Noise reduction and mammography image segmentation optimization with novel QIMFT-SSA method

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Abstract

Breast cancer is one of the most dreaded diseases that affects women worldwide and has led to many deaths. Early detection of breast masses prolongs life expectancy in women and hence the development of an automated system for breast masses supports radiologists for accurate diagnosis. In fact, providing an optimal approach with the highest speed and more accuracy is an approach provided by computer-aided design techniques to determine the exact area of breast tumors to use a decision support management system as an assistant to physicians. This study proposes an optimal approach to noise reduction in mammographic images and to identify salt and pepper, Gaussian, Poisson and impact noises to determine the exact mass detection operation after these noise reduction. It therefore offers a method for noise reduction operations called Quantum Inverse MFT Filtering and a method for precision mass segmentation called the Optimal Social Spider Algorithm (SSA) in mammographic images. The hybrid approach called QIMFT-SSA is evaluated in terms of criteria compared to previous methods such as peak Signal-to-Noise Ratio (PSNR) and Mean-Squared Error (MSE) in noise reduction and accuracy of detection for mass area recognition. The proposed method presents more performance of noise reduction and segmentation in comparison to state-of-arts methods. supported the work.

Keywords: breast cancer, noise reduction, image segmentation, mammography, QIMFT-SSA.

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Introduction

Breast cancer is recognized as a common disease in the today's world in women. Early detection of breast cancer leads to timely analysis of the disease, thus providing a better chance of survival. It is important to perform pre-processing steps before applying any image processing algorithm to mammography images that detect the boundaries for non-strongly induced deviations from the mammography background. It is difficult to interpret digital mammograms as medical images. Therefore, a preparatory step is required for image quality processing and for more precise segmentation consequences [1, 2]. The most important goal of this method is to enhance image and promote processing by eliminating different parts of the mammography background. Extraction of the border region of the breast and removal of the pectoral muscles are also pre-processing elements [3, 4]. Preprocessing is measured as a main step in finding mammographic image orientation and improving image quality. Usually digital mammography images include noise artifacts in the background area. These mammographic images are very complicated to interpret, so preprocessing is important for mammographic images. Analysis and investigation of suitable image processing techniques for mass area detection in mammographic images is presented in this paper. The preprocessing is the first step in noise reduction in breast cancer. Using different types of filters presented to date and examined in [5, 6], which are almost the most optimal filters available in this field, different noise can be detected and one can find out which filtering method to use. It is important to determine the exact area of the tumor using image segmentation after reducing the noise from mammography images. A common strategy for segmentation involves using an image segmentation method to detect local spots on an image to generate a possible outputs network. Therefore, this study presents a method based on an optimized Social Spider Algorithm (SSA) for segmentation of mammographic images with the aim of precise mass areas detection.

Literature review

Optimizing the mass area from mammographic images based on noise reduction and image segmentation is one of the important steps before classifying the type of masses that this research will address. Therefore, studying previous methods of noise reduction and segmentation with the aim of tumor area determination in mammographic images is an important issue that can overshadow future processes. Therefore, this section is divided into two general sections, including a study on noise reduction of mammography images and image segmentation operations.

Noise reduction-based studies

First, there is a need to examine in detail some of the noise in mammographic images. The noises that affect mammographic images are salt and pepper, Gaussian, Poisson and impulse noises. Noises are random fluctuations in image intensities and appear as grains or particles in mammographic images. The image shows the difference in intensity values instead of the original values when the noise is affected.

- Salt and Pepper Noise: Also referred to as impulse valued noise. Other names for this noise include Spike Noise, Random Noise or Independent Noise [7]. The main reason for the noise of salt and pepper in the image is the sharp and sudden disturbance of the image signal. When the image is affected by this type of noises, then the original pixel values are replaced by the pixel values of the noises, eventually the original intensity value can be changed. The presence of such a noises results in inaccurate results and low accuracy in the detection of mass areas. This noise appears as black and white dots in the images. This noise limits the lowest or highest intensities such as 0 or 255, respectively.
- Gaussian Noise: The Gaussian noise follows the Gaussian distribution, meaning that each pixel in the noise image contains the amount of random Gaussian distributed noise and the original pixel value. This noise is due to electronic circuit noise and sensor noise [8].
- Poisson Noise: This type of noise is also called photon noise. This noise is due to the numerical behavior of electromagnetic waves such as X-rays and gamma rays. Poisson noise in the mammogram unit affects the photons. This type of noise follows the Poisson distribution [9].
- Impulse Noise: This noise can be treated as a multiplier noise. The behavior of this noise is similar to Gaussian noise.

There have also been studies of noise reduction from mammographic images, the most recent and optimal ones. In [10] noise has been studied in mammographic images. The noise level in mammographic images strongly influences image analysis and classification accuracy. Therefore, noise reduction in mammography images is an important task. The noise in medical images depends on the imaging modalities. The dominant noise in mammography images is quantum noise. The purpose of this work is to investigate different filters including mean filter, middle filter and different size Wiener filter in window using standard criteria (digital database for mammography screening) DDSM dataset. The higher the noise rating resulted to higher the Peak Signal-to-Noise Ratio or PSNR, the better the image quality than the restored image. The image quality of the restored filters was evaluated with PSNR value. Based on the results, the 3×3 3 window size Wiener filter gives a better result for noise reduction in mammographic images.

In [11], non-local noise analysis-based methods for mammographic nanoparticles have been studied. X-ray grating-based mammography can revolutionize the radiological approach to chest imaging because it works well with conventional X-ray tubes and can recover in a repeat scan, weakness, differential phase, and dark field. However, the images, especially the differential phase and dark field images, are contaminated by noise, which worsens the image quality and makes noise reduction in the image imperative. In this paper, non-local noise-based methods presented as a method for noise reduction for X-ray grating-based mammography images. Since pixel noise variance can be estimated by noise analysis, non-local methods based on noise analysis employ the similarity and dispersion of noise variance to measure pixel intensity as a weighted average weight. To estimate. In addition, in order to more accurately estimate the noise variance for better image quality, a two-step method called non-local noise-based methods, or NLM-NANLM, is proposed. Numerical simulation, sample model and mammography results all confirm the effectiveness of the proposed method.

Pre-processing of digital mammograms of the breast areas using adaptive weighted frost filter is presented in [12]. Mammography is the most effective tool for early detection in patients with breast cancer because it can detect cancer up to two years before the tumor is shown. Pre-processing and post-processing of mammographic image identification process involves high computational cost. Initial processing is one of the essential elements of any imaging method, the most important of which is the implementation of such a process that it can improve the image quality, where it is suitable for further analysis and extraction of important data. This article is about preprocessing, which is very important in mammographic image analysis because of the poor quality of mammography because they are captured at low doses, while too much radiation may endanger the health of the patient. Many techniques have been used to improve image quality, image smoothing and noise restoration. Experimental results conclude that the proposed adaptive weight freeze filter is the best choice for eliminating noise from mammographic images and performs better than that. Comparison of the proposed technique with the various techniques available is both qualitative and quantitative. Experiments of this article have shown that the proposed method yields better results than existing techniques.

In [13], the impulse noise reduction in ultrasound mammography images proposed using the modified Homogeneity Modified Bayes Shrink (HMBS). It used seven different criteria to assess image quality. The pixel intensities are first replaced with homogeneous neighborhood averages, and then the HMBS threshold value is used to detect homogeneous zones from areas with noise from uniform filters. In [14], a deep learning-based approach is used to reduce noise in mammographic images with a physics-driven data augmentation approach. In this study, a deep learning approach based on Convolutional Neural Network (CNN) is proposed to reduce mammographic noise to improve image quality. The noise level is first increased and the ensemble transmission is used to convert Poisson noise to white Gaussian noise. Using this data augmentation, a deep network is trained to learn image noise mapping. The results represented the optimal noise reduction in comparison to previous methods such as BM3D and DNCNN.

Segmentation-based studies

Dissecting cancerous masses in mammograms due to problems such as low contrast, undefined, fuzzy or split boundaries and the presence of severe malformations is a challenging task studied in [15]. These facts complicate the development of computer-aided diagnostics or CAD systems to assist radiologists. In this paper, a new mass separation algorithm for mammograms based on robust multifunctional features and automated and maximal estimation has been proposed to present a Maximum a Posteriori (MAP). The proposed segmentation method consists of four steps: a dynamic contrast enhancement scheme applied to a selected Region of Interest (ROI), correction of background infiltration by matching templates, recognition of mass candidate points by posterior probabilities based on multiple scales Strong integration feature and final definition of the mass area by a MAP scheme. This method of segmentation is based on 480 ROIs used by Ground Truth and two radiologists. Three statistical criteria have been used to compare its effectiveness with advanced segmentation methods. Experimental results represented that the developed methods can compare ill-defined or thickened wastes with other algorithms. Integrating it into a CAD system may help radiologists.

In [16] the classification and diagnosis of breast cancer in mammographic images is presented with a combination of wavelet analysis and Genetic algorithm. According to this article, there is growing concern today about the sensitivity and reliability of detecting malformations in both views of the mammographic images of the cranial-ear (CC) and lateral oblique (MLO). This article presented a set of computational tools to help segment and identify mammograms that contain masses or masses in CC and MLO views. An artifact removal algorithm is first run using the gray level enhancement and gray level amplification method based on wavelet transform and Wiener filter. Finally, a method is used to identify and divide the masses using multiple thresholds, wavelet transforms and Genetic algorithms in mammograms randomly selected from the Digital Mammography Screening Database (DDSM). The developed computer method was evaluated using Area Overlap Metric (AOM). Experiments represented that the proposed method had the potential to be used as a basis for mammogram mass segmentation in CC and MLO views. Another important aspect is that this method overcomes only the analysis of CC and MLO representation.

In [17] also presented a semi-supervised fuzzy GrowCut adaptive algorithm for segmentation of Region of Interests mammographic images. This article proposed a semi-supervised version of the GrowCut algorithm that is studied by modifying the automata evolution law by adding a Gaussian fuzzy membership function to model undefined boundaries. In this method, manual selection of suspected lesion points is replaced by a semiautomatic step, where only the internal points are selected using the differential evolution algorithm. This method was evaluated using 57 lesion images obtained from the MiniMIAS database. Results were compared with BEMD, BMCS, wavelet analysis, LBI, topographic approach and MCW semi-surveillance approaches. The results show that due to the similarity between the segmentation results and the images with the Grand Tract, the method yields better results for the hybridized, thickened and poorly obtained lesions.

In [18], various methods of decoding and encoding by using Convolutional Neural Network are used to mammography image segmentation. The Convolutional Neural Network structure uses both SegNet and UNet. The approach of this research can simultaneously distinguish the masses from the images. The high accuracy of this research in segmentation operations with the aim of identifying the masses, demonstrated its functional superiority over its previous methods.

Other similar approaches to the same article have already been presented. For example, in [19], deep learning based on the 2-Conductive UNet method has been used to segment fibrous and fibroglandular tissue. Multi-task segmentation is also presented in several sections of mammography images to find deep masses based on deep learning and standard Convolutional Neural Network method [20]. Deep learning and V-net Convolution Neural Networks have also been used for segmentation of mammographic and prostate images [21].

In [22], a new fast unsupervised nuclear segmentation and classification scheme proposed for automatic allred cancer scoring in immunohistochemical breast tissue images. Adaptive local thresholding and enhanced morphological procedure used for extraction and segmentation. The obtained result represented 98 % accuracy for tumor area determination. In [23] the segmentation of mammographic images with the aim of identifying and classifying benign and malignant masses is presented with an optimal region grow approach. In the pre-processing phase, Gaussian filtering is used to noise reduction. The Dragon Fly Optimization (DFO) algorithm is then used for image segmentation and then the combined approach of GLCM and GLRLM to extract features as input to the Feed Forward Neural Network (FFNN) method with Back Propagation (BP) training Used. The results represented the 97.8 % accuracy.

Further studies have been performed on the segmentation and detection of breast cancer masses from mammographic images which can be reviewed in general. In [24], region growing segmentation technique with a specific threshold cell neural network was used to segment and detect breast cancer masses. An optimization in detection and classification is also performed with the genetic algorithm. The accuracy of this method is 96.47 %. The use of microarray images to detect breast cancer masses has been studied in [25] with 95.45 % accuracy in detection. The use of Back Propagation neural network for segmentation and detection studied in [26] with 70.4 % detection accuracy. Using the Bayesian theory-based with Naive Bayesian classification method in mammography images with accuracy of 98.54 % is presented in [27]. In [28] an adaptive intelligent decision making system for the detection of breast cancer has been used for mammography images based on regression-based evolutionary methods. Breast cancer recurrence in [29] are presented using optimized ensemble learning or HBPCR method in abbreviation with an accuracy of 85 % of tumor area detection

Proposed method

He main purpose of this study is to present a noise reduction and image segmentation approach to determine the exact area of breast tumors and the principles of the type of mass detection and classification. This approach have two main parts that apply the principles of image processing, machine vision, and statistical and analytical pattern recognition, including pre-processing with the aim of mammographic images noise reduction with presented method means Quantum Inverse MTF Filtering. The segmentation aims to accurately determine the mass area using the optimized Social Spider Algorithm (SSA).

Pre-processing phase

At the first, it is necessary to normalize images. In pre-processing phase, input data must be normalized which have noise and need to enhance. Resizing images to a specified size used with logical filtering named Quantum Inverse MTF Filtering. After the preprocessing steps, the input image is normalized. Each single image in the combination of local threshold and Active Contour is represented by a two-dimensional array of pixels whose values are integers in the range [0, 255]. Local thresholding does the initialization of the images in two steps. Initially, the input noise image is considered as the initial image, which will be used to eliminate the image noise. This is used as local search operators to improve the initial images using the Inverse MFT Filtering method.

The use of local thresholds and Active Contours has been chosen because it is computationally faster than other methods and offers significant results in the work literature. Thus, at the end of the first step, there will be a decomposed image. In the second step, the thresholding is performed on the detail coefficients and one of these decomposed parts is randomly selected and sent to a reconstruction operation. The reconstruction section can be defined as follows:

- Gauss Fading: Filter image using a Gaussian filter. The filter size is selected at random between values of 3 × 3 pixels and 5 × 5 pixels.
- Means Filter (Averaging Filter): Filter image using a mean filter.
- Intensity Change: All image pixels are multiplied by a similar criterion selected at random in the [0.7, 1.3] range.
- Adaptation of light intensities to quantum and inverse processing that performs the Quantum Inverse structure by Inverse MFT Filtering.

Then the following will be apply:

- One-Point Raw: A row of pixels selected randomly.
- One-Point Column: A column of pixels selected randomly.
- Point-to-Point Random: Each pixel is selected from the decomposing until a new image is created randomly.

Identifying all the points as rows and columns in the image and diagonally to reduce the maximum noise in Quantum MFT.

When the selection value is less than the range [0,1] lower than local search rate in the Quantum Inverse MFT Filtering algorithm after decomposing, a new image may pass through the local search operator. All of its image is individually sorted by its pixel value, and the best coefficients in the image are considered as a quantum value of the work in progress when the decomposing is complete.

A signal in mammographic images may be broken down into multiple displaced or resized displays of features known in the feature extraction process. Local thresholding and Active Contour can be used to decompose an image into its components. In fact, image segmentation can be done by applying Quantum Inverse MFT Filtering with local thresholding and Active Contour. In this case, Quantum Inverse MFT Filtering based local thresholding and Active Contour coefficients can be eliminated some details. Local thresholding and Active

Contour based Quantum Inverse MFT Filtering have the great advantage of separating fine details in an image. Active Contour can be used to isolate fine-grained details of an image, while local thresholding can detect gross details and combine fine-grained details and read all rows and columns linearly and diagonally, structurally Quantum Inverse MFT Filtering satisfies to keep minimum noise in the mammographic image. Quantum Inverse MFT Filtering-based local thresholding and Active Contour can produce a much smoother display. A local threshold Function and Active Contour with Quantum Inverse MFT Filtering have two main features, first of which the function is oscillatory or has a wave appearance such as equation (1).

$$\int_{-\infty}^{0} \Psi(t) |^2 \, dt < \infty. \quad (1)$$

In this case most of the energy at $\psi(t)$ is limited to a finite period of time whose relation is in form equation

$$\int_{-\infty}^{0} \Psi(t) dt = 0. \quad (2)$$

The proposed method is generally calculated to reduce the noise in equation.

$$Method(I) = (\sum_{\Omega} \sqrt{1 + \beta^2 |\nabla I|^2}) + \frac{\lambda}{2}(I - I_0)^2. \quad (3)$$

Function (3) is aware of the edges of the image and tries to preserve the important features of the image. $(I - I_0)^2$ Section guarantees a certain degree of validity between the evaluated image and the original image, in which the I evaluated image and the I_0 image are noisy. ∇I. Parameter is the period of adjustment of the sum of the variations, β and λ are the balancing parameters and Ω is the sum of the points in the image. By minimizing equation (3), the goal is to reduce the overall image variability by maintaining accuracy.

Image segmentation phase

Image segmentation is cited as a complex process in digital image processing systems. This complexity stems from the fact that precise identification of the image space requires identifying points of the beak based on the background and foreground. In this section, the edge detection is also possible, and based on the edges, different areas can be separated from each other. It separated in terms of light intensity and color. In fact, the output of the pre-processing section, which performs noise reduction and mammography operations is the input of the segmentation image. Social Spider Algorithm is used for image segmentation. The reason for using this algorithm have two reason, first an image is known as the search space, and this search space can be considered as a correction part by the segmentation operation. Therefore, segmentation improvement can complete dimensionality, features selection and extraction operations as well as complete classification to increase the accuracy and evaluation and validation criteria as much as possible. Second, as well as the high execution speed and convergence and non-local optimum trapping in image processing systems with this algorithm, it can be another issue to choose from in this section. It is necessary to explain the basic theory of this algorithm and then equate it with the segmentation image.

The Social Spider Algorithm formulates the search space of the optimization problem as a very high spider web. Each position on the web presents a practical solution to the optimization problem and all practical answers to the problem that has the answer on the web. The thread is used as the vibration transfer medium produced by the spiders. Each spider on the web demonstrates the ability to find the position and fit the solution based on the objective function as well as the ability to find food sources in the position. Spiders can move freely on the web, but cannot leave the web until they have found a practical answer to the optimization problem. When a spider moves to a new position, it produces a vibration that propagates throughout the web. Each vibration holds the information of one spider, and the other spiders receive information until it receives the vibration.

It is necessary to provide an equivalent in the segmentation image with the Social Spider Algorithm. In fact, the image is referred to as the search space or the web in the Social Spider Algorithm. It is necessary to create an initial population of spiders on the search space or image that is web. In fact, spiders will be the agents. The spiders move on the web, aiming to accurately identify boundary areas, which have different brightness and light intensity than other parts, based on color means black and white histograms for gray-scaled images or in RGB modes. In fact, spiders walk on the edges, moving to the right for precise alignment by shaking the lines or to recognize edges and light intensity to segment image. The fit function is the segmentation of the whole image area which is the termination condition. After the precise segmentation has been done, the features can be identified based on the edge, brightness, light and mass appearance. A training set of $N^2 \times M$ is also constructed where M is the number of sample images. The average image set is calculated by equation (4).

$$\psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i. \quad (4)$$

According to equation (4), ψ is the average image, M is the number of images and Γ_i is the image vector. The components corresponding to the highest eigenvalue are retained. These components define the tumor space. Special space is created by projecting the image to the tumor space, which creates components. So the weight vectors are calculated. Image dimensions are adjusted to view specifications and the image is refined in the preprocessing step of identification. The image weight vector and tumor weight vector are then compared in the image database. The average tumor is calculated and then subtracted from each image in the training set. Matrix A

is constructed using the results of subtraction operations. The difference between each image and the average image is calculated as the equation (5).

$$\phi_i = \Gamma_i - \Psi, \qquad i = 1, 2, \ldots, M. \tag{5}$$

According to equation (5), ϕ_i is the difference between the image and the average image. The matrix obtained by subtraction operation, which is matrix A is multiplied by its transducer and eventually the covariance matrix C is formed whose equation is (6).

$$C = A^T A. \tag{6}$$

According to equation (6), this A is formed by the difference between the vectors with the spider's motion between each feature of light intensity and edge, for example $A = [\phi_1, \phi_2, \phi_3, \ldots \phi_M]$. The dimension of matrix C is $N \times N$. The number of image samples or M is used to form the C matrix. In practice we can say that the matrix C is $N \times M$. On the other hand, when the order A is equal to M, only M of N is a special vector number of non-zero values. Then the eigenvalues of the covariance matrix are calculated. The components are then segmented by a number of images, subtracting the number of special vector classes. The number of specific vector classes means the total tumor or tumors in the image. The selected set of special vectors is multiplied by matrix A to reduce the feature space. Special vectors from smaller eigenvalues correspond to smaller changes in the covariance matrix. Other features of the image are maintained. The number of special vectors depends on the accuracy of the images in the image database. A group of specially selected vectors are called components. Once components are acquired, images are collected in the database of images in component space and image weights in the projected image space. Special coefficients are compared in order to determine an image with a special coefficient of database images. The component is then made in the image. The Euclidean distance between the image component and the component collected in the previous step is calculated. The tumor is identified as an object whose Euclidean distance is less than the threshold value in the component database. If all Euclidean distances are greater than the threshold, then the tumor will not be detected in the image and the image will be ignored.

Simulation and results

Simulation has been done and run in a MATLAB platform with 7-core processor and Intel 3.4 GHz processor with 6 MB of cache as well as 6 GB of memory system. In this research, the MIAS dataset is illustrated using statistical properties. In this dataset, there are images with both breast cancer and non-breast cancer features and suspicious cases that based on the statistical data of this section, this diagnosis will be performed correctly. This dataset can be downloaded at:

http://peipa.essex.ac.uk/info/mias.html link, which contains 7 columns as follows:

1st column:
MIAS database reference number.

2nd column:
Character of background tissue:
F Fatty
G Fatty-glandular
D Dense-glandular

3rd column:
Class of abnormality present:
CALC Calcification
CIRC Well-defined / circumscribed masses
SPIC Spiculated masses
MISC Other, ill-defined masses
ARCH Architectural distortion
ASYM Asymmetry
NORM Normal

4th column:
Severity of abnormality;
B Benign
M Malignant

5th, 6th columns:
x,y image-coordinates of center of abnormality.

7th column:
Approximate radius (in pixels) of a circle enclosing the abnormality.

Simulation is created step by step. Initially, the input image is executed and displayed in the simulation as shown in fig. 1.

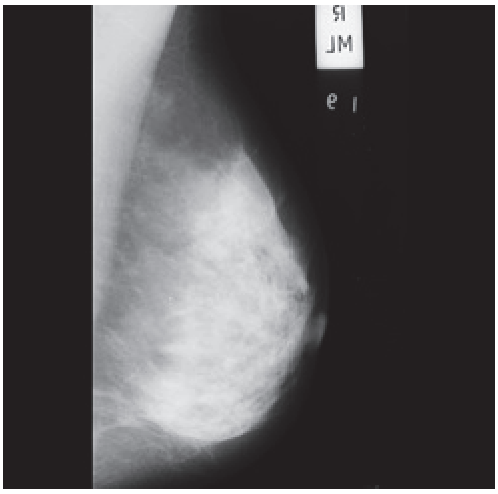

Fig. 1. Input image

The first part of the preprocessing process is then carried out with the aim of reducing the size of the image and making it identical with the initial noise reduction with a simple median filter. Then the proposed Quantum Inverse MFT Filtering method is used to noise reduction and improve the image as a result fig. 2

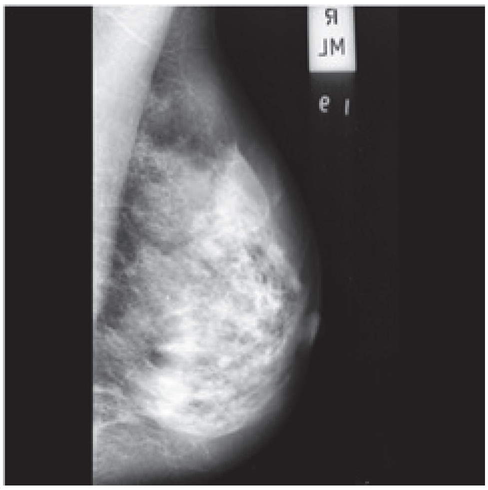

Fig. 2. Noise reduction with quantum inverse MFT filtering

Statistically, the proposed noise reduction approach has a higher capability than previous methods, which is done in tab. 1 which compare some methods in terms of evaluation criteria.

Tab. 1. Proposed noise reduction method in comparison to recent methods

References	Noise reduction method	Windowing size in input image	PSNR (dB)	MSE
Kannan, S., et al., 2016 [10]	Mean Filter	3 × 3 5 × 5 7 × 7	25.08 21.68 20.16	0.9
Kannan, S., et al., 2016 [10]	Median Filter	3 × 3 5 × 5 7 × 7	30.69 23.94 22.51	0.9
Kannan, S., et al., 2016 [10]	Quantum Inverse MFT Filtering	3 × 3 5 × 5 7 × 7	35.69 32.40 30.78	1.4
Devakumari, D., and Punithavathi, V., 2018 [6]	Adaptive Fuzzy Median Filter	3 × 3 5 × 5 7 × 7	33.60 37.15 38.39	1.3
Proposed Method	Quantum Inverse MFT Filtering	3 × 3 5 × 5 7 × 7	34.57 38.41 43.50	0.7

The Segmentation with SSA button is then pressed which performs the image segmentation operation with the Social Spider Algorithm at a speed of 0.5 seconds, which represent the output such as fig. 3.

In the Social Spider Algorithm segmentation operation, operators of this algorithm should be defined including the initial population of spiders with 100 spiders, the vibration rate of the blade equal to 2, and the prey attack rate is 0.02 as standard, and the initial presentation of this algorithm is taken into account. The segmentation is performed at 100 iteration using both edge and color properties. Statistically, the proposed image segmentation approach has a high capability compared to previous methods, which is done in tab. 2 with a comparison in terms of evaluation criteria to other methods.

The whole proposed approach is required to be represented as a ROC diagram from the beginning i.e. preprocessing, segmentation and then feature extraction and classification operations, the output is in the form of fig. 4.

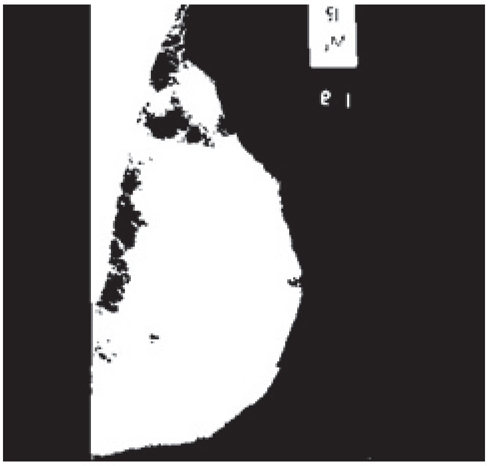

Fig. 3. Image segmentation with social spider algorithm

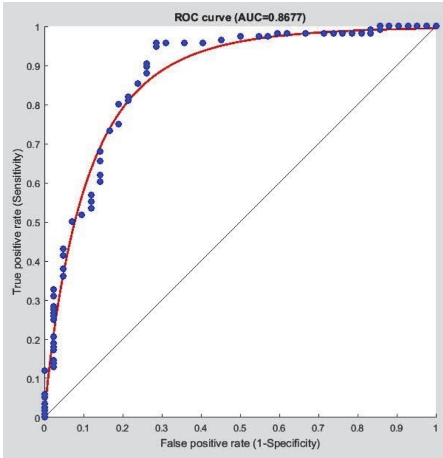

Fig. 4. ROC curve and AUC for overall results of proposed approach

Conclusion

In this study, we presented a noise reduction and segmentation method for mammographic images from the MIAS dataset in order to improve the level of images and to determine the precise location of the tumors. The proposed approach involves the use of a two-step operation involving preprocessing and segmentation. In the pre-processing phase, a method called Quantum Inverse MFT Filtering was presented that in addition to finding noises and reconstructing them in order to minimize as much as possible. This method moves linear, column and diagonal with minimal repetition of the search pixels. Noises reduction such as salt and pepper, Gaussian, Poisson and impulse noises are the main noises in mammography images and MIAS datasets, which this study was able to estimate at best error rates compared to other methods in terms of 0.7 Mean Square Error and PSNR rates in dB in the 3 × 3, 5 × 5 and 7 × 7 windowing sizes with 34.57, 38.41 and 43.50, respectively, which outperformed classical and new methods in this regard. The segmentation operation is also aimed at finding the exact mass area with the optimized Social Spider Algorithm, so that each spider is positioned on the pixels, and according to the operators of this algorithm, start moving based on finding two features, namely the intensity of light and edges as far as it can separate the masses from the surface of the image. The results of this section also show that with 0.5 seconds run time in precise detection of masses at the time of segmentation and also 99.08 % accuracy, it is more efficient than previous methods. Similarly, the result of the ROC and the AUC rate of 0.86 show the improvement of the proposed approach.

Tab. 2. Proposed image segmentation method in comparison to recent methods

References	Segmentation Time (sec)	Accuracy (%)
Abbas, Q., et al., 2013 [15]	10 to 60 sec for different images	92.78 %
Pereira, D. C., et al., 2014 [16]	11.05 sec	93.54 %
Cordeiro, F. R., et al., 2016 [17]	2 sec	92.50 %
El Adoui, Mohammed, et al., 2019 [18]	4 sec	98.50 %
Dalmıs, M. U., et al., 2017 [19]	4 sec	93.30 %
Moeskops, P, et al., 2016 [20]	4 sec	81 %
Milletari, F., et al., 2016 [21]	4 sec	82.39 %
Mouelhi, Aymen, et al., 2018 [22]	2 sec	98 %
Punitha, S., et al., 2018 [23]	1.7 sec	97.8 %
Rouhi, Rahimeh et al., 2015 [24]	1.2 sec	96.47 %
Karabatak, Murat, 2015 [27]	1 sec	98.54 %
Mohebian, Mohammad R., et al., 2017 [30]	14 sec	85 %
Proposed Method	0.5 sec	99.08 %

References

[1] Saxena S, Gyanchandani M. Machine learning methods for computer-aided breast cancer diagnosis using histopathology: A narrative review. J Med Imaging Radiat Sci 2020; 51(1): 182-193.

[2] Joshua LM, Huda F, Rao S, Ravi B. Clinicopathological significance of immunohistochemical expression of Filamin A in breast cancer. J Carcinog 2020; 19: 13. DOI: 10.4103/jcar.JCar_9_20.

[3] Feng H, Cao J, Wang H, Xie Y, Chen B. A knowledge-driven feature learning and integration method for breast cancer diagnosis on multi-sequence MRI. Magn Reson Imaging 2020; 69: 40-48.

[4] Bayraktar S, Batoo S, Okuno S, Glück S. Immunotherapy inbreast cancer. J Carcinog 2019; 18: 2. DOI: 10.4103/jcar.JCar_2_19.

[5] Devakumari, D., and Punithavathi, V. Comparison of noise removal filters for breast cancerdetection in mammogram images. Int J Pure Appl Math 2018; 119(18): 3863-3874.

[6] Batoo S, Bayraktar S, Al-Hattab E, Basu S, Okuno S, Glück S. Recent advances and optimal management of human epidermal growth factor receptor-2-positive early-stage breast cancer. J Carcinog 2019; 18: 5. DOI: 10.4103/jcar.JCar_14_19.

[7] Wajid SK, Hussain A. Local energy-based shape histogram feature extraction technique for breast cancer diagnosis. Expert Syst Appl 2015; 42(20): 6990-6999.

[8] Sangeetha R, Murthy KS. A novel approach for detection of breast cancer at an early stage using digital image processing techniques. Int Conf on Inventive Systems and Control (ICISC) 2017: 1-4.

[9] Chowdhary CL, Acharjya DP. Breast cancer detection using intuitionistic fuzzy histogram hyperbolization and possibilitic fuzzy c-mean clustering algorithms with texture feature based classification on mammography images. Proc Int Conf on Advances in Information Communication Technology and Computing 2016: 21.

[10] Kannan S, Subiramaniyam NP, Rajamanickam AT, Balamurugan A. Performance comparison of noise reduction inmammogram images. Int J Res Eng Technol 2016; 5(2): 31-33.

[11] Jiang X, Wang Z, Zhang L, Stampanoni M. Noise-analysis-based non-local means method for X-ray grating-based mammography denoising. IEEE Trans Nucl Sci 2013; 60(2): 802-809.

[12] Talha M, Sulong G, Jaffar A. Preprocessing digital breast mammograms using adaptive weighted frost filter. Biomedical Research 2016; 27(4): 1407-1412.

[13] Elyasi I, Pourmina MA, Moin M-S. Speckle reduction in breast cancer ultrasound images by using homogeneity modified Bayes shrink. Measurement 2016; 91; 55-65.

[14] Eckert D, Vesal S, Ritschl L, Kappler S, Maier A. Deep learning-based denoising of mammographic images using physics-driven data augmentation. In Book: Tolxdorff T, Deserno T, Handels H, Maier A, Maier-Hein K, Palm C, eds. Bildverarbeitung für die Medizin 2020. Informatik aktuell. Wiesbaden: Springer Vieweg; 2020. DOI: 10.1007/978-3-658-29267-6_21.

[15] Abbas Q, Celebi ME, Garcia IF. Breast mass segmentation using region-based and edge-based methods in a 4-stage multiscale system. Biomed 2013; 8: 204-214.

[16] Pereira DC, Ramos RP, Do Nascimento MZ. Segmentation and detection of breast cancer in mammograms combining wavelet analysis and genetic algorithm. Comput Methods Progr Biomed 2014; 114: 88-101.

[17] Cordeiro FR, Santos WP, Silva-Filho AG. An adaptive semi-supervised Fuzzy GrowCut algorithm to segment masses of regions of interest of mammographic images. Appl Soft Comput 2016; 46: 613-628.

[18] El Adoui M, Mahmoudi SA, Larhmam AM, Benjelloun M. MRI breast tumor segmentation using different encoder and decoder CNN architectures. MDPI Computers 2019; 8(3): 52.

[19] Dalmıs MU, Litjens G, Holland K, Setio A, Mann R, Karssemeijer N, Gubern-Merida A. Using deep learning to segment breast and fibroglandular tissue in MRI volumes. Med Phys 2017; 44: 533-546.

[20] Moeskops P, Wolterink JM, van der Velden BH, Gilhuijs KG, Leiner T, Viergever MA, Isgum I. Deep learning for multitask medical image segmentation in multiple modalities. Int Conf on Medical Image Computing and Computer-Assisted Intervention 2016: 478-486.

[21] Milletari F, Navab N, Ahmadi SA. V-net: Fully convolutional neural networks for volumetric medical image segmentation. Proc 2016 Fourth Int Conf on 3D Vision 2016: 565-571.

[22] Mouelhi A, Rmili H, Ali BJ, Sayadi M, Doghri R, Mrad K. Fast unsupervised nuclear segmentation and classification scheme for automatic allred cancer scoring in immunohistochemical breast tissue images. Comput Methods Programs Biomed 2018; 165: 37-51.

[23] Punitha S, Amuthan A, Joseph KS. Benign and malignant breast cancer segmentation using optimized region growing technique. Future Comput Inf J 2018; 3(2): 348-358.

[24] Rouhi R, Jafari M, Kasaei S, Keshavarzian P. Benign and malignant breast tumors classification based on region growing and CNN segmentation. Expert Syst Appl 2015; 42(3): 990-1002.
[25] Khalilabad ND, Hassanpour H. Employing image processing techniques for cancer detection using microarray images. Comput Biol Med 2016; 81(1): 139-147.
[26] Kaymak S, Helwan A, Uzun D. Breast cancer image classification using artificial neural networks. Procedia Comput Sci 2017; 120: 126-131.
[27] Karabatak M. A new classifier for breast cancer detection based on Naïve Bayesian. Measurement 2015; 72: 32-36.
[28] Wang F, Zhang S, Henderson LM. Adaptive decision-making of breast cancer mammography screening: A heuristic-based regression model. Omega 2018; 76: 70-84.
[29] Mohebian MR, Marateb HR, Mansourian M, Mañanas MA, Mokarian F. A hybrid computer-aided-diagnosis system for Prediction of Breast Cancer Recurrence (HPBCR) using optimized ensemble learning. Comput Struct Biotechnol J 2017; 15: 75-85.

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