore, this paper proposes to study various Non-linear Unsharp Masking (NLUM) algorithms in filtering DBT images. On top of that, the NLUM filters will be compared with the combination of the other type of non-linear filter, which is the Fuzzy Weighted Median Filter (FWMF).

Methodology

The proposed method to enhance the DBT images started from the data collection which then undergoes the pre-processing step before applying the filters for each proposed method. The filtered images then will be applied into the NLUM in the non-linear algorithm in it. The process will then be evaluated using MSE and PSNR. Figure 1 shows the overall stages of this study from pre-processing stages to the performance evaluation of the proposed method.

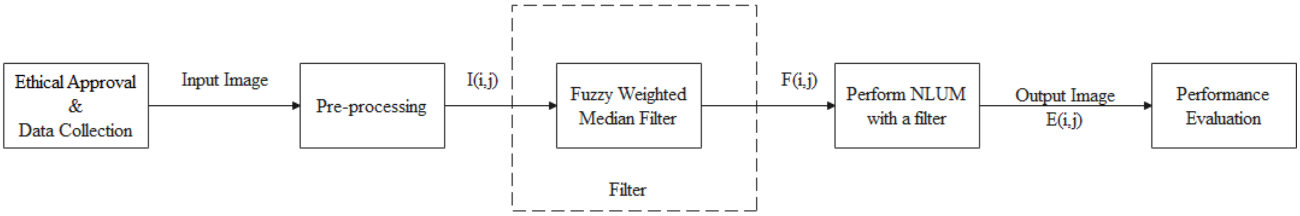


Figure 1: The block diagram of the study

Ethical Approval and Data Collection

The ethical application to the Jawatankuasa Etika Penyelidikan Manusia (JEPeM) of USM is the first step in this project. The ethical application for Digital Breast Tomosynthesis (DBT) data collection with code study: USM/JEPeM/21090622 was approved before the study began. The images will be collected at the Advanced Medical and Dental Institute (AMDI), Bertam at the USM Imaging Unit with the assistance of a trained radiographer using the Picture Archiving and Communication System (PACS). Furthermore, before being made public, the images are deidentified and anonymized in accordance with ethical guidelines.

The input images are DBT images from two patients collected that consist of eleven DBT images. The DBT images were adapted into the MATLAB R2020a software in DICOM type images which were then converted into bitmap type images in order for them to smoothly run in the MATLAB software. These images will then undergo pre-processing steps which are the important step for the DBT images to be prepared before going into the enhancement stage.

Pre-processing Stage

The pre-processing stage is a stage where the input images were prepared for the enhancement step. This stage produces images that help increase the visibility of the microcalcifications to almost absolute white patches which the pixel value of the microcalcifications reaches almost 255-intensity value. For the start, the pre-processing stage starts with increasing the higher intensity value while decreasing the lower intensity value using the minimum threshold value to eliminate lower intensity. While, the maximum threshold value to amplify the higher intensity value without disturbing other value that out of the threshold range. Setting the background to darker intensity helps aiding the background differentiation when the background is set to black with a 0-intensity value which automatically eliminating the background of the breast area. Later, the images with no background and brighter targeted point of interest will go through an enhancement stage, which will smoothen the background objects around the targeted objects, such as microcalcifications.

Fuzzy Weighted Median Filter (FWMF)

The NLUM needs a filter to complete the non-linear algorithm, thus the filter proposed in this study is Fuzzy Weighted Median Filter (FWMF) replacing the median filter in the conventional NLUM. The proposed method overall flow shown in Figure 2.

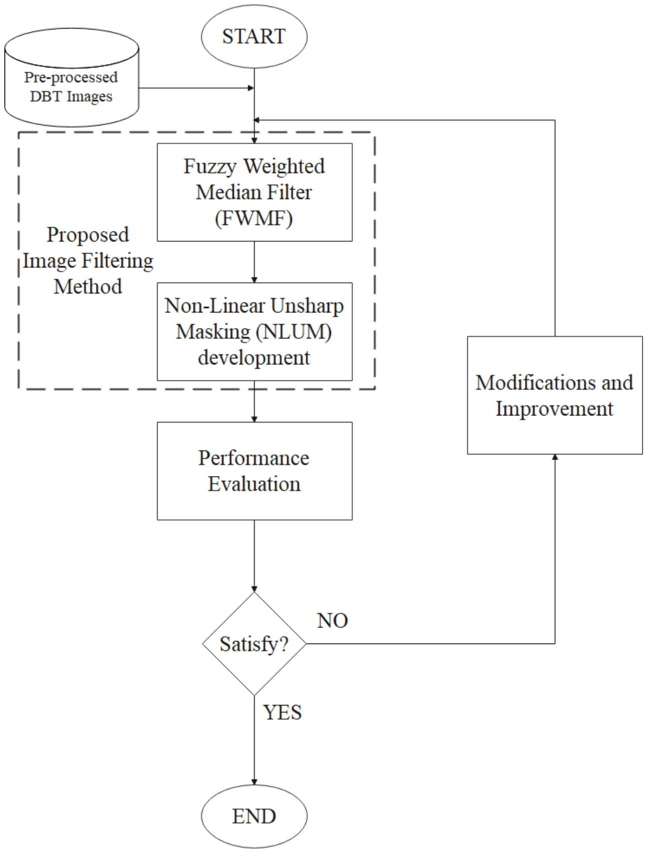


Figure 2: The overall flow of the proposed NLUM

A Fuzzy Weighted Median Filter is a filtering technique that adapts the fuzzy algorithm with conditions to determine the value to weight the median filter. All the 8-neighbouring windows of a targeted pixel, labelled in red will be involved in the algorithms as shown in Figure 3.

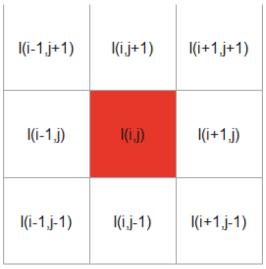


Figure 3: The 8-neighbours window with targeted pixel at center

: Targeted pixel

The value in each of the 8-window neighbors and the targeted pixel at the center, $I(i,j)$ will be extracted their difference. Then, the value of this operation will be declared as d(i,j) which later will be found its maximum absolute value, $D(i,j)$. This maximum absolute value, $D(i,j)$ will be the value that will measured by the fuzzy membership function to determine the value of fuzzy from 0 to 1. The algorithm for the fuzzy weighted median filter started with the correction value equation of linearly-fuzzy weighted then according to the equations, the median filter algorithm, input images, and fuzzy membership function needed to fill this equation, (1). The linearly-fuzzy weighted correction value can be determined as follows (21):

$$X(i,j) = [1 - F(i,j)] \cdot I(i,j) + F_1(i,j) \cdot M(i,j) \qquad (1)$$

Firstly, the algorithm starts with the finding of the median filter, $M(i,j)$ executed from the input images. The median filter can be determined in (2) as:

$$M(i,j) = median\{I(i+k, j+l)\}\ as\ k,l \in (-1,0,1) \qquad (2)$$

Next, the input image will be used to find the absolute luminance difference by subtracting each of the 8-neighbour windows with the targeted pixel. Later, the subtraction process outcomes will express in absolute value. The absolute luminance difference can be expressed in (3) as:

$$d(i+k, j+l) = |I(i+k, j+l - I(i,j))| \qquad (3)$$
$$\text{with } (i+k, j+l) \neq (i,j)$$

Applying the absolute luminance difference before, its maximum value will be used to find local information as expressed in (4) as below:

$$D(i,j) = \max\{d(i+k, j+l)\} \qquad (4)$$

The local information, $D(i,j)$ found before will be used in applying the fuzzy concept which fuzzy membership function will determine its output value, $F(i,j)$ through the maximum absolute luminance difference (21). The fuzzy membership function can be found as $D(i,j)$ in (5):

$$F(i,j) = \begin{cases} 0 & ; D(i,j) < T_1 \\ \dfrac{D(i,j) - T_1}{T_2 - T_1} & ; T_1 \leq D(i,j) < T_2 \\ 1 & ; D(i,j) \geq T_2 \end{cases} \qquad (5)$$

Where the value of T_1 and T_2 were determined during experimenting all the algorithms on the input images. The value of T_1 is 0.1 while the value of T_2 is 0.5 which this determined value produced the most adequate results and expected output that reach the purpose of this study to enhance the DBT images.

Non-Linear Unsharp Masking

This study uses the FWMF for the non-linear element of this NLUM which also the contribution of this study where the use of the modified median filter known as the FWMF in the NLUM filter that usually use normal or standard median filter in the NLUM algorithm. The use of the filtered images from the FWMF are adapted into the NLUM through the variable $F(i,j)$ of NLUM in equations (6).

On the other side of the NLUM algorithm, an input image, $I(i,j)$ is multiplied by A_1. This variable must ranging from 0 to 2 that cannot be less than the range because the result will produced 0 output value. Moreover, A_1 also cannot be greater than 2 because the result will be an infinity value (19). As a result, according to (19), the best value of A_1 is 0.9, which produces the highest enhancement image in range from 0.5 to 1. Furthermore, the value of A_2 was suggested to be the influence on the value of A_1 but multiplied by any number suitable for enhancing DBT images which the value that use in this study as $1/A_1$.

The input image is multiplied by the first equation as equation (6), and the second equation in equation (6) is multiplied by the filtered image over the absolute maximum value of the filtered image and then multiplied with the input image. In the masking stage of this method, both equations are added together. As a result of the addition of both equations, an enhanced image, $E(i,j)$ was produced using the NLUM method with the adaptation of the suggested filter. The enhancement equation can be defined in (6) as below:

$$E(i,j) = A_1 \cdot I(i,j) + A_2 \cdot \frac{F(i,j)}{|F|_{max}} \cdot I(i,j) \quad (6)$$

Performance Evaluation

The proposed method's performance was compared and calculated using the Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR), which are calculated using the input images and the output images. This means that in order to evaluate the proposed method, the input image and the final output image after the enhancement method must be compared.

The MSE is the difference between input and output images that will be measured as the output images change over the input images. As the equation (7) below:

$$MSE = \frac{\sum\left(I(i,j)_{original} - E(i,j)_{filtered}\right)^2}{\text{Image Size}} \quad (7)$$

The mean square error requires the output image and subtracts to the output image, then squares the result before dividing it by the number of image dimensions that are set so that the input image dimension has the same dimension as the output image.

The PSNR will then be evaluated using the MSE value, which is calculated by dividing the square of 255 by the MSE value. The result will be inserted into log with base 10 and multiplied by 10 as in (8). These two (MSE and PSNR) are used to assess the differences and similarities between the restored output image and the input image.

$$PSNR = 10 \, \log_{10}\left(\frac{255^2}{MSE}\right) \quad (8)$$

he PSNR and MSE numbers were analyzed to determine the effectiveness of the proposed method in enhancing DBT images. These two algorithms, conventional NLUM and FWMF in NLUM methods will generate MSE and PSNR, which will then be analyzed in the form of qualitative and quantitative data, and the results will be recorded.

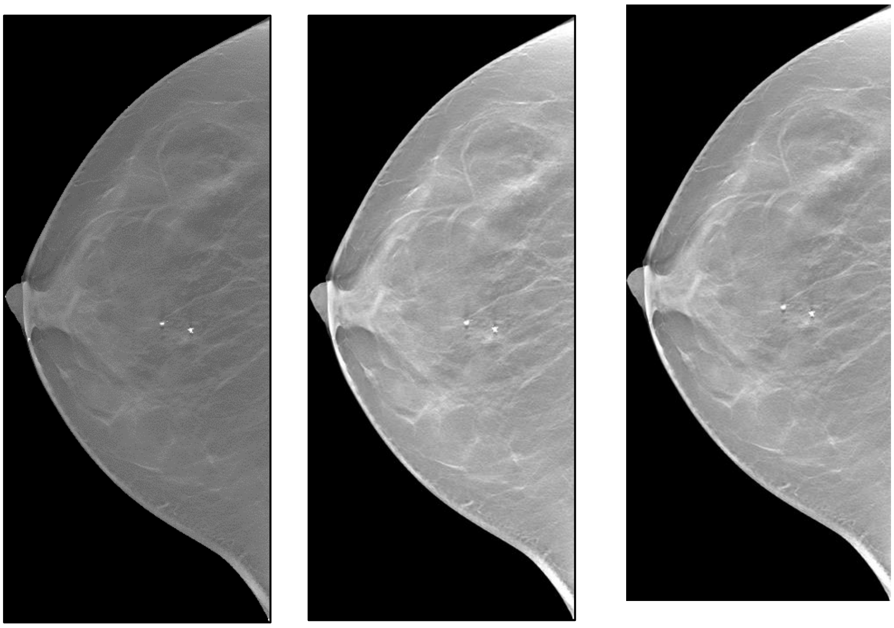
Results and Discussion

This section displays the experimental results of two NLUM algorithms, conventional NLUM and the Fuzzy Weighted Median Filter in NLUM. There were eleven (11) DBT images collected from two (2) patients at AMDI, USM. The enhancement method employed the non-linear unsharp masking method in conjunction with a filter that differed from the conventional filter, the median filter. As a result, the presence of multiple non-linear filters will provide an excellent opportunity to conduct research into their effectiveness in enhancing DBT images to aid radiologist observation.

Qualitative Result

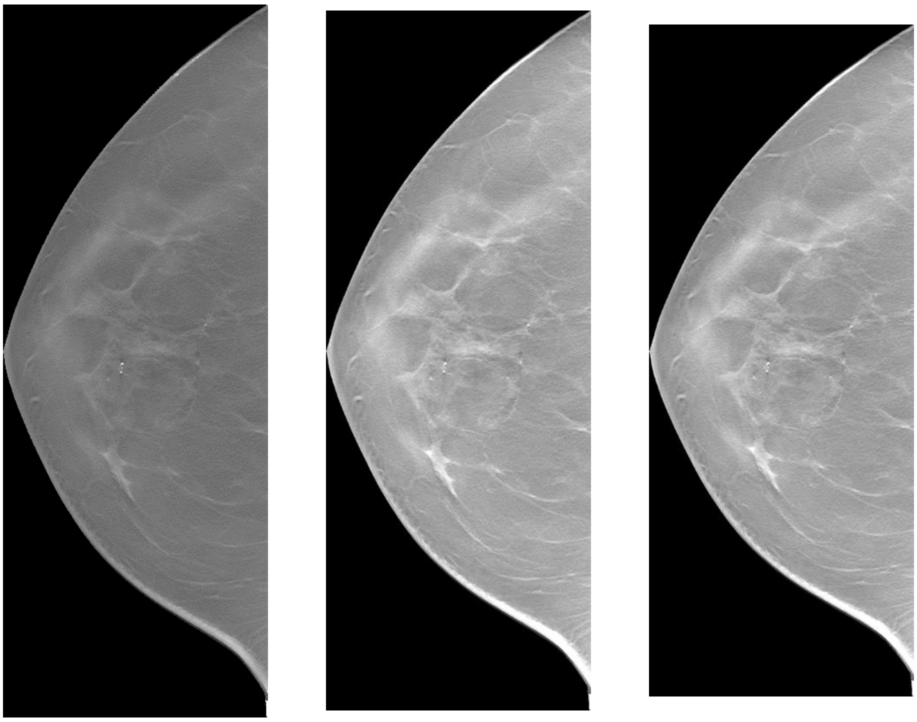
The qualitative results will concentrate on the visibility of microcalcifications on the images produced in comparison to the original images. The visibility of microcalcifications will also be compared in NLUM between results with different filter types to determine which algorithm produces better visibility of microcalcifications. The results produced by the three algorithms shown in Figure 4, Figure 5, and Figure 6.

When compared to conventional unsharp masking, the images produced by the FWMF in NLUM produced the best microcalcifications visibility because the filters tend to choose the higher intensity value to enhance more while other lower intensity levels either remained dim or were not as enhanced as the microcalcifications. The microcalcifications produced also had better visibility than conventional NLUM because the area surrounding the microcalcifications was dimmer, allowing the microcalcifications to be seen and stand out more. Furthermore, when compared to conventional NLUM, the proposed method's background objects, such as breast gland and breast mass, were not brighter than the microcalcifications, making it more difficult to detect microcalcifications in it especially in Figure 7.



(a) (b) (c)

Figure 4: The result of the NLUM with different filters for the DBT enhancement method of Image 1: (a) original image, (b) conventional NLUM, and (c) FWMF in NLUM



(a) (b) (c)

Figure 5: The result of the NLUM with different filters for the DBT enhancement method of Image 2: (a) original image, (b) conventional NLUM, and (c) FWMF in NLUM

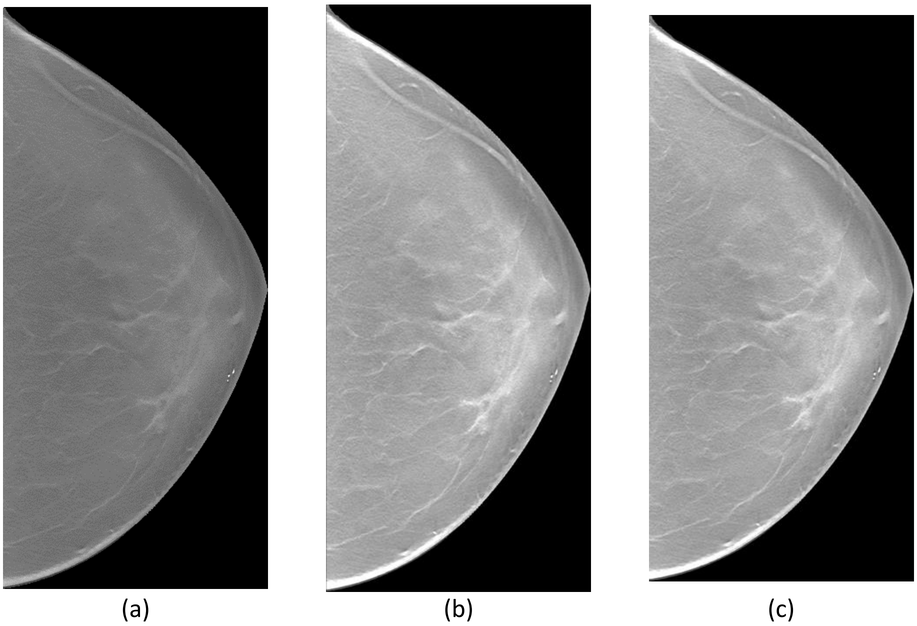


Figure 6: The result of the NLUM with different filters for the DBT enhancement method of Image 3: (a) original image, (b) conventional NLUM, and (c) FWMF in NLUM

Based on Figure 6, the interest region that will demonstrate the efficacy of the enhancement method where the proposed method can enhance the DBT images while brightening the visibility of microcalcifications in the images. The labelled region in the images represents the location of the microcalcifications, whose visibility will be compared to that of the conventional NLUM. According to the images, the FWMF in NLUM appears to produce more contrast microcalcifications to the background, resulting in more visible microcalcifications in enhanced images.

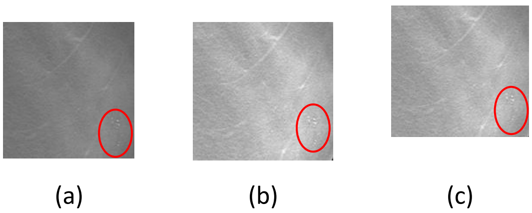


Figure 7: The cropped Image 4 of microcalcifications that seen on the images: (a) Original images, (b) conventional NLUM, (c) FWMF in NLUM

Quantitative Result

This section will prove the qualitative observation with quantitative results showing the MSE and PSNR produced by the filter output towards the input images. The best results were obtained when the number of MSE was the lowest and the PSNR was the highest, indicating that the error between the input images was lower. Furthermore, quantitative results demonstrated that the method could improve DBT images by focusing on microcalcifications. Table 1 shows the result of the image enhancement in this project.

Based on the results in Table 1, Image 6 produced the highest PSNR value of 75.6362 dB with 0.0018 MSE produced by FWMF in NLUM competing with the other method. As a result, the proposed method produced the lowest PSNR value on Image 7, which was 63.8063 dB with 0.0273 MSE. Despite producing the lowest output result, this proposed method produced the best result on Image 7.

Furthermore, the average of MSE and PSNR were calculated from 11 DBT images on each of the filters, revealing that the proposed method, Fuzzy Weighted Median Filter in NLUM, produces the best average MSE and PSNR, with values of 0.0171 and 67.0574 dB, respectively. This proposed method can outperform conventional NLUM at 0.6652 dB of PSNR on average. As a result, the use of FWMF in NLUM produced the best results when compared to the conventional median filter in the NLUM, implying that the proposed method can successfully improve the conventional NLUM and enhance the DBT images.

Table 1: The MSE and PSNR results of the enhancement method on DBT images.

Image	Measurement	Conv	FWMF
1	Processing time	9.7699	13.4977
	MSE	0.0243	0.0214
	PSNR	64.306	64.8587
2	Processing time	10.4755	11.9462
	MSE	0.0246	0.0223
	PSNR	64.2585	64.6864
3	Processing time	9.3063	11.1975
	MSE	0.0275	0.0254
	PSNR	63.7771	64.1144
4	Processing time	10.4134	11.0102
	MSE	0.0245	0.0229
	PSNR	64.2752	64.5671
5	Processing time	10.8236	13.8485
	MSE	0.0033	0.0027
	PSNR	72.9718	73.8064
6	Processing time	11.7687	15.4523
	MSE	0.0021	0.0018
	PSNR	74.9103	75.6362
7	Processing time	12.5097	15.8315
	MSE	0.032	0.0273
	PSNR	63.1158	63.8063
8	Processing time	13.9676	16.3647
	MSE	0.0106	0.0091
	PSNR	67.9143	68.58
9	Processing time	13.3829	17.534
	MSE	0.0115	0.0093
	PSNR	67.5632	68.4834
10	Processing time	6.4877	7.5998
	MSE	0.0297	0.0221
	PSNR	63.4371	64.7298
11	Processing time	6.375	7.6898
	MSE	0.0274	0.024
	PSNR	63.7853	64.3627
Average	MSE	0.019773	0.017118
	PSNR	66.39224	67.0574

Conclusion and Future Works

This study tested the use of non-linear unsharp masking, NLUM, with various filters that had been shown to successfully enhance images, particularly medical images. As NLUM had demonstrated its ability to enhance breast images, these algorithms were tested to determine their ability to enhance DBT images of the breast area in order to aid in the detection of microcalcifications. Thus, the main observation of the images produced by these algorithms was microcalcifications. Subsequently, filters were used to create a non-linear algorithm for unsharp masking, and their effectiveness was evaluated using MSE and PSNR. The results show that the FWMF is the best filter when compared to conventional filters adapted into NLUM, with an average MSE and PSNR of 0.0171 and 67.0574, respectively. This demonstrates that a Fuzzy Weighted Median Filter adapted in NLUM can enhance DBT images and an improved method of the conventional NLUM, with quantitative results supported by images that clearly highlight microcalcifications features and position.

This study proposed an enhancement method for DBT images to assist radiologists in the detection of microcalcifications. The proposed method successfully improved the visibility of the microcalcifications in the DBT images. However, the images produced by the proposed method also improved all higher attenuation elements other than microcalcifications in the breast area, such as breast mass, fat, and glands, which are unimportant during the microcalcifications detection process. As a result of the improvements required for the DBT enhancement stage, the system and algorithms will only enhance the targeted parts or information in the images, in this case, microcalcifications.

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Competing Interests

All authors declare no competing interests.

Ethical Clearance

The ethical approval was obtained from the Jawatankuasa Etika Penyelidikan Manusia (JEPeM) of Universiti Sains Malaysia for DBT data collection with code study: USM/JEPeM/21090622. DBT images with malignancy or suspicious abnormality on breast imaging were collected retrospectively from 40 patients starting December 2019 until December 2021.

Informed Consent

Verbal informed consent was obtained from all subjects before the study. Written consent was not obtained because the data were collected retrospectively, and the subjects were not physically present at the healthcare facility. The images were the property of the institution and local approval has been obtained for both retrieval and publication.

References

1. Breast Cancer: Causes, Stage, Diagnosis & Treatment [Internet]. [cited 2021 Dec 26]. Available from: https://my.clevelandclinic.org/health/diseases/3986-breast-cancer
2. Breast Calcifications: Causes, Types, Treatment & Tests [Internet]. [cited 2021 Dec 26]. Available from: https://my.clevelandclinic.org/health/diseases/17802-breast-calcifications
3. Basile TMA, Fanizzi A, Losurdo L, Bellotti R, Bottigli U, Dentamaro R, et al. Microcalcification detection in full-field digital mammograms: A fully automated computer-aided system. Physica Medica [Internet]. 2019;64(May):1–9. Available from: https://doi.org/10.1016/j.ejmp.2019.05.022
4. Rodriguez-Ruiz A, Teuwen J, Vreemann S, Bouwman RW, van Engen RE, Karssemeijer N, et al. New reconstruction algorithm for digital breast tomosynthesis: better image quality for humans and computers. Acta radiol. 2018 Sep 1;59(9):1051–9.
5. Cho H, Park Y, Cho H, Je U, Park C, Lim H, et al. Evaluation of the image quality in digital breast tomosynthesis (DBT) employed with a compressed-sensing (CS)-based reconstruction algorithm by using the mammographic accreditation phantom. Nucl Instrum Methods Phys Res A. 2015 Dec 21;804:72–8.
6. Choi JS, Han BK, Ko EY, Kim GR, Ko ES, Park KW. Comparison of synthetic and digital mammography with digital breast tomosynthesis or alone for the detection and classification of microcalcifications. Eur Radiol. 2019 Jan 1;29(1):319–29.
7. Sujlana PS, Mahesh M, Vedantham S, Harvey SC, Mullen LA, Woods RW. Digital breast tomosynthesis: Image acquisition principles and artifacts. Vol. 55, Clinical Imaging. Elsevier Inc.; 2019. p. 188–95.
8. Tirada N, Li G, Dreizin D, Robinson L, Khorjekar G, Dromi S, et al. Digital breast tomosynthesis: Physics, artifacts, and quality control considerations. Radiographics. 2019;39(2):413–26.
9. Samala RK, Chan HP, Lu Y, Hadjiyski L, Wei J, Sahiner B, et al. Detection of microcalcifications in breast tomosynthesis reconstructed with multiscale bilateral filtering regularization. Medical Imaging 2013: Computer-Aided Diagnosis. 2013;8670:86701L.
10. Lai X, Yang W, Li R. DBT Masses Automatic Segmentation Using U-Net Neural Networks. Comput Math Methods Med. 2020;2020.
11. Samala RK, Chan HP, Lu Y, Hadjiiski LM, Wei J, Helvie MA. Computer-aided detection system for clustered microcalcifications in digital breast tomosynthesis using joint information from volumetric and planar projection images. Phys Med Biol [Internet]. 2015;60(21):8457–79. Available from: http://dx.doi.org/10.1088/0031-9155/60/21/8457
12. Samala RK, Chan HP, Lu Y, Hadjiiski L, Wei J, Helvie M. Digital breast tomosynthesis: effects of projection-view distribution on computer-aided detection of microcalcification clusters. Medical Imaging 2014: Computer-Aided Diagnosis. 2014;9035:90350Y.
13. Ghani MU, Wu X, Fajardo LL, Jing Z, Wong MD, Zheng B, et al. Development and preclinical evaluation of a patient-specific high energy x-ray phase sensitive breast tomosynthesis system. Med Phys. 2021;48(5):2511–20.
14. Samala RK, Chan HP, Hadjiiski LM, Cha K, Helvie MA. Deep-learning convolution neural network for computer-aided detection of microcalcifications in digital breast tomosynthesis. Medical Imaging 2016: Computer-Aided Diagnosis. 2016;9785:97850Y.
15. Xu N, Yi S, Mendonca P, Tian T peng, Samala R, Chan HP. False positive reduction of microcalcification cluster detection in digital breast tomosynthesis. Medical Imaging 2014: Image Processing. 2014;9034:90342N.
16. Samala RK, Chan HP, Lu Y, Hadjiiski LM, Wei J, Helvie MA. Digital breast tomosynthesis: Computer-aided detection of clustered

microcalcifications on planar projection images. Phys Med Biol. 2014;59(23):7457–77.
17. Zhang G, Lin J, Cao E, Pang Y, Sun W. A Medical Endoscope Image Enhancement Method Based on Improved Weighted Guided Filtering. Mathematics. 2022 May 1;10(9).
18. Mall PK, Singh PK. BoostNet: a method to enhance the performance of deep learning model on musculoskeletal radiographs X-ray images. International Journal of Systems Assurance Engineering and Management [Internet]. 2022; Available from: https://doi.org/10.1007/s13198-021-01580-3
19. Panetta K, Zhou Y, Agaian S, Jia H. Nonlinear unsharp masking for mammogram enhancement. IEEE Transactions on Information Technology in Biomedicine. 2011;15(6):918–28.
20. Ngo D, Lee S, Kang B. Nonlinear unsharp masking Algorithm. 2020 International Conference on Electronics, Information, and Communication, ICEIC 2020. 2020;(1).
21. Sulaiman SN, Isa NAM. Denoising-based clustering algorithms for segmentation of low level salt-and-pepper noise-corrupted images. IEEE Transactions on Consumer Electronics. 2010;56(4):2702–10.