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A Survey on the Preprocessing Techniques of Mammogram for the Detection of Breast Cancer

D.Narain Ponraj, Karunya University, Coimbatore/India, narainpons@gmail.com

M.Evangelin Jenifer, Karunya University, Coimbatore/India, evan.jeni.21@gmail.com

P. Poongodi, PPG Institute of Technology, Coimbatore/India, poongodiravikumar@yahoo.co.in

J.Samuel Manoharan, Karunya University, Coimbatore/India, samuel1530@gmail.com

ABSTRACT

The aim of this paper is to review existing approaches of preprocessing in mammographic images. The objective of preprocessing is to improve the quality of the image and make it ready for further processing by removing the irrelevant noise and unwanted parts in the background of the mammogram. There are different of methods of preprocessing a mammogram image. Their advantages and disadvantages are discussed.

Keywords: *Breast Cancer,Decomposition, Mammogram, Preprocessing, Segmentation.*

1. INTRODUCTION

Cancer begins in cells, the building blocks that make up tissues. Tissues make up the breasts and other parts of the body. Normal cells grow and divide to form new cells as the body needs them. When normal cells grow old or get damaged, they die, and new cells take their place. Sometimes, this process goes wrong. New cells form when the body doesn't need them, and old or damaged cells don't die as they should. The buildup of extra cells often forms a mass of tissue called a lump, growth, or tumor. Cancer that forms in the tissues of breast, usually in the ducts (tubes that carry milk to the nipple) and in the lobules (glands that make milk) is the breast cancer. It occurs in both men and women, although male breast cancer is rare.

In the majority of cases, however, the abnormalities are either micro-calcifications or masses [1]. Micro-calcifications usually form clusters and individual micro-calcifications can range from 20 to several hundred microns in diameter. On the other hand, a breast mass is a generic term to indicate a localized swelling, protuberance, or lump in the breast. A benign mass do not spread to other parts of the body but still may need to be removed because the local tissue may be damaged. On the other hand, a malignant mass can destroy neighboring tissues and spread to other parts of organ or body.

Breast cancer is one of the leading cancers in the female population. About 25% of all cancers diagnosed in women are breast cancers and about 20% of all lethal cancers are breast cancers. It is the leading cause of death due to cancer in women. Because the means to prevent breast cancer have not yet been found, early detection is important. Mammography is a low dose x-ray procedure for the visualization of internal structure of breast. Mammography has been proven to be the most reliable method and it is the key screening tool for the early detection of breast cancer. Mammography is highly accurate, but like most medical tests, it is not perfect [2]. On average, mammography will detect about 80–90% of the breast cancers in women without symptoms. It works fairly well in the postmenopausal women and is inexpensive. In a screening mammogram, each breast is X-rayed in two different positions: from top to bottom and from side to side. When a mammogram image is viewed, breast tissue appears white and opaque and fatty tissue appears darker and translucent. A mammogram mainly contains two regions: the exposed breast region and the unexposed non-breast region. It is necessary to first identify the breast region for the reduction of the processing and then to remove the non-exposed breast region.

2. PREPROCESSING

Image pre-processing techniques are necessary, in order to find the orientation of the mammogram, to remove the noise and to enhance the quality of the image [3]. Before any image-processing algorithm can be applied on mammogram, preprocessing steps are very important in order to limit the search for abnormalities without undue influence from background of the mammogram.

Digital mammograms are medical images that are difficult to be interpreted, thus a preparation phase is needed in order to improve the image quality and make the segmentation results more accurate. The main objective of this process is to improve the quality of the image to make it ready to further processing by removing the unrelated and surplus parts in the back ground of the mammogram.

Breast border extraction and pectoral muscle suppression is also a part of preprocessing. The types of noise observed in mammogram are high intensity rectangular label, low intensity label, tape artifacts etc [4]. The types of noises present in mammogram are represented in Figure.1.

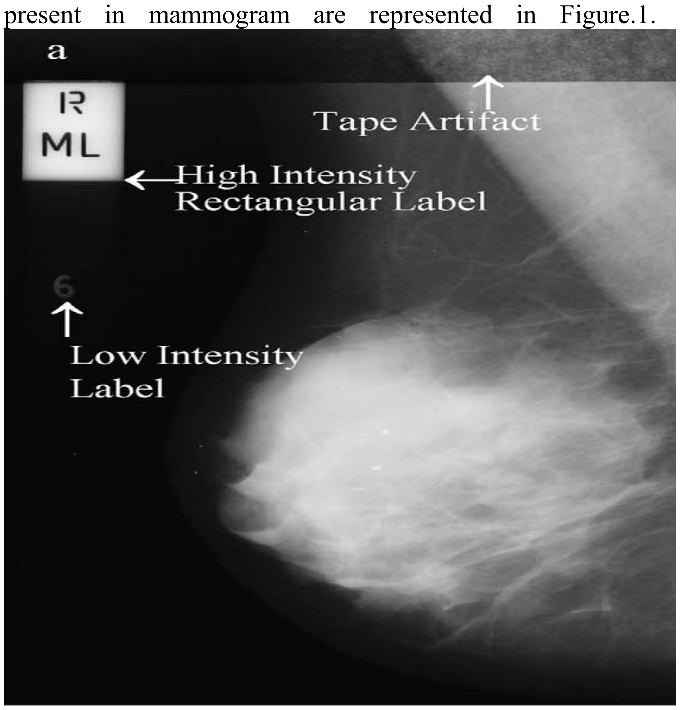

Figure 1: Types of noise observed in mammogram.

2.1 Adaptive Median Filter

Adaptive median filter works on a rectangular region Sxy. It changes the size of Sxy during the filtering operation depending on certain conditions as listed below. Each output pixel contains the median value in the 3-by-3 neighbourhood around the corresponding pixel in the input images. The edges of the images however, are replaced by zeros [6]. The output of the filter is a single value which replaces the current pixel value at (x, y), the point on which S is centered at the time. The following notation
is used:

Zmin = minimum pixel value in Sxy
Zmax = maximum pixel value in Sxy
Zmed = median pixel value in Sxy
Zxy= pixel value at coordinates (x, y)
Smax = maximum allowed size of Sxy

Adaptive Median filtering has been found to smooth the non repulsive noise from two-dimensional signals without blurring edges and preserve image details and it is given in Figure 2.This makes it particularly suitable for enhancing mammogram images.

Therefore preprocessing is used in mammogram orientation, label and artifact removal, mammogram enhancement and mammogram segmentation.

Preprocessing may also involve in creating mask for pixels with highest intensity, to reduce resolutions and to segment the breast [5].

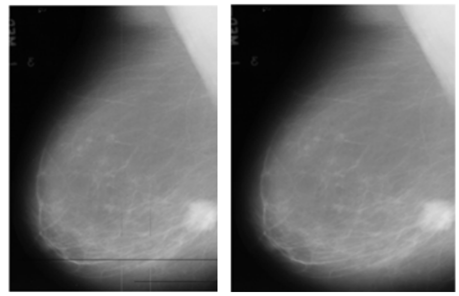

Figure 2:. Mammogram digitization noise removals using 2D median filtering. a) Original image (b) Filtered image after noise removal

2.2 Denoising Using filters

One of the most important problems in image processing is denoising. Usually the procedure used for denoising, is dependent on the features of the image, aim of processing and also post-processing algorithms [7].Denoising by low-pass filtering not only reduces the noise but also blurs the edges. Spatial and frequency domain filters are widely used as tools for image enhancement. Low pass filters smooth the image by blocking detail information. Mass detection aims to extract the edge of the tumor from surrounding normal tissues and background, high pass filters (sharpening filters) could be used to enhance the details of images [8]. Partial low and high pass filter when applied to mammogram image leads to best Image Quality.

2.3 Mean Filter

The mean filter replaces each pixel by the average value of the intensities in its neighborhood. It can locally reduce the variance and is easy to implement [9]. It has the effect of smoothing and blurring the image, and is optimal for additive Gaussian noise in the sense of mean square error. Speckled image is a multiplicative model with non-Gaussian noise [21], and therefore, the simple mean filter is not effective in this case.

2.4 Adaptive Mean Filter

In order to alleviate the blurring effect, the adaptive mean filters [9] have been proposed to achieve a balance between straightforward averaging (in homogeneous regions) and all-pass filtering (where edges exist). They adapt to the properties of the image locally and selectively remove speckles from different parts of the image. They use local image statistics such as mean, variance and spatial correlation to effectively detect and preserve edges and features. The speckle noise is removed by replacing it with a local mean

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value. The adaptive mean filters outperform mean filters, and generally reduce speckles while preserving the edges.

2.5 Histogram Equalization

This technique corresponds to redistribution of gray levels in order to obtain uniform histogram. In this case every pixel is replaced by integral of the histogram of the image in that pixel [10].Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to get better contrast. Histogram equalization accomplishes this by efficiently spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed [11]. In mammogram images, Histogram equalization is used to make contrast adjustment so that the image abnormalities will be better visible.

2.6 Histogram Modified Local contrast Enhancement

HM-LCE method incorporates a two stage processing both histogram modification and local contrast enhancement technique. Figure 3 shows the steps involved in the proposed method specified in [12].The potentiality of this contrast enhancement method is greatly increased to the expected level and this histogram modified LCE technique provides better image contrast enhancement in terms of both subjective as well as objective quality compared with other mammogram image enhancement methods.

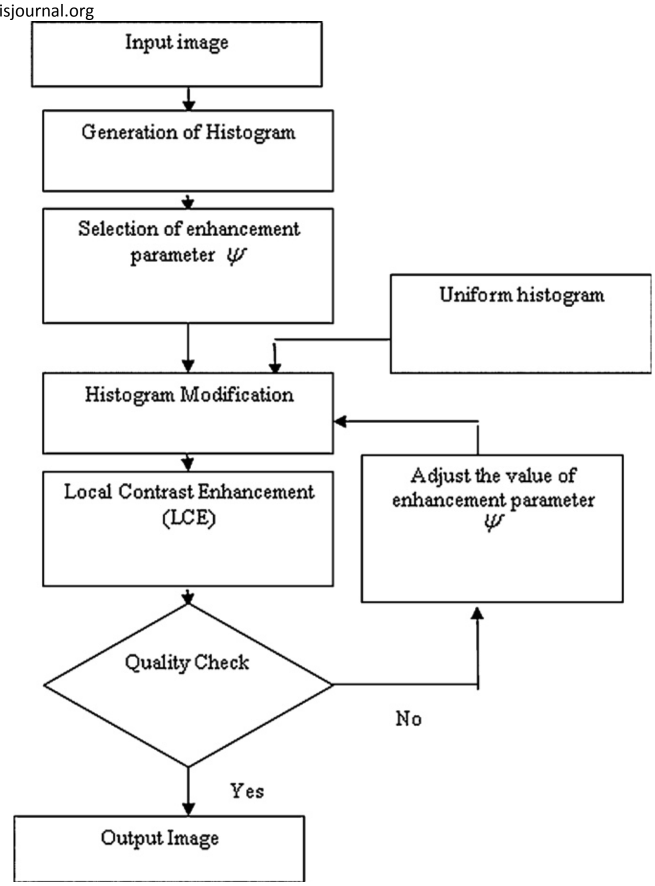

Figure 3: Block diagram of HE-LCE

2.7 Contrast Limited Adaptive Histogram Equalization (CLAHE) technique

The contrast enhancement phase is done using the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique, which is a special case of the histogram equalization technique that functions adaptively on the image to be enhanced [13]. The original image & its enhanced image is given in Figure. 4[a-b]. The CLAHE method seeks to reduce the noise and edge shadowing effect produced in homogeneous areas and was originally developed for medical imaging.

Figure 4: a) Original image b) Enhanced CLAHE image

2.8 Image Orientation

The orientation of the mammogram is determined. The image is rotated and reflected, so that the chest wall location, i.e., the side of the image containing the pectoral muscle, is on the left side of the image and the pectoral muscle is at the

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upper-left corner of the image [4]. In order to determine the chest wall location, the decreasing pixel intensity of the breast tissue near the skin-air interface (breast boundary) is used. This tissue is located by employing the minimum cross-entropy thresholding technique, proposed by Brink and Pendock [14], twice in the original image. By estimating the first derivatives in these pixel transition areas, using the appropriate convolution masks, we can determine the chest wall location. The image is rotated, in order for the chest wall location to be placed on the left side of the image. Next, the top of the image is determined: At first, the vertical centroid of the image is extracted, as the row dividing the skin tissue mask into two equal parts. Then, the asymmetric regions with respect to the vertical centroid are estimated. We assert that the asymmetric region closest to the right side of the vertical centroid is the tip of the breast. The image is flipped vertically, if needed, to place this asymmetric region below the vertical centroid, resulting in an image the right way up.

2.9 Breast Region and Pectoral Muscle Extraction

The Preprocessing step based on segmentation has to be done to remove the background area (High intensity rectangular label, Tape, artifact and noise) and to remove the pectoral muscle from the breast region if the image is a MLO view [15-16]. Generally, pre-processing step is composed of two stages: breast region and pectoral muscle extraction. Figure 5 shows that the Breast region extraction approach is used to separate the breast from the background (first stage), and a pectoral muscle extraction approach (second stage) is used to eliminate the pectoral muscle from breast region.

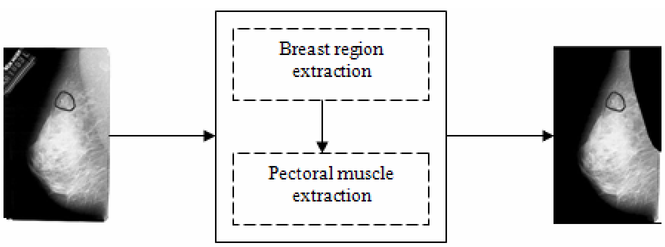

Figure 5: Preprocessing block diagram

Two preprocessing algorithms, one for the breast contour extraction and the other for pectoral muscle segmentation are proposed in [17] in which breast region extraction consist of following steps. They are Histogram equalization, Convolving with mask, Thresholding and labeling, Modifying ends of breast border, Non-Linear Diffusion. Figure 6 shows the block diagram of breast region extraction.

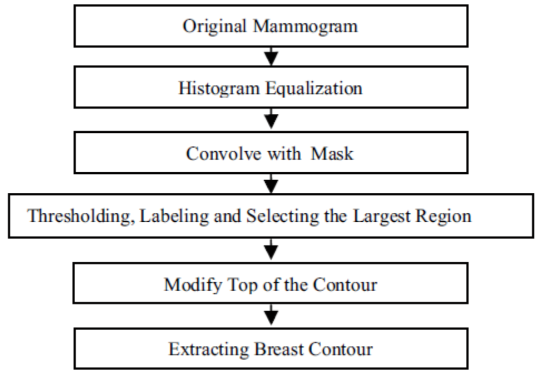

Figure 6: Breast region extraction

The overall method used for pectoral muscle detection is based on region of interest and consequent iterations. Breast contour helps to find the position of the nipple, which its position is important for mass detection in the next stages and presence of pectoral muscle in the mammogram could bias the detection procedures.

2.10 Morphological Operation

Morphology is an operation of image processing based on shapes. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors [18]. The morphological operations are applied on the grayscale mammography images to segment the abnormal regions. Erosion and dilation are the two elementary operations in Mathematical Morphology [31]. An aggregation of these two represents the rest of the operations. The symbols _, Θ, o, and • respectively denote the four fundamental binary morphological operations: dilation, erosion, opening, and closing which act on the structuring element [19]. This may result in contrast enhanced mammogram image. This reduces high frequencies in image (i.e. noise). However, a drawback of the mathematical morphology technique is that a part of the noise still remains. Figure 7 shows the dilated and eroded image.

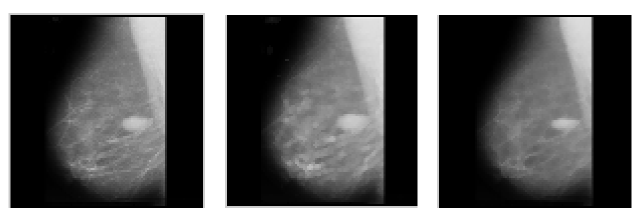

Figure 7: a) Normal Image, B) Dilated Image, c) Eroded Image

3. SEGMENTATION

In Segmentation the inputs are images and, outputs are the attributes extracted from those images. Segmentation divides image into its constituent regions or objects. The level to which segmentation is carried out depends upon the problem being solved. For the segmentation of intensity images like digital mammograms, there are four main approaches, namely, threshold techniques, boundary-based

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methods, region- based methods, and hybrid techniques which combine boundary and region criteria.

3.1 Threshold techniques

These techniques are based on the postulate that all pixels whose value (gray level, color value, or other) lies within a certain range belong to one class. Such methods neglect all of the spatial information of the image and do not cope well with noise or blurring at boundaries .For mammograms, thresholding usually involves selecting a single gray level value from an analysis of the grey-level histogram, to segment the histogram into background and breast tissues. All the pixels with grey level value less than the threshold are marked as background and the rest as breast [20]. Thresholding uses only grey level value and no spatial information is considered .Therefore, the major shortcoming of the threshold is that there is often an overlap between grey levels of the objects in the breast and the background.

3.2 Boundary based methods

The above methods use the postulate that the pixel values change rapidly at the boundary between two regions. The complement of the boundary-based approach is to work with the regions [21].

3.3 Hybrid Technique

These techniques combine boundary and region criteria. This class includes morphological watershed segmentation and variable-order surface fitting. The watershed method is generally applied to the gradient of the image.

3.3.1 Watershed transform

It can be classified as region based segmentation approach is used. Watersheds are one of the classics in the field of topography and have long been admitted as a useful tool in image segmentation [19]. It is based on the morphological concepts and the idea of watershed is straight forward. The idea underlying this method comes from geography: it is that of a topographic relief which is flooded by water, watersheds being the divide lines of the domains of rain falling over the region specified in Figure 8. Basins (also called `catchment basins') will fill up with water starting at these local minima, and, at points where water coming from different basins would meet, dams are built [22]. When the water level has reached the highest point, the landscape is partitioned into or basins separated by dams, called watershed lines or watersheds. Figure 9 explains the flow of watershed segmentation.

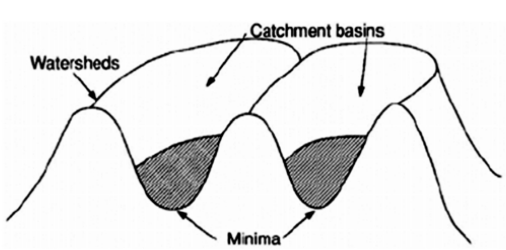

Figure 8: Watershed Segmentation

A binary image is produced by the Watershed Transform, 1(black) is assigned or watersheds, and 0 (white) assigned to regions surrounded by dams.

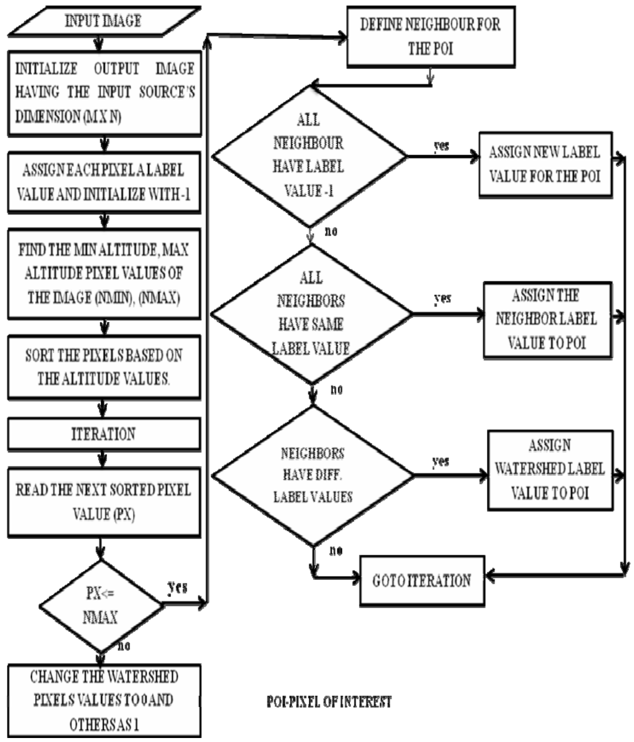

Figure 9: Flow chart of Watershed segmentation

automatically or manually selected. Their automated selection can be based on finding pixels that are of interest, e.g. the brightest pixel in an image can serve as a seed pixel. They can also be determined from the peaks found in an image histogram.The set of immediate neighbours bordering the pixel is calculated. The method has the advantage that it is

3.4 Edge detection

An edge is defined as the boundary between two regions with relationally distinct gray level properties. Since the tumor is circular in shape, one alternative to detect tumors is to extract image edges and then look for ring like structures [24]. Different operators were used for edge detection such as Roberts, Prewitt, Sobel, Laplacian of Gaussian, Zero-cross, Canny etc. From the observations, it is concluded that Sobel operator gives more sharp and clear edges as compared to other operators.

Table I:
Comparison of edge detection techniques

Edge Detection Technique	Processing	Merits	Demerits
Sobel	Discrete differentiatio n operation.	Smoothing the edge is performed in a better way.	High frequency noise effect is not controlled.
Prewitt	Template matching, convolution kernels and orientation based operation.	Easy to find local edge orientation for each pixel.	Direct orientation estimates are not much more accurate.
Roberts	Differential operation.	It was one of the first edge detectors. Simple to design.	Background should contribute as little noise as possible. sensitivity to noise
Laplacian of Gaussian	Difference of two Multivariate normal distribution is used.	Used as an operator in real time algorithms for blob detection and automatic scale selection.	A major drawback of the algorithm is an inherent reduction in overall image contrast produced by the operation.
Zero-cross	Gradient based method.	Smoothing of the edge is performed well.	Choosing the threshold is a tough task.
Canny	Finite Impulse Response Filter (FIR).	Wide range of edges in images is possible.	It is difficult to give a generic threshold that works well on all images. Effectivenes s of the algorithm

3.5 Region based methods

Region based method rely on the postulate that neighbouring pixels within the one region have similar value. This leads to the class of algorithms known as region growing of which the "split and merge" technique is probably the best known. The general procedure is to compare one pixel to its neighbour(s). If a criterion of homogeneity is satisfied, the pixel is said to belong to the same class as one or more of its neighbours.

3.5.1 Split and Merge Technique

The split and merge technique is the other classical region-based segmentation method. As the name indicates, the process consists of recursively splitting the image until all regions satisfy a homogeneity criterion. In an accompanying step, all adjacent regions satisfying a second homogeneity criterion are merged

3.6 Seeded Region Growing

Seeded region growing (SRG), which is closer to that of the watershed with some necessary change is proposed in[21], which is based on the conventional region-growing postulate of similarity of pixels within the regions. For seeded region growing (SRG), seed or a set of seeds can be fairly robust, quick, and parameter free except for its dependency on the order of pixel processing.

3.7 Level Set Segmentation

Level set methods offer a powerful approach for the medical image segmentation since it can handle any of the cavities, concavities, .convolution, splitting or merging. However, this method requires specifying initial curves and can only provide good results if these curves are placed near symmetrically with respect to the object boundary [25]. The level set method has been used to capture rather than track interfaces. Because the method is stable, the equations are not unnecessarily stiff, geometric quantities such as curvature become easy to compute, and three dimensional problems present no difficulties, this technique has been used in a wide collection of problems involving moving interfaces, including the generation of minimal surfaces, singularities and geodesics in moving curves and surfaces, flame propagation, etching etc .

4. DECOMPOSITION

4.1 Gabor Wavelets

Procedure for the analysis of left–right (bilateral) asymmetry in mammograms was proposed in [26]. The procedure is based upon the detection of linear directional components by using a multiresolution representation based upon Gabor wavelets. A particular wavelet scheme with two-dimensional Gabor filters as elementary functions with varying tuning frequency and orientation, specifically designed in order to reduce the redundancy in the wavelet-based representation, is applied to the given image.

The filter responses for different scales and orientation are analyzed by using the Karhunen–Loeve (KL) transform and Otsu's method of thresholding. The KL transform is applied to select the principal components of the filter responses, preserving only the most relevant directional elements appearing at all scales. The selected principal components, threshold by using Otsu's method, are used to obtain the magnitude and phase of the directional components of the image.

4.2 The Dual Tree Complex Wavelet Transform

Complex wavelet transform introduced has been found to solve the problems of DWT namely lack of shift variance and redundancy. But since the filters work with complex coefficients, achieving perfect reconstruction beyond the first level of decomposition was a major issue. For many applications it is necessary that the transform be perfectly invertible. Hence the enhanced version of this was introduced as dual tree complex wavelet transform(DTXWT) which was able to retain the attractive properties of complex wavelets as shift invariance, good directional selectivity, limited redundancy and efficient N- order computation[9]. The DTXWT comprises of two parallel wavelet filter bank trees that contain carefully designed filters of different delays that minimize the aliasing effects due to down sampling.

4.3 The Pyramid-Structured Wavelet Transform

The pyramid-structured wavelet transform, the texture image is decomposed into four sub images, in low-low, low-high, high-low and high-high sub-bands. At this point, the energy level of each sub-band is calculated. First level decomposition is indicated in Figure 10. Using the low-low sub-band for further decomposition, fifth level decomposition is reached. The reason for the basic assumption is that the energy of an image is concentrated in the low-low band. Its name comes from the fact that it recursively decomposes sub signals in the low frequency channels [27]. It is mostly significant for textures with dominant frequency channels. For this reason, it is mostly suitable for signals consisting of components within formation concentrated in lower frequency channels. Due to the innate image properties that allows for most information to exist in lower sub-bands, the pyramid-structured wavelet transform is highly sufficient.

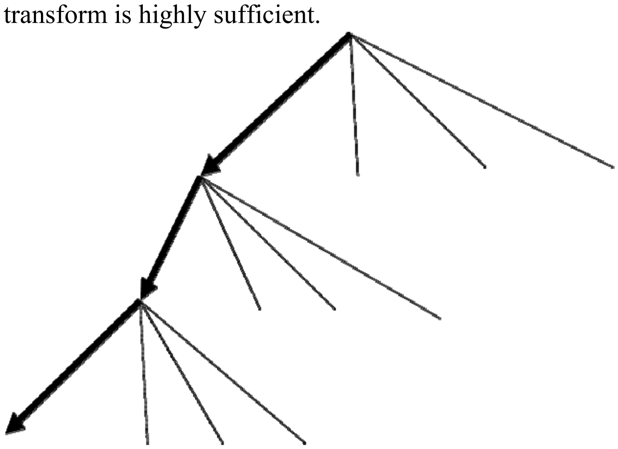

Figure 10: Pyramid structure wavelet transform

4.4 3D Wavelet

A separable 3D wavelet, taking full advantage of the 3D structures correlation, decomposes the original volume into sub volumes which can be separately quantized by a uniform scalar quantizer or by a 3D lattice vector quantizer [28]. Concentric hyper-pyramids lying on the cubic lattice are used for searching code words. A distortion minimization algorithm both selects the best number of decomposition and the best set of quantizers in order to minimize the overall mean square error. The whole algorithm is applied on a 3D image data base issued from the Morphometer (a new true 3D X-Ray scanner). The results presented include traditional signal-to-noise ratio performances and a subjective evaluation made by radiologists.

4.5 Curvelet

Curvelet was developed by Candes and Donoho, for providing efficient representation of smooth objects with discontinuities along curves. Detecting and enhancing the boundaries between different structures is very important in image processing, especially in medical imaging. In many important applications, images exhibit edge discontinuities across curves [29].

Some studies have been done with curvelet in image processing Dettori and Semler presented a comparative study between wavelet, ridgelet and curvelet transform on some computed tomography (CT) scans. The comparative study indicated that curvelet yields better results than wavelet or ridgelet.

4.6. Quadtree Decomposition

In this technique the image is decomposed into a number of non-overlapped squares, since the moment computation of squares is easier than that of the whole image. The proposed sequential algorithm reduces the computational complexity significantly [30]. By integrating the advantages of both optical transmission and electronic computation, the proposed parallel algorithm can be run in $O(1)$ time using N x $N^{1+1/c}$ processors when the input image is complicated. If the input image is simple (i.e., the image can be represented by a few quadtree nodes), the proposed parallel algorithm can be run in O (1) time using N x N processors. In the sense of the product of time and the number of processors used, the proposed parallel algorithm is time and cost optimal and achieves optimal speed-up.

4.7. Discrete Wavelet Transform

The discrete wavelet transform (DWT) translates the image into an approximation sub-band consisting of the scale coefficients and a set of detail sub-bands at different orientations and resolution scales composed of the wavelet coefficients. DWT provides an appropriate basis for separating the noise from an image. As the wavelet transform is good at energy compaction, the small coefficients more likely represent noise, and large coefficients represent important image features. The coefficients representing features tend to persist across the scales and form spatially connected clusters within each sub-band. These properties make DWT attractive for denoising. A number of wavelet-based despeckling techniques have been developed. The general procedure is: (1) calculate the discrete wavelet transform; (2) remove noise by changing the wavelet coefficients and (3) apply the inverse wavelet transform (IDWT) to construct the despeckled image. The techniques are grouped as: (1) wavelet shrinkage; (2) wavelet despeckling under Bayesian framework; and (3) wavelet filtering and diffusion.

5. CONCLUSION

Review of preprocessing has been presented with contrast enhancement, segmentation, decomposition, pectoral muscle detection and suppression. Therefore preprocessing is used to reduce noise, edge-shadowing effect, accurately detect pectoral muscle, and suppress the pectoral muscle successfully without losing any information from the image. The resultant mammogram can be used further for the automated abnormalities detection of human breast like calcification, circumscribed masses, spiculated masses and other ill-defined masses, circumscribed lesions, asymmetry analysis etc. Further works may be conducted to develop efficient preprocessing methods.

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