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Literature Review on Classical Mammogram Enhancement Techniques

Ms. Divya Christopher

Assistant Professor in CS & IT, Lourdes Matha College of Science and Technology, TVM

Abstract: Breast Cancer is one among the dreadful cancer diseases and the second-leading cause of cancer deaths, which are mostly seen in middle-aged women between ages of 35 and 55. According to the estimation done in 2016 by American Cancer Society at U.S, 1,685,210 new cancer cases were diagnosed with breast cancer and 595,690 women have died due to breast cancer. Mammography has been found as an effective imaging modality for detecting and diagnosing breast cancer. Mammograms often feature vagueness and inhomogeneity in its background compared to other images. Hence different enhancement techniques were developed to improve the overall visibility of mammograms, in order to facilitate early detection of breast cancer. This paper discusses few novel methods developed in enhancing mammogram images.

Keywords: contrast, lesion, ROI, mass, calcifications, mammogram.

INTRODUCTION

Mammogram is an X-ray image of the breast tissue consisting of two pictures, one of left breast tissue and right breast tissue where Radio-lucent areas correspond to fatty tissue and Radio-opaque areas correspond to fibrous tissue. Mammography equipment records the following two views of left and right breast tissue: Craniocaudal View and Mediolateral Oblique View. Craniocaudal (CC) view displays the top-to-bottom view of a mammogram whereas Mediolateral Oblique View (MLO) displays the side-to-side view of a mammogram taken at an angle. The most important mammographic indicators of breast cancer depicted in Fig. 1 are Masses, Clusters of Micro-calcifications and Architectural Distortion, which are mostly found in ducts, lobules and lymph nodes of the breast tissue.

Masses are defined as a space-occupying lesion seen in at least two different projections and are often described by their shape and margin characteristics. Spiculated masses are characterized by spicules radiating in all directions from the margin of a mass. Micro-calcifications are tiny calcium deposits which appear as small bright spots on the mammogram and are invisible to the human eye, since they appear with low contrast in an inhomogeneous background. They are often characterized by their type and distribution properties. An architectural distortion is a normal breast architecture distorted, with no definite mass visible. This includes spiculations radiating from a point and focal distortion at the edge of the breast parenchyma. Two types of abnormalities are often seen in mammograms; benign masses that are mild, harmless and harmful malignant masses that have a spiculated appearance. The Medical Association Group of doctors are looking forward to researchers for development of new enhancement techniques for better visualization of all features inside mammograms.

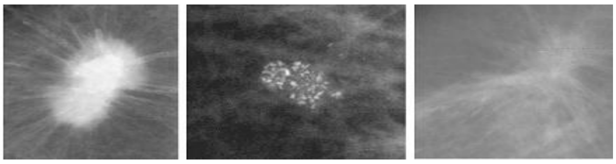

Fig 1(a) Mass (b) Cluster of micro-calcifications (c) Architectural Distortion

Younger women having dense breast tissue with more fibro glandular tissues are as shown in Fig. 2 (a) as it hides the tumor, by making it difficult for diagnosis of disease. Older women having fewer fibro glandular tissue and excessive fat tissue as shown in Fig. 2(b) makes it easy to detect cancer.

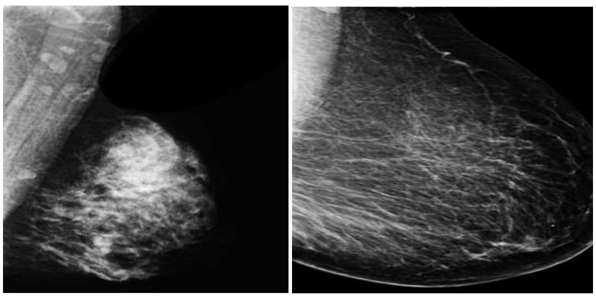

Fig. 2(a) Fibrous glands in dense breast tissue hiding tumor, in younger women, 2(b) Less dense breast tissue of older women

TRADITIONAL MAMMOGRAM ENHANCEMENT ALGORITHMS

The contrast of mammogram is increased either globally or locally for sharpening the edges of ROIs. Global contrast enhancement techniques changes image contrast, regardless of image contents whereas local contrast

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enhancement techniques changes image contrast locally based on image contents and statistical properties in the neighborhood of a pixel. Therefore, local contrast enhancement is most suitable for detecting tumors in mammograms. The basic image enhancement techniques performed with mammograms are summarized below.

(i) Contrast stretching – This transformation function increases the dynamic range of gray-levels in image, thus improving contrast of poor-contrast mammograms.

(ii) Histogram based contrast enhancement - Histogram of an image represents the relative frequency of occurrence of various gray levels in an image whereas in histogram equalization, the frequently-occurring pixel values in the original image occupy a bigger dynamic range in the processed image. This image stretching procedure has improved the visibility of an image such that the pixel intensity values are equally distributed across the spectrum, by avoiding the display of a very dark or a very bright image.

Contrast limited adaptive histogram equalization technique (CLAHE) makes use of a clip-level, to limit the amount of contrast enhancement for each pixel in an image. This method has eliminated the drawbacks of adaptive histogram equalization resulting in several high peaks in enhanced image. All pixel values beyond the clip-level are re-distributed using an interactive binary search procedure.(iii)

(iii) Linear filtering – This filter performs a linear operation on all the pixels in a window on an image. E.g. Mean filter computes the mean of all the pixels in a window and its center pixel is replaced with the mean value. This process is continued for the entire image, resulting in a smoothened image free of noise and highlighting the gross detail. Linear enhancement techniques often leads to insufficient usage of the dynamic range available on the display screen by giving more emphasis to strong edges which makes it difficult to detect the subtle features in mammograms

(iv) Non-linear filtering operation – This filter performs a non-linear operation on all the pixels in a window on an image. E.g. median filter results in better noise suppression, as it computes the median value of the pixels within a window and its center pixel is replaced with the median value. Small features within each scale are enhanced without blurring the edges of large features. However by assigning large gain factors to pixels with low contrast, low contrast area can be enhanced more than high contrast area.

(v) Hybrid filtering – This filtering technique includes both morphological top-hat and bottom-hat filtering operations applied on a gray-scale or binary image, using a single structuring element object to enhance the image details smaller than the structuring element S. These image processing techniques deal with morphology features in an image. Top-hat filtering technique enhances small bright details from a non-uniform uneven dark background whereas Bottom-hat filtering technique extracts dark features from a bright background. The top-hat image contains peaks of objects that fit the structuring element and the bottom-hat image shows the gap between objects of interest. The function, imtophat(im,se) subtracts a morphologically opened image from original image. The function, imbothat(im,se) subtracts original image from a morphologically closed version of image. The enhanced image is obtained by adding original and top-hat filtered image and then to subtract newly added image from the bottom-hat filtered image.

Imenhancement=imsubtract(imadd(Itophat,I),Ibothat)

This operation is done to maximize contrast between objects and gaps in order to separate them from each other. Dilation and erosion are the two fundamental morphological operations, where dilation adds pixels to and erosion removes pixels from the object boundaries. The number of pixels added or removed from the object depends on the size and shape of the structuring element used to process the image. Thus this technique can also be used to improve the local contrast of a mammogram. The next two, very important morphological operations, are opening and closing. The opening of image I by a structuring element S is defined as erosion followed by dilation, while closing has the opposite order of these operations. With gray-scale opening one can remove bright details smaller than the structuring element. Conversely, closing operation removes dark details smaller than the structuring element. By combining morphological opening and closing, various image processing tasks can be performed.

vi) Homomorphic Filtering – This technique eliminates multiplicative noise by normalizing brightness across the entire mammogram. This filter function decreases the energy of low frequencies and increases the energy of high frequencies in a mammogram. Both the multiplicative components of an image, illuminance and reflectance are made additive by taking the logarithm of the image intensities such that they can be separated linearly in the frequency domain.

(vii) Unsharp masking – In this filtering technique original image is subtracted from its low-pass filtered, blurred image (unsharpened image) to form a mask (high-pass filtered image), which is multiplied by a gain factor and added back to the original image. This process has improved the contrast of a mammogram by emphasizing its boundary and fine details. The processed image appears sharper, because the low-frequency information in the mammogram is reduced in intensity, while the high frequency details are amplified.

(viii) Wavelet-based enhancement – This technique makes use of the multi-resolution decomposition of an image into several subbands, each subband containing a feature at different scales. The original image is decomposed into

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four sub-bands, called approximation coefficients and detail coefficients including Horizontal (H), Vertical (V) and Diagonal (D) coefficients. Small features like micro-calcifications will be prominent in one subband and large features like masses will be prominent in a different subband. The enhanced image is reconstructed back from the decomposed subband images.

The sub-images obtained using wavelet decomposition is often noted with "LL", "HL", "LH" and "HH" as shown below in Fig 3. "LL" is the approximation image, "LH" and "HL" are the horizontal and vertical detail images and "HH" is the diagonal detail image.

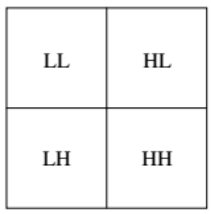

Fig 3. Analogy after first-level wavelet decomposition

A scenario of wavelet image decomposition for one level is shown below in Fig 4.

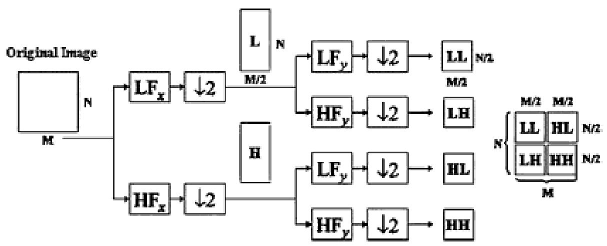

Fig 4. Wavelet Image Decomposition for one level

The original image has a size of m x n, LFx and HFx are the low-pass and high-pass analysis filters of the row, LFy and HFy are the low-pass and high-pass analysis filters of the columns. ↓2 represent the downsampling operator by a factor of 2, by first downsampling the rows and then the columns. The input image is recursively decomposed into four sub-band signals, a coarse signal and three detail signals of three resolutions. In inverse wavelet transformation, these signals are recursively combined to reconstruct the output signal. At each level of decomposition and reconstruction, Forward and Inverse DWTs are first applied to every row of the signal and then applied to every column of the resulting data.

(ix) Fuzzy-logic techniques

Fuzzy set theory is a useful tool in enhancing mammogram images as it has some degree of fuzziness like indistinct borders, ill-defined shapes and different densities. Fuzzy image enhancement is based on gray-level mapping into fuzzy plane, based on a membership transformation function. A poor contrast image is enhanced by assigning a larger weight to the gray levels, closer to the mean gray level of an image. Each gray level value has a membership value denoting the degree of brightness of the gray level. An intensification operator is used to reduce the fuzziness of an image, which results in an increase in image contrast. The minimum, maximum and mean gray values in an image are computed to calculate the membership values. Fuzzy rules have been written to map the dark, gray and bright gray levels to black, gray and white. The Image fuzzification process sets the membership values of gray levels to dark, gray and bright, such that the gray-level intensity values falls into the range, [0, 1]. Finally, the image defuzzification process uses the minimum, medium and maximum gray level values to obtain the new enhanced image. The index of fuzziness was defined by Kaufmann and Fuzzy entropy by De Luca and Termini and it reflects the ambiguity in an image by measuring the distance between its fuzzy property plane and nearest ordinary plane. Grey-level contrast in the spatial domain is transformed to fuzzy-image contrast in the fuzzy domain, by creating a fuzzy image having fuzzy membership values between 0 and 1. The lower the fuzziness, the clearer the image will be.

A. OTHER ENHANCEMENT TECHNIQUES IN SPATIAL DOMAIN

Image enhancement algorithms falls into two categories: direct and indirect. Direct image enhancement is done with the help of histograms, whereas in indirect image enhancement the contrast of the image is defined first and then only the image is enhanced. Direct enhancement techniques like unsharp masking improves the image contrast by manipulating a local contrast measure related to the edge and local statistics information of an image. Histogram equalization is a popular indirect enhancement technique that attempts to redistribute the image intensities over the entire dynamic range.

G Ramponi proposed Rational UM method [1], where control term which is a high-pass filter in traditional UM is replaced by a rational function operator expressed as a ratio of two polynomials of the local input data. It enhances the fine details in images that contain low and medium sharpness without amplifying the noise or affecting the steep edges. Thus, the overshoot effects on sharp edges are limited.

G Ramponi also proposed a Cubic UM method [2], which clearly discriminates signal and noise resulting in good background noise suppression. The correction term expressed as a quadratic function of the local gradient privilege high gradient areas and suppresses noise.

Zhe Wu proposed a modified unsharp masking method [3] based on region segmentation and improved high-pass filter for enhancing mammogram images. The region segmentation procedure was implemented based on adaptive UM. The method effectively enhances edges of lesions and at the same time suppresses noise in uniform background areas. This method has a good effect on sharpening edges of lesions using low enhancement factors.

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Iyad F. Jafar proposed a modified unsharp masking technique [4] for image contrast enhancement. Higher contrast level is achieved by scaling edge image automatically before adding it to the original image. The threshold value partitions the edge image into smooth and edge regions. This is done by excluding the bins that contain the pixels of smooth region to avoid noise amplification and by limiting the stretching of bins towards the two ends of the histogram to reduce edge ringing artifacts. The histogram equalization technique is then applied on limited regions of the edge histogram identified through a set of thresholds automatically computed using K-means clustering algorithm, which partitions the edge image into two clusters, each representing the low and high edge values. Thus a better contrast image is produced.

Andrea Polesel and G Ramponi proposed an adaptive UM technique [5] for enhancing contrast of images. Tian Xiurong adopted adaptive unsharp masking algorithm for improving contrast of medical images. An adaptive filter included in the correction path controls contribution of sharpening path in such a way that maximum contrast enhancement occurs in high detail areas and little or no image sharpening occurs in smooth areas. The scaling factor at each location and coefficients of two adaptive directional filters, horizontal and vertical filters are updated using Gauss-Newton Adaptation algorithm, to reduce squared error between desired and actual local dynamics. The desired local dynamics of output image is specified by classifying each pixel in the input image to one of the three regions, by adaptively computing the activity level or local variance in an image over a 3x3 pixel block. This method divides original image into low-detail region corresponding to the low-frequency part of the images (breast tissue), medium-detail region corresponding to characteristics of mass and high-detail region corresponding to micro-calcifications. The objective is to emphasize medium-contrast details in input image more than large contrast details such as abrupt edges to avoid unpleasant overshoot artifacts. This method is useful for sharpening the borders and smoothing the uniform areas.

Siddharth et al proposed an improved unsharp masking algorithm [6] for enhancing mammographic masses. The combination of improved high-pass filter with conventional unsharp masking method based on region segmentation not only enhances the contrast of lesion, but also suppresses background noise. This method divides entire image into three segments, and a pixel is assigned to one of three regions by computing a local variance over the 3x3 pixel block. Using background prediction process, a high-frequency image is produced by suppressing background noise.

Tarik Arici et al proposed a locally adaptive non-linear filter [7] for contrast enhancement of mammograms. The unsharp mask obtained from this filter preserves the edges in images, while filtering out local details by effectively preventing undershoot and overshoot effects. Local mean is computed by averaging horizontal and vertical filter outputs running on a single row. The enhanced image has improved the visual quality of image.

Karen Panetta et al proposed a non-linear unsharp masking (NLUM) [8] method for enhancing mammograms which has improved disease diagnosis by enhancing fine details with no prior knowledge of the image contents. Human Visual System decomposition is also used for analyzing and visualizing the mammogram enhancement which has been performed.

M. Sundaram proposed a modified local contrast enhancement method based on histogram equalization for mammograms [9]. Traditional HE results in excessive contrast enhancement due to lack of control on the level of enhancement. This method is implemented in two stages: First stage is a histogram modification technique applied on the input mammogram for better contrast enhancement such that difference between modified and input histogram is small; where modified histogram is a weighted average of input and uniform histogram. Second stage is a local contrast enhancement technique applied on the histogram modified image for bringing hidden fine details by applying a local transformation function based on gray-level distribution of every pixel within its local neighborhood. This method has improved the detectability of masses and micro-calcifications.

M. Sundaram also has proposed a method for improved micro-calcification detection based on Histogram Modified Contrast Limited Adaptive Histogram Equalization [10], in order for the better adjustment of level of contrast enhancement. This method is also implemented in two stages: first stage is a histogram modification technique applied on input mammogram and the second stage is a Contrast Limited Adaptive Histogram Equalization method applied on the histogram modified image, such that the clip level of histogram could be chosen, to reduce undesired noise amplification. This combination of methods results in a better quality image with improved naturalness and contrast, while preserving the local information of mammograms.

Jose George et al proposed a fast adaptive anisotropic technique [11] for medical image enhancement for different modalities including mammograms. Adaptive Anisotropic Filtering (AAF) deals with the adaptive image texture enhancement and image denoising simultaneously with respect to input image. AAF has a flexible framework for image enhancement and is hence divided into three main steps: Local structure analysis or Tensor field estimation within the local neighbourhood, Tensor processing to process estimated tensor field in order to enhance different structures and Image reconstruction. After these steps, a filter unique for every spatial neighbourhood is synthesized. User can steer the high-frequency content of a signal using a few parameters. This

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method effectively suppresses high-frequency noise while preserving anisotropic image structures in medical images. Yicong Zhou et al introduced a new powerful nonlinear filter called Alpha Weighted Quadratic Filter (AWQF) [12] for mammogram enhancement. Nonlinear filtering is known for its ability to enhance images by simultaneously preserving edge details and removing noise. This method effectively enhances the global and local contrast, local fine details and dark regions in mammograms to achieve better visibility for human observers.

Wei Qian proposed a symmetric multi-stage tree-structured non-linear filter [13] that uses central weighted median filters as basic sub-filtering blocks and a dispersion edge detector for image enhancement. The proposed filter suggested better detail preservation, noise suppression and edge detection than other previous approaches. This method has been proved as a useful tool for computer-assisted-diagnosis in digital mammography.

B. OTHER ENHANCEMENT TECHNIQUES IN FREQUENCY DOMAIN

Li et al developed a two – step process pixel-based method for detecting spiculated masses [14]. In the first step, lesion site location was determined using morphologic enhancement and stochastic model–based segmentation technique. Then, a finite generalized Gaussian mixture distribution was used to model the histogram of mammograms. The expectation maximization algorithm was used to determine the parameters of the model. In the second step, segmentation was achieved by classifying the pixels using Bayesian relaxation labeling technique.

Petrick et al presented a two-stage algorithm for enhancing suspicious mass regions in digitized mammograms using adaptive density-weighted contrast-enhancement (DWCE) filter and Laplacian-of-Gaussian (LoG) edge detector [15]. DWCE enhances the structures within the digitized mammogram so that a simple edge detection algorithm can be used to define the boundaries of objects. Once the object boundaries are known, morphological features are extracted from each object and used by the classification algorithm to differentiate mass and non-mass regions within an image. In the first stage, DWCE filter was used to enhance masses and suppress background structures and a simple edge detector, LoG was used to extract the ROIs containing potential masses. The output of the DWCE filter is a nonlinear rescaled version of the weighted contrast image. Finally, to reduce the number of false positives, a set of texture features was used for classifying detected objects as masses or normal. This DWCE filter implementation along with edge detection and morphological feature classification provides a new approach for automatic segmentation of digitized mammograms.

Ho-Kyung Kang proposed a robust contrast enhancement method for enhancing micro-calcifications in mammograms [16]. This method makes use of modified homomorphic filtering in the wavelet domain based on background noise information. Wavelet transform analyzes the different frequencies of the image using different scales. The homomorphic filter function decreases the energy of low frequencies and increases the energy of high frequencies in the image. An adaptive denoising technique is included in the enhancement framework, for reducing the noise as well as enhancing the micro-calcifications in mammograms.

Xiaoming Liu proposed a multi-scale image decomposition scheme for enhancing calcification[17]s. In this method, original image and its normalized gradient image are first decomposed into multi-level Gaussian Pyramid and Laplacian Pyramid using a multi-scale image decomposition scheme. Gaussian pyramid is a smoothed representation of an image at different levels, scales and resolutions. A Laplacian image is the difference between the two levels of the Gaussian pyramid and the Laplacian pyramid is a sequence of these differences. Features extracted in different scales are enhanced level by level based on a contrast measure and different weights are introduced to control the weight of the laplacian component. This method separates the image into coarse and fine scales such that the original shape and general features lies on coarse scales whereas detail and indistinguishable features lies on fine scale.

Zhuangzhi Yan et al proposed a novel approximation-weighted detail contrast enhancement (AWDCE) filter for enhancing the mammograms [18] using multi-level daubechies wavelet transform for improved lesion detection. In this method, a rescaling transform is applied on an original image to produce a normalized image, on which 2D-Wavelet Transform is applied to produce a detail image and approximation image. A non-linear grey-scale transform of the approximation image is computed to produce a weighting factor image, which is multiplied by normalized detail image to produce a modified image. Finally, an enhanced image is obtained by adding the approximation image to the modified image. This filter also automatically enhances the mass contrast.

Peter Heinlein et al proposed a two-step method for enhancing micro-calcifications in mammograms [19] using discrete wavelet decompositions called integrated wavelets that can easily access local features in mammograms. First step computes an adapted multi-resolution decomposition of mammogram into wavelet coefficients using integrated wavelet transform. In the second step, a local enhancement operator is applied on the wavelet coefficients. Weighting the wavelet coefficients by a factor, allows better separation of micro-calcifications from the line-like structures in mammograms. Finally, an enhanced image free of artifacts is reconstructed.

Spyros et al proposed a breast Component Adaptive Wavelet Enhancement for Soft-Copy display of Mammograms [20]. The human visual system is characterized by a multi-resolution organization, such that objects which appear well-defined at a fine scale are

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progressively lost when moved to coarser scales. This method outperforms Multi-resolution enhancement for optimal visualization of the entire breast area. The edge detection step separates breast area from mammogram background and a Gaussian mixture modeling technique which models breast area as a linear combination of k-weighted Gaussian distributions. It segments the breast components, as Uncompressed Fat (UF), Fat and Dense Tissues. The original image is decomposed using Redundant Discrete Wavelet Transform (RDWT) to obtain a multi-resolution representation of the original image and then its magnitude coefficients are linearly mapped to each corresponding breast component based on a Gain factor, provided by the parameters of the modeled breast component. The processed image is then derived by reconstructing the modified wavelet coefficients. Every pixel in the reconstructed image as shown in Fig 4 is gray-level coded to reflect the appropriate breast component, as Uncompressed Fat (UF), Fat (F) and Dense (D) breast tissue. This method is useful for better visualization of anatomical features in the breast area.

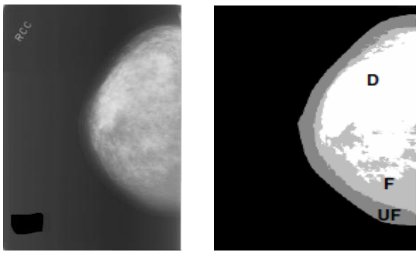

Fig. 4 (a) Original Mammogram (b) Segmented mammographic components, using a mixture of three Gaussian functions, provided by Expectation Maximization (EM) algorithm.

Gordana et al proposed a Wavelet Image Interpolation (WII) technique for enhancing mammograms [21]. It involves the application of a Forward Wavelet Transform that decomposes the image into approximation and detail coefficients and finally applying an Inverse Wavelet Transform (IWT) to a coarse or degraded image by interpolating the image to reveal higher degree of details to produce an enhanced higher resolution image of micro-calcifications.

Barba J Leiner proposed a method to detect micro-calcifications through 2-D discrete wavelet transform and image enhancement techniques [22], for noise removal and improved contrast. The first step is a segmentation process by applying histogram equalization and thresholding operation, which eliminates the regions in the image. Then, the image is passed through the unsharp masking filter to improve the image contrast, thereby clarifying the fine details like micro-calcifications. A histogram modification technique is employed to achieve better visualization of the micro calcifications. Finally, an IDWT recovers the image showing only the lesion. This method has helped the radiologists in effectively detecting the abnormality in mammogram images.

Mohamed Meselhy Eltoukhy presented a study between wavelet and curvelet transform for breast cancer diagnosis in breast cancer [23]. Mammograms are decomposed into different resolution levels using wavelet and curvelet separately, which are sensitive to different frequency bands using multi-resolution analysis. Features are often extracted from the ROI, based on a multi-resolution wavelet transform as shown in Fig 5. The first step is to differentiate between different types of tissues and the second step is to classify different types of abnormalities, based on its geometrical properties.

Discrete Curvelet Transform is a new image representation approach proposed by Candes and Donoh, from the idea of representing a curve as a superposition of functions of various length and width, obeying the curvelet scaling law, width ≈ length^2.

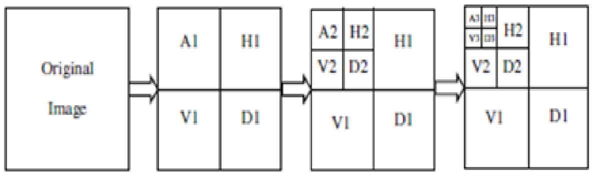

Fig.5 Wavelet multiresolution decomposition for three levels

The author suggests that the curvelet transform outperforms wavelet transform. Curvelet transform works better for optimally sparse representation of objects with edges, optimal image reconstruction of objects in severely ill-posed problems. This method is found better at diagnosing the abnormalities in mammograms.

Chun-Ming Chan proposed an artifact-free enhancement algorithm based on multiscale representations of mammographic features like tumor mass, density, size, borders, shape and local distribution of calcifications. First, the mammogram image is decomposed using fast wavelet transform algorithm. At each level of analysis, energy and phase information are computed via a set of separable steerable filters. Features like stellate patterns of spicules advanced in distinct directions can be more precisely extracted from these separable steerable filters. Then, a measure of coherence within each level was obtained by weighting an energy measure with the ratio of projections of local energy within a specified window. Finally, a nonlinear operation, integrating both coherence and orientation information is applied to modify the transform coefficients within distinct levels. These modified coefficients were reconstructed, via inverse fast wavelet transform, resulting in an improved visualization of mammographic features. This method is effective in removing the artifacts in reconstructed images and detecting directional multi-scale features in mammograms. Jose Manuel Mejia Munoz et al. has proposed a novel method for mammogram enhancement using a nonsubsampled contourlet transform [24], which decomposes the mammogram into multi-directional and multi-scale subbands for better feature extraction and an

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edge Prewitt filter is used to enhance the directional structures of the image in the contourlet domain. Finally, am inverse contourlet transform is applied to recover an approximation of the mammogram with the enhanced micro-calcifications having better visual characteristics.

Mohamed S Elsherif proposed an algorithm for denoising and enhancement of mammogram images at different scales in the wavelet packet domain [25]. The wavelet packet transform decomposed the mammograms into wavelet packet multiresolution representation, using three different types of mother wavelets, daubechie-8, symmlet-8 and coiflet-5. A non-linear enhancement function based on soft-thresholding scheme was applied to decomposed images, and these coefficients are again applied to sharpening filter, to improve the contrast of mammogram images. This method has improved detection performance of the algorithm.

C. REGION-BASED CONTRAST ENHANCEMENT ALGORITHMS

Duan Zhu et al presented a region and feature-based algorithm for mammogram enhancement [26] which outperforms traditional methods. Region-based algorithm enhances the image such that the resultant image is free of noise with improved details whereas feature-based algorithm enhances suspicious ROI and removes background noise. Wavelet transform technique detects micro-calcifications.

Renbin Peng et al proposed a selective enhancement technique for different ROIs [27]. In this method, region containing lesions are automatically determined and an adaptive grey-level stretching method is used to increase the contrast in ROI and to suppress background noise. Finally, an adaptive Wiener filter is used for de-noising and further smoothing resulting in an enhanced mammogram.

Bandyopadhyay S.K et al developed a method for early detection of abnormal masses in mammograms [28] where the identification technique is divided into two distinct parts: formation of homogeneous blocks to eliminate inhomogeneity and color quantization after preprocessing to break color space into eight equal-sized color regions, each region representing a specific part in the image and satisfying specific properties.

William M M et al developed an adaptive neighbourhood region-based contrast enhancement (ANCE) technique [29] to easily improve contrast of specific regions in mammograms of varying size and shape. Contrast is improved based on local region background, contrast, neighbourhood size and seed pixel value for region-growing process based on a seed-fill algorithm. Pixel value within a specified gray-level deviation from the seed pixel value is the foreground, f surrounding the seed pixel. Other pixel values outside the range are classified as background, b surrounding the foreground. The region's contrast is a function of the mean gray levels of the foreground and the background. The Contrast, C of a region is given by, C= (f-b) / (f+b). This ratio is similar to Weber's ratio, which is the ratio of luminance (difference b/w noticeable object and background) to its background luminance. Only low-contrast regions are enhanced, while the high-contrast regions with steep edges remain unaffected.

D. OBJECT RECOGNITION TECHNIQUES

Lai et al developed a template matching algorithm to detect only the circumscribed masses in mammograms [30]. The images were enhanced using a modified median filtering technique to remove background noise. To cope up with the variations in mass sizes, various templates with radii ranging from 3 to 14 pixels were used. To measure the similarity between a potential mass and template, normalized cross-correlation metric was used. Finally the ROIs are classified using two features, circularity and rectangularity which are used to characterize the shape of an object.

N Allec et al proposed a method for single-layer and dual-layer contrast enhancement of mammograms [31] using amorphous selenium flat panel detectors. In this method, two acquired images are combined together to form an enhanced image. The dual energy subtraction which uses a single detection layer suffers from motion artifacts due to patient motion, and thus a dual-layer detector composed of two layers was used to simultaneously acquire the low and high energy images, thus eliminating motion artifacts.

Huai Li et al proposed a method to model the mammographic parenchymal, ductal patterns and then to enhance the micro-calcifications using deterministic fractal approach [32]. Iterated Function Systems (IFS) and collage theorem are the mathematical foundations of fractal image modeling. Mammographic patterns were modeled based on background structure of breast tissue using a set of parameters of affine transformations. The whole image is split into different layers using different models, according to the difference in the properties of disease patterns. One layer containing disease-pattern and other layer containing non-disease pattern (background) information. The micro-calcifications were then enhanced using deterministic fractal approach by taking the difference between original and modeled image obtained after n iterations such that the background structures are removed from the enhanced image. Final enhanced image is obtained after thresholding. This method is an effective way to enhance micro-calcifications, as it explores self-similarity of images.

Tomislav Stojić et al developed two methods based on multi-fractal and mathematical morphology approach for enhancing micro-calcifications in mammograms [33]. In a multi-fractal approach, a multi-fractal "image" is created from the initial mammogram, through which a radiologist can change the level of segmentation in an interactive manner. The fractal dimension of human tissue structure varies with observed scale and is characterized by a high-degree of self-similarity by describing global and local features of an image, through which defects are easily

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extracted from background. This iterative method is suitable for real-time mammogram processing as it highly emphasizes the small-sized bright details, like micro-calcifications on mammograms.

Michael Wirth also proposed a method to enhance micro-calcifications based on a combination of morphological enhancement, which preserves fine details and non-flat or 3-D "ball-shaped" structuring elements, which shows greater accentuation of micro-calcifications than flat structuring elements, by separating peaks of micro-calcifications more effectively.

Jianmin Jiang proposed a combined approach with fuzzy logic operator and structure tensor operator arranged in parallel to process input mammograms which resulted in improved enhancement of micro-calcifications. The mammogram is normalized and transformed to fuzzy domain to calculate fuzzy contrast. The structure tensor operator is a reliable tool for analyzing coherent flow-like structures and it produces a corresponding Eigen image highlighting the ROIs.

A. DATA SOURCES

Real medical images are not available for access and experimentation due to privacy issues. All methods in this survey makes use of images obtained from Mammographic Image Analysis Society (MIAS) dataset comprised of 322 images. Each image falls into one of the following categories: normal, benign and malign. Every 8-bit gray-level image is digitized at a resolution of 1024x1024 pixels. The malign cases are further classified into six namely: circumscribed masses, spiculated masses, micro-calcifications, ill-defined masses, architectural distortion and asymmetry. This collection has been employed in numerous researches towards automatic classification.

PERFORMANCE ACCURACY OF CLASSIFICATION

The performance and accuracy of the mammogram image processing algorithms are computed by calculating accuracy, precision, sensitivity or true positive rate (TPR) and false positive rate (FPR) of benign-malignant classification. Receiver Operating Characteristic (ROC) Curve is determined by True positive (TP) and False negative (FN) results in an experiment. The larger the area (total area is 1), the better the classification is. A typical ROC curve with 100% detection performance with A=1 is depicted below in Fig. 6.

The efficiency of a CAD system is measured using TP, TN, FP and FN rates. True positives (TPs) occur when the radiologist identifies suspected abnormality as malignant whereas True negatives (TNs) occur when suspected abnormality in a healthy person is benign. The two typical errors caused in mammogram examinations are false positives and false negatives. False positives (FPs) occur when radiologist identifies a breast area as cancerous, when it is benign. False negatives (FNs) occur when an abnormality is not detected by the radiologist.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$precision = \frac{TP}{FP + TP}$$

$$TPR = \frac{TP}{FN + TP}$$

$$FPR = \frac{FP}{TN + FP}$$

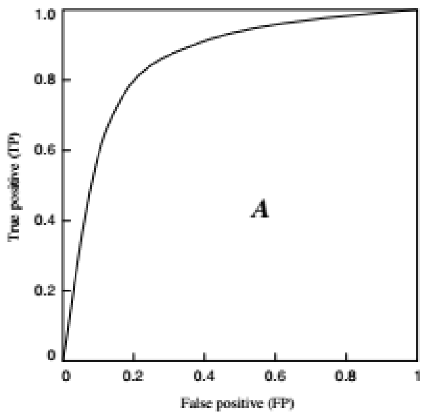

Fig.6 A typical Receiver Operating Characteristic (ROC) Curve

CONCLUSION

The field of breast-specific imaging has undergone robust change since today. All image enhancement techniques are useful in improving visual quality of the entire image for better interpretation by radiologists and surgeons. This paper details novel mammogram enhancement algorithms developed in the recent years. It has been observed that there is an improvement in the algorithms throughout years, but still it is not perfect. The area under ROC curve is rarely above 90% which means that there are still many false positive outputs. Masses and calcifications are sometimes hidden within the dense tissue which makes enhancement difficult. Further developments in each algorithm are required to improve the overall performance of mammogram enhancement.

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BIOGRAPHIES

Divya Christopher received the M.Tech. degree in Computer Science with specialization in Digital Image Computing from University of Kerala, India. She is currently an Assistant Professor in the Computer Science and Information Technology department at Lourdes Matha College of Science and Technology, Kuttichal, Thiruvananthapuram.

Her research interests include Medical Image Enhancement, Image Processing, Pattern Recognition, Computer Networking and Web Applications Development.