MAMMOGRAM ENHANCEMENT AND SEGMENTATION METHODS: CLASSIFICATION, ANALYSIS, AND EVALUATION

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Abstract

Breast cancer is the leading cause of deaths among female cancer patients. Mammography is the most effective technique for breast cancer screening and detection of abnormalities. However, early detection of breast cancer is dependent on both the radiologist’s ability to read mammograms and the quality of mammogram images. The aim of this paper is to conduct a comprehensive survey of existing mammogram enhancement and segmentation techniques. Each method is classified, analyzed, and compared against other approaches. To examine the accuracy of the mammogram enhancement and segmentation techniques, the sensitivity and specificity of the approaches is presented and compared where applicable. Finally, this research provides taxonomy for the available approaches and highlights the best available enhancement and segmentation methods.

Keywords: Mammogram enhancement, Mammogram segmentation, Breast mass detection, Image Calcification, detection

1. INTRODUCTION

Globally, breast cancer is ranked first among the leading causes of cancer affecting females. Statistics have shown that 1 out of 10 women are affected by breast cancer in their lifetime. There are several ways in which breast cancer can be diagnosed, including breast self examination (BSE), clinical breast exam (CBE), imaging or mammography, and surgery. A mammogram is the most effective technique for breast cancer screening and early detection of masses or abnormalities; it can detect 85 to 90 percent of all breast cancers. The most common said abnormalities that indicate breast cancer are masses and calcifications.

Depending on its shape, a mass screened on a mammogram can be either benign or malignant. Usually benign tumors have round or oval shapes, while malignant tumors have a partially rounded shape with a spiked or irregular outline. Noncancerous or benign tumors include cysts, fibro adenomas, and breast hematomas. A cancerous or malignant tumor in the breast is a mass of breast tissue that grows in an abnormal and uncontrolled way [8]. The malignant mass will appear whiter than any tissue surrounding it. Calcifications (both macro-calcification and micro-calcification), the second abnormality that can be seen on mammogram images, are most of the time not malignant and not a sign of cancer. Successful diagnosis in mammography is dependent on detecting cancer in its earliest and most treatable stage. The challenge is to employ computer aided detection (CAD) techniques for the purpose of assisting radiologists in the early detection of cancer, by processing and analyzing mammogram images. The majority of the proposed cancer detection techniques in literature share the common steps of image enhancement, segmentation, quantification, registration, visualization [1], [44]. These techniques can be differentiated by the varying algorithms employed at each step. One of the challenges faced by the current mammogram image detection techniques lies in the difficulty of analyzing dense tissues. This difficulty can be attributed to the breast region which appears white in the mammogram images making masses and specifically micro-calcification highly invisible intermixed with the background tissue. Mammogram image enhancement is the process of manipulating mammogram images to increase their contrast and decrease the noise present in order to aid radiologists in the detection of abnormalities. Mammogram image segmentation is the process of partitioning mutually homogeneous regions into meaningful regions of interest.

A few papers have been written surveying the techniques used in cancer detection of mammogram images. Cheng et al., [14], summarized the enhancement, segmentation, and detection techniques of mammogram images. The authors categorized the micro-calcification enhancement techniques into three categories: conventional enhancement techniques, region-based enhancement, and feature based enhancement. The conventional enhancement techniques are in turn divided into contrast stretching, histogram equalization, convolution mask enhancement, and fixed and adaptive neighboring enhancement. Oliver et al., [39] reviewed the existing techniques for cancerous mass detection and segmentation. In their paper, the authors categorized mammogram segmentation techniques into mass detection using a single view and mass detection using multiple views. The mass detection using single view segmentation in turn is divided into four categories: (1) model-based methods, (2) region-based methods, (3) contour-based methods, and (4) clustering methods. Only
the model based methods are considered supervised segmentation methods, while the remaining three methods are considered unsupervised segmentation methods. The image segmentation techniques using multiple views are divided into three categories: left and right mammograms, two mammographic views (CC and MLO) of the same breast, and same view mammograms taken at different times. Bandyopadhyay [6] surveyed some commonly used mass segmentation methods. Raba et al., [42] reviewed breast region segmentation methods developed and proposed in the 80’s, 90’s and 2000. The techniques that were surveyed included: histogram based techniques, gradient based techniques, polynomial modeling based techniques, active contour based techniques, and classifiers based techniques. In this paper, the authors’ review the algorithms that have been proposed in the literature to enhance and segment mammogram images that contain both masses and micro-calcifications.

The goal of this paper is to provide a comprehensive review, comparison, and analysis of the available mammogram enhancement and segmentation algorithms. The rest of this paper is organized as follows: section 2 presents details of mammogram image enhancement techniques, section 3 presents the mammogram image segmentation techniques, section 4 evaluates the proposed approaches. Finally, section 5 presents the conclusion and the future work.

2. MAMMOGRAM IMAGE ENHANCEMENT TECHNIQUES

Mammogram image enhancement is the process of manipulating mammogram images to increase their contrast and decrease the noise present in order to aid radiologists in the detection of abnormalities. The methods used to manipulate mammogram images can be categorized into four main categories; the conventional enhancement techniques, the region-based enhancement techniques, the feature-based enhancement techniques, and the fuzzy enhancement techniques as shown in Figure 1. Conventional enhancing techniques are fixed neighborhood techniques and they are used to modify images based on global properties. Although region-based methods are used in segmentation, they are also used for enhancing the contrast of mammogram features according to the surroundings. On the other hand, feature based enhancement methods are those methods that are based on wavelet domain enhancement. And the fuzzy enhancement techniques are methods that apply fuzzy operators and properties to enhance mammogram features. Table 1 shows what each of the four mammogram image enhancement categories is primarily used for.

<table>
<thead>
<tr>
<th>Enhancement Category</th>
<th>Used for the enhancement of masses</th>
<th>Used for the enhancement of calcifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>√</td>
<td>x</td>
</tr>
<tr>
<td>Enhancement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region-based</td>
<td>√</td>
<td>x</td>
</tr>
<tr>
<td>Enhancement</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Main usage of mammogram enhancement categories

2.1 CONVENTIONAL ENHANCEMENT TECHNIQUES

The conventional enhancement techniques are mostly used to enhance masses in mammogram images; as an example, Bovis and Singh [9] and Antonie et al., [3] used histogram equalization to enhance the mammogram images before segmentation and mass detection. However, Schiabel et al., [47] used the histogram equalization technique accompanied with other techniques and as a part of a pre-processing step for mammogram enhancement. Whereas, Pisano et al., [40] used the contrast limited adaptive histogram equalization (CLAHE) in order to determine whether such a method can improve the detection of stimulated speculations in dense mammograms.

Hemminger et al., [26] compared between contrast-limited adaptive histogram equalization (CLAHE) and histogram-based intensity windowing (HIW) in order to determine which of them outperforms the other in the detection of simulated masses in dense mammograms. Yu and Bajaj [64] described a fast approach based on localized contrast manipulation to enhance image contrast. This method is based on fast computation of local minimum, maximum, and average maps using a propagation scheme. Kom et al., [29] presented a linear transformation filter for mammogram enhancement. Their algorithm modifies the local contrast of each pixel according to two linear functions and two constant values.

2.2 REGION-BASED ENHANCEMENT

Similar to the conventional enhancement methods, the region-based enhancement methods are mostly used for the enhancement of masses. An example of this is the work conducted by Dominguez and Nandi [23] who presented an enhancement algorithm as a part of an automatic detection of mammogram mass method. Sampat and Bovik [45] propose a filtering algorithm that enhances speculations (i.e. linear features of masses) in mammograms as a part of a speculated mass detection technique. of the image is computed to obtain the enhanced image.

2.3 FEATURE BASED ENHANCEMENT:
Feature based enhancement methods can be used to enhance both masses and micro-calculcations. Gagnon et al., [24] proposed a simple multi-scale sharpening enhancement algorithm based on the hidden zero-crossing property of the complex symmetric Daubechies wavelets. The algorithm was tested using low contrast digitized mammograms. Chang and Laine [12] presented an enhancement algorithm based on over-complete multi-scale wavelet analysis. Dabour [19] introduced an algorithm based on wavelet analysis and mathematical morphology for digital mammograms enhancement. The authors tested this algorithm on several mammograms from the MIAS database. The algorithm was also compared with various algorithms and the experimental results and showed a better contrast improvement index. Rodz et al., [4] used the wavelet-based sharpening algorithm to enhance the contrast of mammogram images. Laine et al., [30] introduced a method for mammographic feature analysis by multi-resolution representations of the dyadic wavelet transform. Scharcanski and Jung [46] described an approach for noise suppression and enhancement of mammogram images and that can be effective in screening dense regions of the mammograms. Stefanou et al., [50] compared between the adaptive enhancement algorithm and the typical method of enhancement.

### 2.4 FUZZY ENHANCEMENT METHODS

Fuzzy enhancement methods can be used to enhance masses and micro-calculcations, and as an example of enhancing mammograms containing masses, Singh and Al-Mansoori [49] compared between fuzzy enhancement techniques and histogram equalization. Mohanalin et al., [35] presented fuzzy algorithm based on Normalized Tsallis entropy to enhance the contrast of micro-classifications in mammograms. Jiang et al., [28] described a combined approach of fuzzy logic and structure tensor, to enhance micro-calculcations in digital mammograms. Cheng and Xu [16] proposed an adaptive fuzzy logic contrast enhancement method to enhance mammogram features. Table 2 summarizes the mammogram enhancement methods previously reviewed, specifying the year of the research, enhancement category, database used, and the number of mammograms used for testing.

<table>
<thead>
<tr>
<th>Author</th>
<th>Enhancement category</th>
<th>Used database</th>
<th>used mammogram(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yu and Bajaj [64]</td>
<td>Conventional</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Kom et al [29]</td>
<td>Conventional</td>
<td>YGOPH</td>
<td>61</td>
</tr>
<tr>
<td>Dominguez and Nandi [23]</td>
<td>Region-based</td>
<td>Mini-MIAS</td>
<td>N/A</td>
</tr>
<tr>
<td>Sampat and Bovik [45]</td>
<td>Region-based</td>
<td>DDSM</td>
<td>N/A</td>
</tr>
<tr>
<td>Gagnon et al [24]</td>
<td>Feature-based</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Dabour [19]</td>
<td>Feature-based</td>
<td>MIAS</td>
<td>N/A</td>
</tr>
<tr>
<td>Scharcanski and Jung [46]</td>
<td>Feature-based</td>
<td>MIAS</td>
<td>N/A</td>
</tr>
<tr>
<td>Mohanalin et al [35]</td>
<td>Fuzzy</td>
<td>MIAS</td>
<td>50</td>
</tr>
<tr>
<td>Jiang et al [28]</td>
<td>Fuzzy</td>
<td>UCSF</td>
<td>197</td>
</tr>
<tr>
<td>Cheng and Huijuan Xu [16]</td>
<td>Fuzzy</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 2: Results of mammogram enhancement techniques

### 3. MAMMOGRAM IMAGE SEGMENTATION TECHNIQUES

Mammogram image segmentation is the process of partitioning mutually homogeneous regions of a mammogram image into meaningful regions of interest. The algorithms used for segmentation can be categorized into two distinct categories according to the regions to be segmented; breast region segmentation and region of interest (ROI) segmentation. Breast region segmentation is the process of splitting the mammogram image into a breast region and a background in order to focus and limit the search for abnormalities on the breast region without the effect of the background on the results resulting in better detection. On the other hand, region of interest segmentation is the process of segmenting the suspicious regions to be analyzed for abnormalities.
While segmentation using multiple views can be categorized into left and right mammograms, two mammographic views (craniocaudal (CC) and mediolateral oblique (MLO)) of the same breast, and same view mammograms taken at different times. Unsupervised segmentation using a single view can in turn be categorized into six classes, region-based segmentation, contour-based segmentation, clustering segmentation, pseudo-color segmentation, graph segmentation, and variant-feature transformation. Figure 2 illustrates this categorization.

### 3.1 BREAST REGION SEGMENTATION

Breast segmentation techniques set the focus of the search for abnormalities on the region of the breast excluding its background. The techniques used for segmenting are similar to those used in the regions of interest segmentation and can also be categorized with the same perspectives though it’s not the interest of this paper. As an example of approaches that can be listed under the clustering segmentation method is the novel approach proposed by Shahedi et al. [48] for breast region segmentation based on local threshold. The Ojala et al. [38] which is based on histogram thresholding, morphological filtering, and contour modeling. This approach is applied by Wang et al., [59] as the first step in their automatic framework to identify differences between corresponding mammographic images. Raba et al., [42] proposed an automatic technique for segmenting a digital mammogram into a breast region and a background based on a “two-phase” approach. Bovis and Singh [9] applied the technique proposed by Chandrasekhar and Yitikiozel [12] adding to it an additional step, in order to segment the breast region from its background. Wirth and Stapinski [61] described an approach that automatically segments the breast region and extracts the breast contour in mammogram images using snakes or active contours. Wei et al., [60] presented a novel approach that extracts the contour of a region of interest in mammogram images. Chen and Zwiggelaar [13], which is a histogram thresholding, edge detection in scale space, contour growing and polynomial fitting base technique for segmenting the breast region. Yapa and Harada [63] presented a breast skin-line estimation and breast segmentation algorithm using fast marching approach. Table 3 summarizes the breast region segmentation methods described above, providing the year of the research, the database used, the number of mammograms used, the accuracy of segmenting the breast boundary, the pectoral muscle extraction accuracy, and the ability of the method to extract the nipple.

### 3.2 REGIONS OF INTEREST SEGMENTATION

Regions of interest segmentation is divided into two main categories, as mentioned previously in this paper, segmentation using a single view and segmentation using multiple views. This section lists some algorithms under each category.

#### 3.2.1 Segmentation using single view

Regions of interest segmentation using a single view are divided into supervised and unsupervised segmentation. This section will mainly list the unsupervised segmentation algorithms under the six categories described previously. Each category of unsupervised segmentation is

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Used database</th>
<th>Number of mammograms</th>
<th>used mammogram</th>
<th>Breast boundary accuracy</th>
<th>Pectoral extraction accuracy</th>
<th>Muscle extraction accuracy</th>
<th>Ability of nipple extraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shahedi et al [48]</td>
<td>2007</td>
<td>Mini-MIAS</td>
<td>66</td>
<td>86%</td>
<td>94%</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Raba et al [42]</td>
<td>2005</td>
<td>Mini-MIAS</td>
<td>320</td>
<td>98%</td>
<td>86%</td>
<td>N/A</td>
<td>N/A</td>
<td>√</td>
</tr>
<tr>
<td>Wirth and Stapinski [61]</td>
<td>2004</td>
<td>MIAS</td>
<td>32</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>√</td>
</tr>
<tr>
<td>Wei et al., [60]</td>
<td>2008</td>
<td>MIAS</td>
<td>322</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>√</td>
<td></td>
</tr>
<tr>
<td>Chen and Zwiggelaar [13]</td>
<td>2010</td>
<td>EPIC</td>
<td>240</td>
<td>98.4%</td>
<td>93.5%</td>
<td>N/A</td>
<td>N/A</td>
<td>√</td>
</tr>
<tr>
<td>Yapa and Harada [63]</td>
<td>2008</td>
<td>Mini-MIAS</td>
<td>100</td>
<td>99.1%</td>
<td>N/A</td>
<td>√</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Results of breast region segmentation techniques

<table>
<thead>
<tr>
<th>Author</th>
<th>Segmenting category</th>
<th>Used database</th>
<th>used mammogram</th>
<th>Masses</th>
<th>Calcifications</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schialle et al [47]</td>
<td>Region-based</td>
<td>UNESP</td>
<td>130</td>
<td>√</td>
<td>X</td>
<td>90%</td>
<td>92%</td>
</tr>
<tr>
<td>Cascio et al [11]</td>
<td>Contour-based</td>
<td>MAGIC-5</td>
<td>N/A</td>
<td>√</td>
<td>X</td>
<td>82%</td>
<td>N/A</td>
</tr>
<tr>
<td>Kom et al., [29]</td>
<td>Clustering</td>
<td>YGOPH</td>
<td>61</td>
<td>√</td>
<td>X</td>
<td>95.91%</td>
<td>N/A</td>
</tr>
<tr>
<td>Zheng et al [66]</td>
<td>Variant feature</td>
<td>N/A</td>
<td>510</td>
<td>√</td>
<td>X</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Menzatini et al [34]</td>
<td>Region-based</td>
<td>DDM</td>
<td>200</td>
<td>√</td>
<td>X</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Zhang et al [65]</td>
<td>Contour-based</td>
<td>DRSM</td>
<td>N/A</td>
<td>√</td>
<td>X</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Muralidhar et al [37]</td>
<td>Contour-based</td>
<td>DDM</td>
<td>N/A</td>
<td>√</td>
<td>X</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Cao et al [10]</td>
<td>Clustering</td>
<td>MIAS</td>
<td>N/A</td>
<td>√</td>
<td>X</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Comer et al [18]</td>
<td>Clustering</td>
<td>U.South Florida</td>
<td>N/A</td>
<td>√</td>
<td></td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Anguh and Silva [2]</td>
<td>Pseudo-color</td>
<td>U. of South Florida</td>
<td>50</td>
<td>√</td>
<td></td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Bagger et al [5]</td>
<td>Graph</td>
<td>Mini-MIAS</td>
<td>55</td>
<td>√</td>
<td>X</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Guan et al [25]</td>
<td>Variant feature</td>
<td>MIAS</td>
<td>N/A</td>
<td>X</td>
<td>√</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Stojc et al [51]</td>
<td>Variant feature</td>
<td>Mini-MIAS</td>
<td>N/A</td>
<td>X</td>
<td>√</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Bhattacharya and Das [7]</td>
<td>Variant feature</td>
<td>MIAS</td>
<td>65</td>
<td>X</td>
<td>√</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 4: comprehensive summary of the previously mentioned unsupervised ROI segmentation methods using a single view
specialized in segmenting abnormalities such as masses and calcification.

### 3.2.1 Region-based methods:

Region growing segmentation techniques are used to segment both masses and calcifications. As an example of mass segmentation methods, Mencattini et al., [34] proposed a mass segmentation module for a CAD system implemented using a new region growing algorithm. Schiabel et al., [47] described a methodology for segmenting suspicious masses in dense mammograms. This methodology is based on the Watershed transformation. Wang and Karayiannis [58] applied the watershed algorithm to segment micro-calcification in the segmentation phase of the approach proposed by the authors to detect micro-calcifications employing wavelet-based sub-band image decomposition.

### 3.2.2 Contour-based methods:

Most of the research conducted using the contour-based methods segmented masses rather than segmenting calcification. An example of such a method, is the work conducted by, Zhang et al., [65] proposed a contour-based segmentation method for mass segmentation. The authors tested their approach on ROI marked mammograms from the digital database for screening mammography (DDSM). Cascio et al., [11] proposed a contour based mass segmentation algorithm, that was tested on the mammograms from the Medical Applications on a Grid Infrastructure Connection (MAGIC-5 collaboration) which consists of 3762 mammograms. Singh and Al-Mansoori [49] compared between region growing and gradient-based segmentation techniques. Muralidhar et al., [37] describe a mass classification method, based on the snakes segmentation method which is an evidence active contour algorithm developed by the authors. The authors tested this method using mammograms from DDSM database and the results of using snakes are promising.

### 3.2.3 Clustering methods:

Clustering segmentation methods can segment both masses and calcifications. And as an example of segmenting masses using clustering, Kom et al., [29] developed a local adaptive thresholding technique for mass segmentation.

Velthuizen [56] developed a segmentation method based on an initial unsupervised clustering. Dominguez and Nandi [23] applied density slicing technique proposed by Mudigonda et al., [36] to segment masses. This technique was used as a part of a method the authors presented for mass detection in mammograms. Cao et al., [10] proposed an information based algorithm for mass segmentation on digital mammograms. This algorithm is called cshells based on deterministic annealing (CSDA).

Cheng et al., [15] who used the iterative threshold selection method [43] to implement the segmentation process as a part of a novel approach based on fuzzy logic for micro-calcification detection. Moreover, clustering can be used for the detection of masses and micro-calcifications together, as shown by the statistical algorithm for mammogram segmentation presented by Comer et al., [18].

### 3.2.4 Pseudo-color segmentation:

Pseudo-color segmentation methods can be used to detect masses and micro-calcifications together. Such an algorithm is used by the approach presented by Anguh and Silva [2].

### 3.2.5 Graph segmentation:

Graph segmentation methods can be used to segment masses. Bajger et al., [5] employed a graph segmentation method in his approach to automatically segment mammogram masses using minimum spanning trees (MST). The authors tested their approach using two sets of mammograms. The first set consists of 55 mammograms from the Mini-MIAS database, and the second set consists of 37 mammograms from a local database. Ma et al., [31] presented a method based on the adaptive pyramid (AP) segmentation and sublevel set analysis of mammograms. In another work, Ma et al., [32] compared between the performance of the minimum spanning trees (MST) based segmentation method and that of the adaptive pyramid (AP) based segmentation method in terms of robustness. Graph segmentation methods can also be used to segment micro-calcifications. D’Elia et al., [20] and D’Elia et al., [21] used the tree-structured markov random field (TS-MRF) based segmentation method (D’Elia et al., [22]) to segment mammograms in order to detect abnormalities.

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**Table 5: ROI segmentation techniques using multiple views**

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Segmentation category</th>
<th>Used database</th>
<th>Number of used mammograms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bovis and Singh [9]</td>
<td>2000</td>
<td>Left and right mammograms</td>
<td>MIAS</td>
<td>144</td>
</tr>
<tr>
<td>Xu et al [62]</td>
<td>2010</td>
<td>Left and right mammograms</td>
<td>DDSM</td>
<td>60</td>
</tr>
<tr>
<td>Wang et al [59]</td>
<td>2006</td>
<td>Left and right mammograms</td>
<td>MIAS</td>
<td>N/A</td>
</tr>
<tr>
<td>Marti et al [33]</td>
<td>2006</td>
<td>Left and right mammograms</td>
<td>N/A</td>
<td>64</td>
</tr>
<tr>
<td>Velkova et al [55]</td>
<td>2009</td>
<td>Two mammographic views (CC and MLO) of the same breast</td>
<td>N/A</td>
<td>1063</td>
</tr>
<tr>
<td>Pu et al [41]</td>
<td>2008</td>
<td>Two mammographic views (CC and MLO) of the same breast</td>
<td>N/A</td>
<td>200</td>
</tr>
<tr>
<td>Sun et al [52]</td>
<td>2004</td>
<td>Two mammographic views (CC and MLO) of the same breast</td>
<td>N/A</td>
<td>100</td>
</tr>
<tr>
<td>Alrichter et al [1]</td>
<td>2005</td>
<td>Two mammographic views (CC and MLO) of the same breast</td>
<td>DDSM</td>
<td>N/A</td>
</tr>
<tr>
<td>Timp et al [54]</td>
<td>2005</td>
<td>Same view of mammograms taken at different times</td>
<td>N/A</td>
<td>389</td>
</tr>
<tr>
<td>Timp and Karssemeijer [53]</td>
<td>2006</td>
<td>Same view of mammograms taken at different times</td>
<td>DBSP</td>
<td>2873</td>
</tr>
<tr>
<td>Wirth et al [67]</td>
<td>2002</td>
<td>Same view of mammograms taken at different times</td>
<td>MIAS</td>
<td>N/A</td>
</tr>
<tr>
<td>Mudigonda et al [36]</td>
<td>2001</td>
<td>Same view of mammograms taken at different times</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

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481
3.2.1.6 Variant feature transformation

Variant feature transformation can be used in mammogram mass segmentation. Zheng et al., [66] used a technique of single-image segmentation with Gaussian band-pass filtering. This technique is used as a segmentation part of a CAD system for mammogram mass detection. The authors tested their CAD system on 510 mammograms and the results showed that single-image segmentation method have a high sensitivity. However, variant feature transformation methods are mostly effective in segmenting micro-calcification along with mammogram masses. As an example of segmenting micro-calcification, Guan et al., [25] proposed an approach based on scale invariant feature transform (SIFT) to segment micro-calcifications automatically in mammograms. Stojic et al., [51] modified the multi-fractal (MF) segmentation method to improve the segmentation of micro-calcification. Bhattacharya and Das [7] presented a novel approach for segmenting mammograms in order to accurately detect micro-calcification clusters. Table-4 provides a comprehensive summary of the previously mentioned unsupervised ROI segmentation methods using a single view, specifying the year of the research, the segmentation category, the database used, the number of mammograms used, the ability of the method to segment masses, and the ability of the method to segment micro-calcifications, sensitivity, and specificity.

3.2.2 Segmentation using multiple views

Breast images can be taken from different angles, the most common views are; mediolateral oblique (MLO) view which is the most important and the cranio-caudal view (CC). According to the previous image views, image segmentation techniques using multiple views can be divided into three categories: left and right mammograms, two mammographic views (CC and MLO) of the same breast, and same view mammograms taken at different times. In the left and right mammograms, the evaluation is done by checking the symmetry of the fibroglandular tissue in the two breasts. In the two mammographic views (CC and MLO) of the same breast, the evaluation is done by checking the fibroglandular tissue in CC and MLO images of the same breast. However, in the same view mammograms taken at different times, the evaluation is done by checking the changes of the fibroglandular tissue of the breast at different times.

3.2.2.1 Left and right mammograms:

Bovis and Singh [9] applied the region splitting technique on the two images obtained from a bilateral subtraction technique. While, Xu et al., [62] presented a CAD algorithm for mass detection using bilateral asymmetry. In this algorithm, the left and right mammograms are aligned, then a bilateral subtraction technique is applied. Wang et al., [59] proposed an automatic registration framework, in order to identify the differences between corresponding mammograms. The authors used mammograms from MIAS database to test their framework. Martí et al., [33] presented a novel method for mammogram image registration. The authors tested this method using 64 mammograms containing malignant masses.

3.2.2.2 Two mammographic views (CC and MLO) of the same breast:

Velikova et al., [55] proposed and applied the Bayesian network multi-view system for the detection of abnormalities. Pu et al [41] developed a computer scheme based on an ellipse-fitting algorithm. This scheme is used to build a Cartesian coordinate system in order to match the breast masses depicted in the two mammograms. Sun et al [52] presented ipsilateral multi-view CAD scheme to detect masses in digital mammograms. Altrichter et al., [1] proposed a procedure for joint analysis of breast’s two views, by combining the results of algorithms detecting mass and micro-calcifications detection. The authors tested their algorithm using mammograms from the DDSM database. Results showed that this technique can reduce the number of false negatives significantly.

3.2.2.3 Same view of mammograms taken at different times:

Timp et al [54] developed an automatic regional registration method for mass detection in mammograms; the authors tested this method using 389 mammograms. Wai and Brady [57] presented a landmark-based registration framework of mammograms. However, Timp and Karssemeijer [53] developed a regional registration technique to link a suspicious location on prior and current mammograms. Wirth et al., [67] proposed a non-rigid mammogram registration approach to match mammograms. The authors tested the proposed approach using mammograms from the MIAS database. Table-5 summarizes the ROI segmentation techniques using multiple views discussed above, specifying the year of the research, the segmentation category, the database used, and the number of mammograms used.

4. EVALUATION

In this research, the performance of the Mammogram enhancement and segmentation methods is evaluated using different databases. However, most of the methods were evaluated using two main databases, the MIAS and the DDSM. The MIAS database is a digital mammography database produced by the UK research group. The MIAS database contains left and right digital mammograms for 161 patients with a total of 322 images of 50X50 micron resolution, and with 8-bit pixel depth. The images included all types of breast tissues; normal, benign and malignant. The DDSM database contains 2500 studies; each study includes two images of each breast. An abnormality in a mammogram is diagnosed either positive, i.e. predict that the person has cancer, or negative, i.e. predict that a person does not have cancer. To aid this diagnosis in CAD systems, mammogram enhancement and segmentation techniques should be applied. These enhancement and segmentation algorithms can be evaluated...
Other techniques can be employed to evaluate the enhancement and segmentation algorithms such as, sensitivity and specificity, receiver operating characteristic (ROC) and free-ROC (FROC). The results of diagnosing a mammogram can be classified as follows:

- True positive (TP): sick people correctly diagnosed sick.
- False positive (FP): healthy people incorrectly diagnosed sick.
- True negative (TN): healthy people correctly diagnosed healthy.
- False negative (FN): sick people incorrectly diagnosed healthy.

Sensitivity and specificity are performance evaluation statistical measures [17], where sensitivity (true positive fraction (TPF)) is the fraction of sick people who are correctly diagnosed as positive, and specificity (true negative fraction (TNF)) is the fraction of healthy people who are correctly diagnosed as negative. These measures specify the accuracy of the system for identifying the actual positive and actual negative patients respectively. However, the false-positive-fraction (FPF) and the false-negative-fraction represent the frequencies of incorrect diagnoses, therefore: False-negative-fraction = 1 - TPF, and False-positive-fraction = 1 - TNF. There is an interrelationship between these measures which makes it important and meaningful to specify a single pair, either sensitivity and specificity, or TPF and FPF, but it is inadequate to use only one measure alone. Equation 1 shows sensitivity measure, while equation 2 shows specificity measure.

\[
\text{Sensitivity} = \frac{\text{number of TP}}{\text{number of TP} + \text{number of FN}}
\]

\[
\text{Specificity} = \frac{\text{number of TN}}{\text{number of TN} + \text{number of FP}}
\]

The disadvantage of using a pair of either sensitivity and specificity, or TPF and FPF for a test is to have higher sensitivity (higher TPF) but lower specificity (higher FPF), i.e. one test is more accurate for actually positive patients and other is more accurate for actually negative patients, which makes it difficult to indicate which test is better. This limitation can be resolved using ROC curves. ROC analysis is used to provide a comprehensive description of diagnostic accuracy by estimating and reporting all combinations of sensitivity and specificity. ROC curves are presented by plotting sensitivity as a function of FPF (1-specificity). On the other hand, ROC curves depend on the skill of the radiologist, and, the imaging procedure’s technical aspects such as, spatial resolution, noise and contrast (Swets, 1979). However, FROC analysis accommodates multiple lesions on each image by allowing multiple reports, and is represented by plotting the fraction of lesions detected as the vertical axis and the average number of false-positive detections per image as the horizontal axis which is not normalized, instead, it is extended to an arbitrary large number of FP reports per image. FROC analysis provides greater statistical power than conventional ROC analysis, and the results of its analysis depend on the number of locations allowed by the data analyst. Table-3 through Table-5 summarizes the results.

5. CONCLUSION

This paper presented a comprehensive classification and evaluation of mammogram enhancement and segmentation algorithms. The enhancement techniques were categorized into four distinct techniques. From the review, it is obvious that the results produced from the fuzzy enhancement techniques are best suited for enhancing both masses and micro-calculcations. On the other hand, the mammogram segmentation techniques were categorized into two distinct categories, and the regions of interest segmentation techniques were further categorized into sub-categories. From the review of the literature, it can be inferred that the variant feature transformation category listed under the unsupervised single view segmentation techniques are better suited for the segmentation of masses and micro-calculcations. However, segmentation using multiple views can also give good results.

References