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## A combined approach for the enhancement and segmentation of mammograms using modified fuzzy C-means method in wavelet domain

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### Abstract

In this paper, a combined approach for enhancement and segmentation of mammograms is proposed. In preprocessing stage, a contrast limited adaptive histogram equalization (CLAHE) method is applied to obtain the better contrast mammograms. After this, the proposed combined methods are applied. In the first step of the proposed approach, a two dimensional (2D) discrete wavelet transform (DWT) is applied to all the input images. In the second step, a proposed nonlinear complex diffusion based unsharp masking and crispering method is applied on the approximation coefficients of the wavelet transformed images to further highlight the abnormalities such as micro-calcifications, tumours, etc., to reduce the false positives (FPs). Thirdly, a modified fuzzy c-means (FCM) segmentation method is applied on the output of the second step. In the modified FCM method, the mutual information is proposed as a similarity measure in place of conventional Euclidian distance based dissimilarity measure for FCM segmentation. Finally, the inverse 2D-DWT is applied. The efficacy of the proposed unsharp masking and crispering method for image enhancement is evaluated in terms of signal-to-noise ratio (SNR) and that of the proposed segmentation method is evaluated in terms of random index (RI), global consistency error (GCE), and variation of information (VoI). The performance of the proposed segmentation approach is compared with the other commonly used segmentation approaches such as Otsu's thresholding, texture based, k-means, and FCM clustering as well as thresholding. From the obtained results, it is observed that the proposed segmentation approach performs better and takes lesser processing time in comparison to the standard FCM and other segmentation methods in consideration.

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### Full Text

#### Introduction

According to American Cancer Society's, the Cancer facts and Figures 2013, [1] breast cancer is the most common cancer among women, except for skin cancers. About 1 in 8 (12%) women in the US will develop invasive breast cancer during their lifetime. The American Cancer Society for breast cancer in the United States for 2013 estimates that about 232,340 new cases of invasive breast cancer will be diagnosed in women, about 64,640 new cases of carcinoma in situ (CIS) will be diagnosed (CIS is non-invasive and is the earliest form of breast cancer), and about 39,620 women will die from breast cancer. Women in the India have about a 1 in 9 lifetime risk of developing invasive breast cancer. The early detection and diagnosis of breast cancer can increase the survival rate and effective treatment options in time. In screening mammography, radiographic imaging of the breast is currently the most effective and cheap tool for early detection of breast cancer. In screening mammogram program, the digital mammographic images are obtained and collected for the suspicious cases and the radiologists visually examine the mammograms for specific abnormalities. Breast image analysis can be performed using many imaging modalities such as digital mammography, magnetic resonance imaging (MRI), nuclear imaging and ultrasound. But the digital mammography is more popular and commonly used imaging tool for breast cancer detection due to its cost effectiveness as well as its higher ability to detect the disease. Mammography is low dose X-ray procedure that allows visualisation of internal structure of the breast. The most common breast abnormalities that may indicate breast cancer include masses, calcifications, architectural distortion, and bilateral symmetry. The breast lesions have a wide range of features that can indicate malignant changes, but can also be part of benign changes. They are sometimes indistinguishable from the surrounding tissue which makes the detection and diagnosis of breast cancer more difficult. Knowing the limitations of human observers and its difficulty for radiologists to provide both accurate and uniform evaluation for the enormous number of mammograms generated in widespread screening, automation of the breast cancer detection and diagnosis through a software CAD tool may help in accurate and uniform detection and diagnosis of breast cancer. Computer aided detection (CADe) and diagnosis (CADx), combined called as CAD, is used to help radiologists in interpretation of mammograms and is usually used as a second opinion by the radiologists. Improving CAD performance increases the treatment options and a cure is more likely. Also, to help the radiologists in screening large number of mammograms, the use of a CAD tool maybe helpful in exact prognosis free from human error analysis.

The major steps involved in the design and analysis of an automated CAD tool for cancer detection from mammograms include: Preprocessing (restoration and enhancement), image segmentation, feature extraction, feature selection and classification. The design and analysis of efficient algorithms for each step play an important role in deciding the efficacy and correctness of the overall CAD tool. Image enhancement and segmentation plays an important role in the design and development for the said CAD tool. In image segmentation the basic aim is to separate the suspicious region, that may contain abnormalities in mammograms such as micro-calcifications, tumors etc., from the background tissue. The segmentation process partitions the mammogram into several non-overlapping regions, extract regions of interests (ROIs), and locate the suspicious areas, such as micro-calcifications and tumours which are candidates for ROIs. The suspicious area is an area that is brighter than its surroundings, has almost uniform density, has a regular shape with varying size, and has fuzzy boundaries. [2] A better image enhancement technique, applied prior to segmentation process, for highlighting and enhancing the abnormalities in mammograms may further reduce the false positives (FPs) during cancer detection. Hence, image segmentation is a very essential and important step that determines the sensitivity of the overall CAD tool. The results for segmentation is supposed to include the regions containing all abnormalities even with some FPs, if left out, which can be removed at a later stage of the algorithms for CAD tool design. An overview of enhancement and segmentation techniques for mammograms is given as below.

#### Overview of enhancement techniques for mammograms

The various methods [3],[4],[5],[6] which exists in literature for the enhancement of mammograms may be broadly divided into three categories which include global approaches, [7],[8],[9],[10] local approaches, [11],[12],[13],[14],[15] and multiscale processing based approaches. [16],[17],[18],[19],[20] The global approach based methods reassign the intensity values of pixels to make the new distribution of the intensities uniform to the maximum extent. This method is effective in enhancing the entire image with low contrast. The main disadvantages of global schemes are that they cannot enhance the textual information and working only for the images having one object. The local approaches for image enhancement are feature-based or use nonlinear mapping locally. These methods are effective in local texture enhancement. The main disadvantages of the local schemes are that they cannot enhance the entire image very well. The multiscale processing based enhancement techniques are based on wavelet transformation and they are flexible to select local features to be enhanced and able to suppress the noise. If the mother wavelet and weight modification functions are chosen carefully, the wavelet based method can perform very well. [16] Some of the commonly used methods available in literature for the enhancement of mammograms include contrast limited histogram equalization (CLAHE) based technique, [11] density-weighted contrast

enhancement (DWCE), [21] logic filters, [9],[22],[23] iris filters [24],[25] and difference of Gaussians (DoG), [26] The DWCE is used in two stages, at first it is applied globally to isolate the suspected area, then it is used locally to refine the segmentation. It works in conjunction with Laplacian of Gaussian (LoG) filter. The logic filter is a nonlinear filter, and logic operators AND, OR, and XOR are used. The concrete logic expressions depend on the prior information, and the filter structure influences the results. Iris filter is an adaptive filter and it is applied locally. The Gaussian filter ROIs are highlighted by a DOG filter and it can reduce number of FPs during segmentation process.

Here, in this paper, in addition to image enhancement we propose to incorporate an unsharp masking and crispening operator to further highlight and sharpen the abnormalities using a nonlinear complex diffusion based approach.

Overview of segmentation techniques for mammograms

In literature, [28],[29],[31],[32] supervised and unsupervised are two types of image segmentation approaches. The supervised segmentation or model based method use the prior knowledge about the object and background regions to be segmented. The prior information is used to determine if specific regions are present within an image or not. The unsupervised segmentation partitions an image into a set of regions which are distinct and uniform with respect to specific properties, such as grey-level, texture or color. The classical approaches for solving unsupervised segmentation are divided in three major groups namely region-based methods, which divide the image into homogeneous and spatially connected regions; contour-based methods, which depends on the boundaries of regions; and clustering methods, which group together those pixels having the same properties and might result in non-connected regions. According to their natures, there are four broad categories of image segmentation approaches in literature [3] for the segmentation of mammograms which include classical techniques, fuzzy techniques, bilateral image subtraction, rough set based approaches [57],[58],[59],60 and multiscale techniques. A brief review of various segmentation approaches may be found in paper. [3]

In this paper, a modified fuzzy c-means (FCM) segmentation method based on mutual information in wavelet domain is proposed for segmenting the abnormalities in mammograms. Before applying the proposed segmentation approach, a PDE based unsharp masking and crispening method is proposed and applied on the mammograms to highlight the details of the abnormalities such as micro-calcifications etc., to reduce the false positives (FPs) during segmentation process. The proposed segmentation method is compared with the Otsu's optimal thresholding, [34],[35],[37] texture based segmentation method, [36] k-means segmentation, [31] and FCM based thresholding [3],[37] based segmentation method.

Reasons for using fuzzy technique based image segmentation algorithm [3],[37] are as follows: Since the contrast in mammograms is very low and the boundary between normal tissue and tumours is unclear, the traditional segmentation methods might not work well. The classical region growing based segmentation technique tries to precisely define ROIs, but to find a criterion for segmentation is difficult as most of the malignant tumors with fuzzy boundaries extend from a dense core region to the surrounding tissues. Similarly, the classical global or local thresholding techniques [3] try to segment ROIs, but the techniques are only effective for the objects with clear boundaries. The fuzzy logic based approaches are useful for segmenting suspicious regions [3],[32] and are capable of addressing above issues.

The categorization and summary of various commonly used mammogram segmentation methods are presented in [Table 1],[Table 1]

The organization of the paper is as follows: Section 1 of the paper presents the brief introduction of the problem; Section 2 of the paper presents the methods and models, that is the proposed method in detail along with the justification for the proposed models; Section 3 of the paper presents the results, performance analysis, and discussions; Section 4 of the paper presents the conclusions of the work.

## Materials and Methods

In this paper, an image enhancement and segmentation technique is proposed for the segmentation of mammograms for breast cancer detection. The proposed method consists of following steps as illustrated in [Figure 1],[Figure 1]

Algorithm for the proposed method

Step 1: In the first step, CLAHE based enhancement technique is applied on original low contrast mammogram to enhance them in to good contrast images.

Step 2: Two levels of 2D discrete wavelet transform (DWT) is applied on the output obtained in the first step.

This step is applied to perform the segmentation at various scales (multi-resolution) and also the wavelets can detect more easily the transient signals or abrupt changes caused by various gray level changes in images due to micro-calcifications and other abnormalities.

The other advantage being the faster processing of FCM based clustering method used in segmentation step.

Step 3: In this step, the proposed nonlinear complex diffusion based unsharp masking and crispening method is applied on the enhanced mammogram to further enhance and highlight the abnormalities and fine details present in mammograms such as micro-calcifications and tumors. This step help the segmentation process in producing the good results and increase the cancer detection rate by the CAD tool by reducing the false positives.

Step 4: The proposed modified FCM thresholding based image segmentation is applied on mammograms obtained in step 3.

Step 5: Inverse wavelet transform is applied to reconstruct the final segmented image in spatial domain.

In step 2 of the algorithm, it had been practically examined that two levels of DWT based segmentation is providing better results and very close to that of third level of DWT decomposition. Three levels of DWT decomposition may also be used but for large scale processing of mammograms computational complexity may increase.

The proposed steps 3 and 4 of the algorithms are described as follows:

Nonlinear complex diffusion based approach for unsharp masking and crispening of mammograms

The basic procedure [27],[39] for unsharp masking and crispening the image is as follows: In the first step, a low-pass filter is applied on the original image for smoothening the same. In the second step, the edge description and other desired high frequency components of an image are calculated by subtracting the smoothened image obtained in the first step from the original image. In the third and last step, the edge image obtained in second step is used for sharpening the edges and other high variation components of original image by adding back it to the original signal. The unsharp masking produces an edge image  $I_e(x, y)$  from an input image  $I(x, y)$  via

[INLINE:1]

Another method used in place of discrete Laplacian is Laplacian of Gaussian (LoG). In this case since the kernel peak is positive, the edge image is subtracted, rather than added back to the original image. The disadvantages of these schemes are that gradient images produced by both filters, Laplacian and LoG, produces the side effects of ringing or introduction of additional intensity image structure and this ringing occurs at high contrast edges. Hence, the unsharp filter is a powerful sharpening operator, but it also produces a poor result in the presence of noise.

In Eq. (4), the second term of RHS is Laplacian which is used as unsharp mask to produce the edge image defined as,  $I_{smooth}(x, y) = I(x, y)$  is a Heat equation which performs the isotropic diffusion to de-noise the image. The smoothing process can be regarded as an evolution process governed by a PDE that performs regularization of the image [40] as follows.

[INLINE:2]

where the function  $c = c(I, I_x, I_{xx}, \dots)$  is a function of local image differential structure that depends on local partial derivatives.

The above anisotropic diffusion based process involves the properties of forward diffusion on real axis which is more useful for analysing real valued grey images but may not be useful for reducing those noises which are near to threshold values and may produce staircase and ringing effects. Hence, to overcome these issues, in this paper, a nonlinear complex diffusion based filter as defined in [41] is used. In complex diffusion based processes, the imaginary part serve as an edge detector, smoothed second derivative scaled by time, when the

complex diffusion coefficient approaches the real axis. The complex diffusion based processes do not produce blocky artefacts or stair casing effects during the evolution process of the image. It also preserves the edges and fine structures within the image and results do not change by changing illumination conditions. These properties are helpful in mammographic image analysis for better diagnosis. The nonlinear complex diffusion based filter reads [41] :

[INLINE:3]

The last step (4) is used to obtain the sharpened with crisped edges and  $k$  is a scaling constant,  $k > 0$ . The reasonable values for  $k$  varies between 0.2-0.8, with the larger values providing increasing amount of sharpening.

Proposed modified fuzzy c-means thresholding based image segmentation using mutual information

The working of the FCM clustering approach is given as follows: [37],[38],60

In fuzzy approach based partitioning, the Gaussian membership matrix  $(U) = [u_{ij}]$  is randomly initialized according to Eq. (10), where  $u_{ij}$  being the degree of membership function of the data point of  $i$ th cluster  $x_i$ . The membership matrix  $U$  is allowed to have elements with values between 0 and 1 but the summation of degrees of belongingness of a data point to all clusters or partitions is always equal to unity:

[INLINE:4]

The FCM algorithm works iteratively through the above two conditions until there is no more improvement.

The limitations of the standard FCM based segmentation algorithms are as follows:

The main requirement of this algorithm is that the number of clusters should be known apriori. The performance of FCM depends on the initial membership matrix values hence the algorithm is run for several times, each starting with different values of membership grades of data points. Although the original intensity-based FCM algorithm functions well on segmenting most noise-free images, it fails to segment images corrupted by noise, outliers, and other imaging artifacts, such as the intensity inhomogeneity induced by the various abnormalities such as micro-calcifications in mammograms, and thus leads to its non-robust results mainly due to the use of (a) Non-robust Euclidean distance and (b) disregard of spatial contextual information in image. [43] Hence, FCM lacks enough robustness to noise and outliers and is not suitable for revealing non-Euclidean structure of the input data due to the use of Euclidean distance ( $L_2$  norm). To deal with this problem, some researchers adopted robust distance measures such as  $L_p$  norms ( $0 < p \leq 1$ ) [44],[45],[46] to replace the  $L_2$  norm in the FCM objective function for reducing the effect of outliers on clustering results, and while many other algorithms have also been proposed to deal with the second problem by incorporating spatial information into original FCM objective function. [47],[48],[49],[50]

Hence, to deal with above issues, in this paper, a mutual information based distance measure available in [30] is used for FCM. The other advantage of using mutual information as distance measure is that it can capture any correlative behaviour (positive, negative, and nonlinear) between image pixel values whereas the Euclidean distance measure can capture only positive correlations between pixel patterns.

Therefore, the Euclidean distance measure, used in classical FCM segmentation as a distance function for dissimilarity measurement to from the clusters of similar pixels, is replaced by the distance measure defined in terms of mutual information due to the reasons discussed as above. In this paper, the idea for the gene clustering based on cluster wide mutual Information used in paper [30] is adopted to define the distance measure used by FCM for the segmentation of mammograms.

For discrete variables, the mutual information  $I$  of two variables  $X$  and  $Y$  is defined as measure of information about  $X$  (or  $Y$ ) contained in  $Y$  (or  $X$ ) [30] :

[INLINE:5]

Where  $H(X)$  and  $H(Y)$  are entropies of  $X$  and  $Y$  respectively;  $H(X/Y)$  and  $H(Y/X)$  are conditional entropies of  $X$  and  $Y$  respectively;  $H(X, Y)$  is joint entropy of  $X$  and  $Y$ ; and  $N_x, N_y$  are possible values of  $X$  and  $Y$  that it can take. The mutual information is always nonnegative, which is  $I(X; Y) \geq 0$ . [51] Since the mutual information of two data variable  $X$  and  $Y$  defined as above is not normalized;  $I(X; Y)$  can be quite small even if  $X$  and  $Y$  are highly correlated. Hence, the mutual information must be normalized by the maximal entropy of each of the contributing  $X$  and  $Y$ . The basic advantage of normalization is that it gives a high value for highly correlated data or pixel values in an image independent of the individual entropy. The normalized mutual information is defined as [30] :

[INLINE:6]

The working of the clustering approach is as follows: In each iteration, the pixel that has a minimal distance to the target pixel to the cluster is added. The process continues until the distance threshold is not crossed. A second candidate cluster is formed by starting with the second pixel and the same procedure is repeated. The pixels from the first candidate cluster are not removed from consideration and this process continues for all pixels. The largest candidate cluster is selected and retained. The pixels in the largest candidate cluster are removed from the whole image pixel set, and the entire procedure is repeated on the smaller pixel set. When the number of clusters reaches to a predefined cluster number, all the remaining pixels to the last cluster are added. The threshold may be chosen as the mean of the distances of all pixel pairs.

In this paper, the three classes of FCM clustering were used. These three classes include small, middle, and large. A switch-off cut-position (SWC) were used to select among the classes. The SWC having value zero and one gives cut between small and middle classes and cut between middle and large classes respectively. The threshold values for segmentation were calculated as follows:

[INLINE:7]

## Results and Performance Analysis

In this section, results and performance analysis of the proposed enhancement and segmentation techniques are presented. For evaluation of the various mammogram segmentation approaches with the proposed one have been performed in terms of random index (RI), variation of information (Vol), and global consistency error (GCE). These performance measures are discussed as follows:

Mammogram segmentation performance measures

Random index

The RI measure [52],[53] was initially proposed for the evaluation of general clustering algorithms. The RI between test ( $S$ ) and ground truth ( $G$ ) is estimated by summing the number of pixel pairs with same label and number of pixel pairs having different labels in both  $S$  and  $G$ , and then dividing it by total number of pixel pairs. This gives a measure of similarity with value ranging from 0 when the two segmentations have no similarities (when one consists of a single cluster and the other consists only of clusters containing single points) to 1 when the segmentations are identical, that is when a higher value of RI close to 1 is preferred for perfect segmentation.

[INLINE:8]

where  $H(X)$  and  $H(Y)$  are entropies of  $X$  and  $Y$ ; and  $I(X, Y)$  is mutual information between  $X$  and  $Y$ .  $Vol(X, Y)$  measures how much the cluster assignment for an item in cluster  $X$  reduces the uncertainty about the item's cluster in cluster  $Y$ . The value of  $Vol$  lies in between 0 and  $d$ , where  $d$  is the distance between clusters. Since it is a distance measure, hence a lower value of  $Vol$  close to zero indicates best segmentation.

Global consistency error

In papers [54],[56] authors propose two metrics that can be used to evaluate the consistency of a pair of segmentations. These measures are designed in such a way that they are tolerant to refinement, i.e., if subsets of regions in one segmentation consistently merge into some region in the other segmentation the consistency error should be low. To compute the

consistency error for a pair of images, at first a measure of the error at each pixel  $p_i$  is defined as follows:

[INLINE:9]

Since  $LCE \leq GCE$ , hence GCE is a tougher measure than LCE and that's why it is used in this paper. A small value of GCE close to zero represents better segmentation. GCE quantify the amount of error in segmentation i.e., 0 signifies no error and 1 indicates no agreement.

## Results and Discussions

The proposed unsharp masking and crispensing techniques were evaluated in terms of improvement in signal-to-noise ratio of the sample test mammographic images and its overall effect on the proposed segmentation method is also evaluated. The comparative study of the proposed combined enhancement and segmentation technique is presented with the other popular methods used for segmentation of mammographic images such as Otsu's thresholding, Texture based thresholding, k-means clustering, and FCM clustering based segmentation method based on Euclidian distance measure. For experimentation purposes, the 256 histogram bins were used in Otsu's gray level thresholding method. For k-means, fuzzy c-means, and the proposed segmentation method the initial number of clusters for the proposed FCM based segmentation method was set to three as it was associated with better performance. In texture based segmentation, an entropy based filter was used. For experimentation purposes, 25 test sample digital mammographic images were used. The average performance measures for the 10 sample images are shown in this paper; however the performance trend remained the same for other test images as well. The proposed segmentation approach was also tested on mammographic image analysis society (MIAS) database. [Figure 2] shows the visual results of unsharp masking and crispensing procedure in spatial domain. [Table 2] and [Figure 3] present results in terms of signal-to-noise ratio (SNR) of original sample mammogram and improvement in SNR (ISNR) after applying proposed unsharp masking and crispensing method in wavelet domain. From [Table 1] and [Figure 3], it is observed that the proposed nonlinear complex diffusion (a partial differential equation based approach-PDE) based unsharp masking and crispensing methods is showing a good improvement over SNR values of the original mammogram which justifies that the proposed method is better capable of enhancing and highlighting the abnormalities in mammogram in details. [Figure 2] [Table 2] [Table 3] [Figure 3]

The first top row of [Figure 4] shows visual results for initial steps before segmentation, in initial steps of the proposed method, the visual results of the original mammogram, enhanced image by CLAHE method, unsharp masking and crispensing, and results after applying two levels of wavelet decomposition (bi-orthogonal) used in proposed method. During the 2D discrete wavelet decomposition (DWT) wavelet decomposition, a bi-orthogonal wavelet was used as a mother wavelet as it provides complete reconstruction of images.

The bottom row of [Figure 4] shows the visual results for the various segmentation methods such as Otsu's thresholding, texture segmentation, k-means segmentation, Fuzzy S-means segmentation and the proposed segmentation method. From visual results, it is observed that the proposed segmentation approach is providing the better segmentation results in comparison to other methods and it is well capable of segmenting the all possible types of abnormalities such as tumours, micro-calcifications etc., that may be present in mammogram for breast cancer diagnosis. [Figure 4]

[Table 3] presents the evaluation of various segmentation methods and the proposed one in terms of RI, Vol, and GCE for 10 sample mammograms. The averaged values of RI, Vol, and GCE for 10 sample images are also shown which gives the average performance of the methods. For better segmentation results the value RI should be close to one and higher than the values related to other segmentation methods; and the values of Vol and GCE should be lower than that of the other segmentation methods.

[Figure 5] shows comparison of RI values of various segmentation methods for 10 sample images. From [Figure 5], it is observed that the values of RI for each sample image for the proposed method are higher than that of other methods signifying that the proposed method is performing better in comparison to other methods. [Figure 6] shows comparison of average RI values of various segmentation methods for 10 sample images and the average RI value for proposed method is larger in comparison to other methods. [Figure 5] [Figure 6]

[Figure 7] shows comparison of GCE of various segmentation methods for 10 sample images and [Figure 8] shows comparison of average GCE values of various segmentation methods for 10 sample images. From [Figure 7] and [Figure 8], it is observed that the GCE value of the proposed method is smaller than that of the other methods. [Figure 7] [Figure 8]

[Figure 9] shows comparison of Vol values of various segmentation methods for 10 sample images and [Figure 10] shows comparison of average Vol values of various segmentation methods for 10 sample images. From [Figure 9] and [Figure 10], it is observed that the GCE value of the proposed method is smaller than that of the other methods. [Figure 9] [Figure 10]

[Table 4] shows comparison of execution time (in seconds) of various segmentation methods for sample image, image1.jpg of  $2770 \times 1770$ . Here, again it is observed that the proposed method is taking 6.561 seconds whereas the traditional FCM method is taking 148.94 seconds.

Therefore, from the results obtained it is observed that the proposed segmentation method is performing better in comparison to all other methods in consideration and it is well capable of segmenting the abnormalities in mammograms. [Table 4]

## Conclusions

In this paper, a nonlinear complex diffusion based unsharp masking and crispensing method was proposed for enhancement of abnormalities found in mammograms for the breast cancer detection. Further, a modified FCM segmentation method was proposed in wavelet domain. The distance measure for clustering purposes, in the proposed segmentation method, was based on the mutual information of image pixels. Two levels of (DWT) was used for image decomposition and transformation. The mother wavelet used for the wavelet decomposition was bi-orthogonal wavelets as it provides full reconstruction of images. For experimentation purposes, the initial number of clusters for the k-means, fuzzy c-means, and the proposed segmentation method was set to three as it was associated with better performance. The performance of the proposed enhancement method was evaluated in terms of signal-to-noise ratio (SNR). The performance of the proposed segmentation method was evaluated in terms of three measures such as RI (RI), GCE, and Vol. The performance of the proposed method and other segmentation methods in consideration were evaluated both qualitatively and quantitatively. The execution time of the proposed method was also lower in comparison to its best counterpart which was FCM with Euclidian distance. The comparisons of the performances of the proposed method with the other segmentation methods were also presented in the paper. Therefore, from the obtained results, it can be concluded that the proposed enhancement and segmentation framework is computationally cheaper, producing better results in comparison to other methods, alleviate the problems related to the Euclidian distance measure in traditional FCM based segmentation and reduces the false positives and outliers during the segmentation of the mammograms. Hence, the proposed method may be a better choice for segmentation of mammograms for the breast cancer detection.

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