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Enhancement and Segmentation for Detection of Breast Cancer in Mammograms

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Abstract: Decimated wavelet transform have previously been used in detection of breast cancer in mammograms though their use always come with a rigorous drawback due to the absence of translation invariance of the representations and as a result, a large artifacts number is introduced into the reconstruction after the wavelet coefficients are processed. However, an undecimated wavelet transform effectively copes with this drawback since its providence of a redundant representation leads to the exhibition of the translation variance thus improving the enhancement and segmentation results.

Keywords*:* Mammograms, Undecimated Wavelet Transform (UWT), Decomposition, Reconstruction, Translation Invariance, Segmentation, Enhancement

I. INTRODUCTION

Breast cancer is an ill dwelling and thriving in our midst and it continues to claim one out of every eight women in America today [23]. With its major causes being an unknown mystery, early detection of this disease becomes a necessity. Early detection of breast cancer can significantly reduce its mortality rates. Though mammography is the most efficient way of detecting breast cancer, typical breast cancer signs like micro-calcifications are hard to detect since mammograms are noisy and low contrast images [21]. Consequently, this paper proposes a new algorithm for mammogram image enhancement and segmentation that uses multi-scale transforms based on undecimated wavelet transformation.

Luminance, spatial limited resolutions can merely not be solved by improvements on computer hardware's and programming [22]. Application of multi-scale transforms segmentation and enhancement techniques derived from curve lets and non-linear models offer a probable solution [20]. For this article, an undecimated wavelet transform (UWT) will be used as an image enhancement technique [1].

The investigation mainly involves four major steps which are; decomposition of a mammogram image using multi-scale transform based on curve lets, a search for suitable statistical models for the decomposition co-efficient, a procession of the co-efficient and the synthesis of the enhanced/segmented image.

A. Decomposition of the Mammogram Image; Undecimated Wavelet Transformation for Detecting Micro-calcifications in Mammograms:

This section clearly describes a decomposition method that accomplishes multi-scale enhancement of a mammogram image by the use of linear and non-linear operators for enhancement in the wavelet transform framework. Linear operators for enhancement maps the wavelet coefficients by the linear algorithm $Em = Gm^{s}$. S depicts every wavelet coefficient where the gain Gm is in general terms dependent on the levels [17]. Non-linear enhancements are used to prevent the saturation of coefficients that of high value since they can lead to loss of information after the process of reconstruction [4].

Nevertheless, modeling non-linear functions of enhancement is a tedious task entangled by various constraints such as low contrast areas require more enhancement than high contrast areas and the non-linear algorithm $Em\,(^{s})$ has to undergo monotonical increment in order to ensure the non-production of artifacts during the reconstruction and procession. It's upon this constraint that Laine and Fan [15] introduced a non-linear function that maps $Em\,(^{s})$ with the form;

$$Em\,(^{s}) = \begin{cases} s-(Gm-1)T, & s< -T \\ Gm^{s}, & |s|\leq T \\ S+(Gm-1)\,T, & s>T. \end{cases}$$

This is a very critical in the decomposition procedure since the parameters *Tm* and *Gm spells* out the boundaries between the soft and hard enhancements which are the unitary slope ad the Gm slope respectively. The adoption of these parameters makes the use of the multi-scale transformation of the undecimated wavelet framework [13].

II. SEGMENTATION

Algorithm approaches use two distinct techniques of segmentation which are 'region growing' and 'contour discrete models. 'The second focuses on edge detection though this does not produce exact results. The first focuses setting the region in advance though it's problematic when the image has a rugged outline [30]. The segmentation introduced in this paper combines both the edge information and the region structures by designing a background algorithm founded on morphological filter properties [12]. These filters are signal transformations with non-linear functions that modify geometric signal features locally [4]. This is based on the fact that dilation and erosion can represent a large number of filters. With Z denoting the integer sets and f(x,y) being the discrete signal of the image whose main set is presented as $\{x,y \in N\ 1 * N$

2}, with N 1, N 2 Z. B being a subset of Z^2 and bears a geometric shape, the dilation and erosion can be presented as in the functions below, respectively.

$(f \oplus B)(x, y) = max\{f(x+t1, y+t2)\ (t1, t2), \in B\}$

$(f \ominus B)(x, y) = max\{f(x-t1, y-t2), (t1, t2), \in B\}$

The closing and opening are delineated respectively as;

$(f.B)(x, y) = [(f \oplus B) \ominus B](x, y)$

$(f\ o\ B)(x, y) = [(f \ominus B) \oplus B](x, y)$

Given a mammogram image, the opening eliminates having objects smaller than the elements used in the structuring [25]. Hence, with specified elements for structuring, one is able to extract different contexts of the image by counting on the distinction between the processed image (processed by the opening machine) and the original [29]. This process is known as the tophat operation and dual morphological series of tophat operations implements the algorithm, that goes along with a subtraction defined as;

$YB1\ [f(x, y)] = max\ [0, f(x, y) - (f\ o\ B1)(x, y)]$

The tophat operation the specified element of structuring $B1$ and the original mammogram image f (x, y) is denoted by YB1. The size of the specified structuring element should be smaller than the usual size of the masses. With Y $B2$ being the mass pattern of the image enhanced, using the 2nd tophat operation, the background correction is defined as;

$Y\ B2\ [(x, y)] = max\ [0, f(x, y) - (f\ o\ B2)(x, y)]$

With $B2$ being the specified element of structuring with its size being larger than the mass. As a matter of obviousness, B2 and B1 values are dependent on the resolution of the image. In this particular case, the image resolution of the mammogram is 40µm, and thus, the values in this investigation are tuned to 180 and 36 respectively. Thus, the results of the image can be defined as;

$R(x, y) = max\ (0, YB2 - YB1).$

III. ENHANCEMENT

Having obtained the segmentation of the mammogram image above, the resultant binary image depicted as S(x, y) can e used as a sorting map for operating a selected enhancement in the domain of the wavelet. Only correspondent wavelet coefficients (correspondent with the mass segmented) undergo enhancement and hence multiplied for a defined user gain Go

$$Em\ [s(x, y)] = \begin{cases} Go\ s(x, y), & S(x, y) = 1 \\ s(x, y), & S(x, y) = 1 \end{cases}$$

A. The Experimental Results and Discussion:

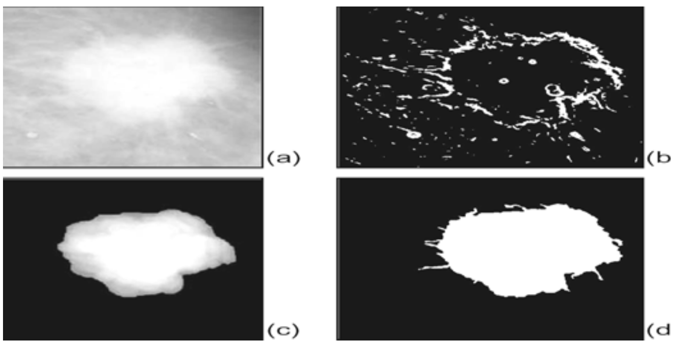

Figure 1; below effectively relays the steps used in the segmentation [1].

a) The original image of the mammogram
b) The upshot of the gradient/slope process
c) Mammogram image after the filtering morphological procedure
d) The final results of the segmentation

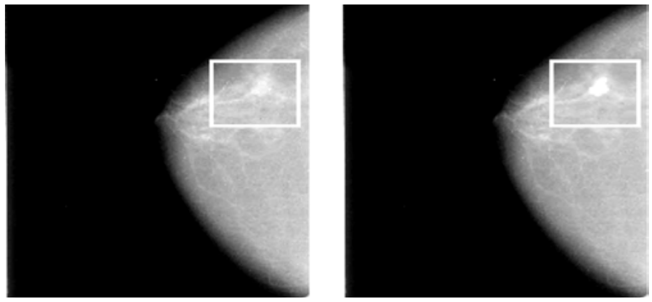

Figure 2 ; below relays the upshot of the enhancement on the image with the first figure representing the original image and the second representing the image after being processed where the lesion mass appears more recognizable and enhanced [1].

It can therefore be construed that segmentation aids in the defacement of the mass lesion boundaries and also aid the enhancement of the mass lesion without emphasizing the structures of the background [16]. Figure 2 above clearly proves that the procedure used provides an important improvement in the quality of the entire mammographic image. A mass lesion evaluation should always consider the identification of the lesion and its exact edge detection [28]. This helps in understanding its true nature.

Lesions are identified by its contour edges or a circle surrounding the lesion [18]. Basing on the experiments in this investigation, it is clear that the circle surrounding the lesion is accurately identified. As for the contour edges, a ratio greater than 0.5 should be allowed, which enables one to determine the performance of the algorithm [22]. The results of the algorithm are demonstrated in the figure 3 below.

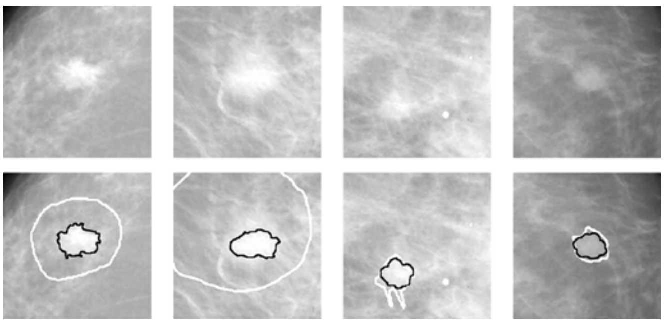

Figure 3; Results of the Algorithm and comparison between the algorithm results and mass edge results [1].

The figures on the top represent the original mammogram images while the figures at the bottom represent the comparision between mass edge identificarion (white line) and algorithim identification (black line). Majority of radiologists use the mass edge identification and this image proves the effectiveness of algorithm identification of the mass lension [10].

IV. CONCLUSION

Image segmentation and enhancement are of crucial importance in screening mammograms. The algorithm used in this investigation bears numerous advantages [14]. Firslty, different scales details can be identified and enhanced which is a process suitalbe for micro-calfication detection since calcification appear in distincitve scales [3]. More so, this procedure can be used in the early detection of breast cancer tumors since in the early stages, the cancerous tumor is usually subtle. Hence, the proposed algorithm can segment and enhance the subtle tumor accurately [2]. The procession for the coefficients using statistical models can be presented in a step by step series summary as indicated below.

a. Wavelet transforms computation of the mammogram image.
b. Repetition of the sub-steps below for every level of decomposition.
   i. Formation of an average weight of all the images details.
   ii. Quantization of the average image details.
   iii. Accomplishment of threshold selection.
   iv. The quantization of the threshold image and formation of a binary map that estimates the position of the micro-calcification.
c. Combination of the multi-resolution representations produced at different decomposition levels in detecting the binary map.
d. Completion of all the above steps leads to the detection of the micro-calcifications on the related regions of the map.

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