WAVELET TRANSFORMATION-BASED DETECTION OF MASSES IN DIGITAL MAMMOGRAMS

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Abstract

A Novel Wavelet Transformation-Based Detection of Masses in digital mammograms (WTBDM) is proposed in this paper that enables for the early prognosis of breast cancer. The wavelet analysis is explored for analyzing and identifying strong variations in intensities within the mammographic data which highlights and recognizes the masses effectively. The proposed algorithm, in addition to wavelet transformation, uses morphological preprocessing, region properties and seeded region growing to remove the digitization noises, to remove the pectoral muscle and to suppress radiopaque artifacts, thus segmenting the abnormal masses accurately. The combined potential of wavelet and region growing helps for effective mass segmentation that vouches the merit of the proposed technique.

Key Words: *Wavelet; Median filtering; Mammogram; Pectoral Muscle; Region growing.*

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1. INTRODUCTION

Digital Image Processing (DIP) helps to enhance images to make them visually pleasing or accentuate regions or features of an image to better represent the content. The application of DIP in Medical Image Processing is much useful in the automated detection and diagnosis of medical images. Image segmentation, an element of DIP that deals with subdividing an image into its constituent regions or objects, is a challenging task in health diagnosis. Effective and accurate segmentation results help to capture the necessary vital objects/regions of interest with respect to a given property and ignore the insignificant details of an image [1, 2].

Breast cancer is one of the frequent and leading causes of mortality among women in the world. The tumor of Breast cancer starts from the breast cells grows into surrounding tissues and does spread to other areas/organs of the body. Early detection of breast cancer minimizes the suffering and paves the way for proper treatment in time [3, 4]. According to the data from Indian Council of Medical Research (ICMR), it is a serious health problem for women in India. Digital Mammography is widely recognized as the most reliable imaging technique for the early detection of breast cancers. Interpretation of a mammogram is often difficult for radiologists to find out the suspicious lesion present in it. This may lead to give results with missing true positive masses or sometimes resulting in detection of some false negative masses [5-7, 13-15].

Wavelet analysis is an efficient methodology capable of revealing aspects of data by compressing or de-noising a signal without appreciable degradation. Wavelet analysis decomposes complex information to elementary forms at different positions and scales, which can be easily reconstructed with high precision [8, 9]. In each level of transformation, the data is divided into different scaling component that helps radiologists/CAD in analyzing the strong variations in intensity levels in the processing image [10-12, 16-18].

In this paper, section II describes the basics of wavelet transformation, median filtering, morphological operations and region growing. Section III presents the computational methodology of the proposed mass detection and segmentation. The results and discussion are presented in section IV and the conclusions are drawn in section V.

2. TECHNIQUES USED IN THE PRESENT WORK

2.1 Wavelet Transformation Analysis

The use of wavelets in medical image processing makes the process easier to compress, transmit and analyze medical images. Wavelet transforms are based on small waves, called wavelets, of varying frequency and limited duration. Wavelet transformation is used to analyze a signal (image) into different frequency components at different resolution scales and allows revealing image's spatial and frequency attributes simultaneously [9, 11, 12].

- **2D-Discrete Wavelet Transform (2D-DWT)**

The DWT provides a compact representation of a signal's frequency components with strong spatial support. DWT decomposes a signal into frequency subbands at different scales from which it can be perfectly reconstructed. 2-D signals such as images can be decomposed using many wavelet decomposition filters in many different ways. One such is the Daubechies wavelets.

- **The Daubechies Wavelet Transform**

The Daubechies wavelet is a discontinuous function which resembles a step function. For a function **f**, the Daubechies wavelet Transform [9] is defined as

$$f \rightarrow (a^L \mid d^L) \quad (1)$$

$$a^L = \left(a_1, a_2, \ldots, a_{N/2}\right) \quad (2)$$

$$d^L = \left(d_1, d_2, \ldots, d_{N/2}\right) \quad (3)$$

where L is the decomposition level, **a** is the approximation subband and **d** is the detail subband.

$$a_m = \frac{f_{2m} + f_{2m-1}}{\sqrt{2}} \qquad for\ m = 1,2, \ldots, N/2 \quad (4)$$

$$d_m = \frac{f_{2m} - f_{2m-1}}{\sqrt{2}} \qquad for\ m = 1,2, \ldots, N/2 \quad (5)$$

For example, if $f = \{f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8\}$ is a time-signal of length 8, then the Daubechies wavelet transform decomposes **f** into an approximation subband containing the Low frequencies and a detail subband containing the high frequencies:

$$Low = a = \{f_2 + f_1, f_4 + f_3, f_6 + f_5, f_8 + f_7\}/\sqrt{2} \quad (6)$$

$$High = d = \{f_2 - f_1, f_4 - f_3, f_6 - f_5, f_8 - f_7\}/\sqrt{2} \quad (7)$$

To apply Daubechies wavelet transform on image, we first apply a one level Daubechies wavelet to each row and secondly to each column of the resulting image of the first operation. The resulted image is further decomposed into four subbands: LL, HL, LH and HH subband. (L=Low, H=High). The LL-subband contains an approximation of the original image while the other subbands contain the missing details. The LL-subband output from any stage can be decomposed further.

- **Inverse Daubechies Wavelet Transform**

The inverse of the Daubechies wavelet transform [11, 12], is computed in the reverse order as follows:

$$f = \left(\frac{a_1 - d_1}{\sqrt{2}}, \frac{a_1 + d_1}{\sqrt{2}}, \ldots, \frac{a_{N/2} - d_{N/2}}{\sqrt{2}}, \frac{a_{N/2} - a_{N/2}}{\sqrt{2}}\right) \quad (8)$$

To apply Inverse Daubechies wavelet transform on images, firstly a one level inverse Daubechies wavelet is applied to each column and secondly to each row of the resulting image of the first operation.

2.2 Median Filtering

Order statistic filters are non-linear spatial filters whose response is based on ordering the pixels contained in an image neighbourhood and then replacing the value of the center pixel in the neighbourhood with the value determined by the ranking result. The best-known order statistic filter in digital image processing is the median filtering technique which corresponds to the 50th percentile. The median filter compares each pixel in the image to its surrounding neighbour pixels and classifies pixels as noise. Then these noise pixels are replaced by median pixel value of the neighbourhood pixels. The approach of Median filtering is a useful tool to smoothen the image and to reduce the excessive distortions such as thinning or thickening of object boundaries. Median filtering helps to remove the digitization noise and high frequency components from the mammography images [1, 2, 15, 19-21].

2.3 Morphological Operations

In digital image processing segmented image may contain imperfection in many forms like noise/artifacts presented in the image, uneven boundaries as a result of thresholding, etc. These imperfections can be resolved by morphological operations. Morphological operation smoothen the region boundaries for shape analysis, remove artifacts in an image and match particular pixel configuration in an image for simple object recognition. In digital morphology, a small pattern or shape, which is known as structuring element, probes the image. The morphological operation used in the present paper opening is an important morphological transformation created as a result of erosion followed by dilation. Opening with the structuring element is used to eliminate specific image details smaller than the structuring element. The definitions of these operations are dependent on the image types, such as binary, gray level or color of the image being processed [1, 2, 15, 19-21].

3. METHODOLOGY

The proposed system involves breast region extraction, noise removal, enhancing the visibility, suppression of pectoral muscle and artifacts and thereby segmenting the mass successfully. Initially, removal of non-breast region is done on the input mammogram image I to minimize the computational time for subsequent processing. This is carried out successfully with the help of region properties of the image, in which the connected components of the image are determined. The biggest among is found by counting the number of pixels in each connected region. The result obtained is the breast region. The extrema coordinates are extracted to separate the breast region from the input mammogram to acquire I_B. Noise is a form of degradation in image by random variation of brightness. In common, the mammogram images are corrupted by salt and pepper noise while digitizing the mammogram. As median filter is beneficial over preserving edges in the image while reducing random noise, it is chosen to perform on the extracted breast region image I_B well particularly to remove impulsive or salt and pepper noise to acquire I_F.

Median filter is applied to each pixel in the extracted input image I_B. For each pixel, taken as central pixel, a window of size three is selected. The median value is then calculated within the window and it becomes the value of the pixel being processed. The output of median filter is a denoised image I_F. Still it is hard to detect the masses from I_F directly or indirectly because, in mammograms, masses are made up of vector of characteristics called numeric signature. As, wavelets are good for the extraction of those vectors of characteristics, two level Daubechies wavelet decomposition is applied on the denoised image I_F and then contrast adjustment is further applied on the approximation coefficient using (9) which is given below

$$ts'(i,j) = \begin{cases} 2 * ts(i,j) - fmax & if\ ts(i,j) \geq fmax/2 \\ 0 & otherwise \end{cases} \quad (9)$$

where ts(i,j) is the pixel value at coordinate(i,j) and *fmax* is the maximum gray value in the image which is set as 255. Then the reverse wavelet transform is performed on the transformed image for the reconstruction of the image to produce I_W in which the masses are finely brought up into attention.

Though the wavelet transformation improves the visibility, the resultant image I_W still contains normal breast tissues too in addition. To suppress those normal breast tissues, each pixel is divided by its number of occurrences in that image. On dividing, it produces zero for breast region and non zero for tumor region, thus acquiring I_{WB}. By transforming the values to binary, the resulting image I_{WB} contains pectoral muscle, detected masses and some unwanted artifacts. Now, the pectoral muscle removal is done with the help of region properties which finds the components that appeared in the top of the mammogram. The pixels identified in that region are replaced by zero. Thus the pectoral muscle is being removed and also non-tumor objects appeared on the top are removed to produce I_{WP}.

After the suppression of pectoral muscle, still some non tumor artifacts remain in the resulting image I_{WP}. Those are buried by morphological operations. For this, morphological opening operation using the cross-shaped structuring element of which diameter is three is employed to eliminate those small objects to acquire I_{MASS} which results in the mass detection. Finally region growing technique is applied on the detected image I_{MASS} to segment the abnormal mass with exact edge information and the pixel values are replaced with its contrast enhanced value. It starts with determining the seed point and the criteria decided. The maximum intensity value in the image is chosen as the seed pixel. To grow the region, the similarity of the eight neighbours is checked. The criteria set would look the difference between the seed and neighbouring pixel. If it is less than three then the pixel is added to the region, otherwise it will be omitted. The new region is now the seed and the process is repeated until all the neighboring pixels of the region fails against the criteria. After finding an object, the proposed technique moves on to the new seed, which is having the maximum value in the image as well as greater than the mean value of the image. If any such pixel exists, the process continues the same as above. The resulting image I_{FINAL}, out of region growing, projects the final segmented mass.

The algorithm for the above methodology is given as follows.

Algorithm :Segmentation of masses from mammogram

Aim :To segment the masses from mammogram

Input : A 2-Dimensional mammogram image I

Output :Segmented tumor mass from mammogram

STEP 1 : Read the input mammogram image I.

STEP 2 : Compute connected components in an image and identify the biggest of it. Then extract the components from the mammogram to acquire I_B which gives the breast region.

STEP 3 : Apply median filter on image I_B with the window size 3×3 for the removal of digitization noise to acquire the filtered image I_F.

STEP 4 : Apply two level Daubechies wavelet transform on the image I_F and calculate its coefficients.

STEP 5 : Apply contrast adjustment on those coefficients to highlight the mass area to acquire I_E using

$$ts'(i,j) = \begin{cases} 2 * ts(i,j) - fmax & if\ ts(i,j) \geq fmax/2 \\ 0 & otherwise \end{cases}$$

STEP 6 : Reconstruct the transformed image by applying inverse Daubechies wavelet transform to acquire the enhanced image I_W.

STEP 7 : Acquire I_{WB} by eliminating the normal breast tissues from the transformed image I_W using

$$I_{WB} = ceil\,(I_W(i,j)/No.of.Occurances\ of\ I_W)$$

STEP 8 : Remove pectoral muscle from I_{WB} with the help of region properties of the image and acquire I_{WP}.

STEP 9 : Suppress protrusions of the image I_{WP} using morphological opening operation with cross shaped structuring element of size three to obtain I_{MASS}.

STEP 10 : Apply region growing on I_{MASS} to extract the final segmented I_{FINAL} by applying the criteria

$$wndw(inti, intj) > M\ \&\&\ abs\left(seed - wndw(inti, intj)\right) \leq 3$$

where wndw(int i, int j) is the neighboring pixel of seed pixel which belongs to N_8(seed) and M is the image's mean.

STEP 11 : Output the final segmented mass $I_{FINAL.}$

STEP 12 : Stop.

The above methodology is represented diagrammatically in the flowchart in Fig. 1

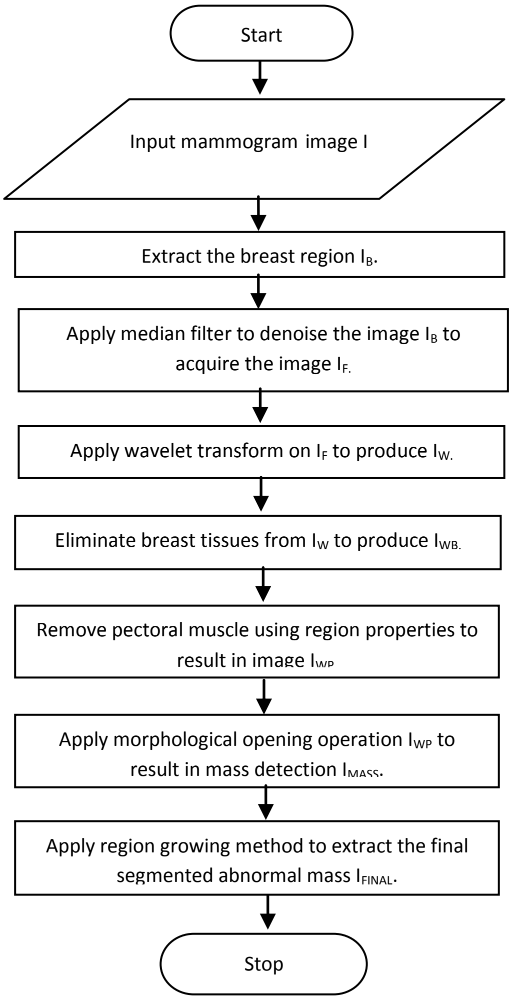

Fig.1 Flowchart for the computational methodology of WTBDM

4. RESULTS AND DISCUSSION

The proposed methodology WTBDM is implemented using Matlab 9.0. Experiments are carried out on different mammogram images collected from MIAS database [22, 23]. The proposed algorithm is tested on over thirty mammograms with different orientations. For the illustrative purpose of the entire stages of the proposed wavelet transformation based mammogram mass segmentation, four mammograms (mdb010.pgm, mdb025.pgm, mdb028.pgm and mdb081.pgm) are depicted in *Figure 2- Figure 9.* The input original mammogram images of mdb010.pgm, mdb025.pgm, mdb028.pgm and mdb081.pgm are depicted in *Figure 2 (a1)-(a4).*

Initially, to minimize the computational time for processing the mammograms, removal of non breast region is carried out on the input mammogram images with the help of region properties. Those images with the extraction of breast region alone are shown in *Figure 3 (a1)-(a4).*

As the extracted breat region is a medical image that is difficult to interpret, a preprocessing phase is carried out to remove the digitization noise. This is implemented by the use of median filter and those filtered images are given in *Figure 4 (a1)-(a4).*

Now, for mass detection, two level Daubechies wavelet transformation is applied on the filtered image. For this, the filtered image is decomposed into horizontal, vertical and diagonal coefficients. Further applying contrast adjustment on these coefficients, the transformed image is built from those coefficients using inverse wavelet transformation. Those wavelet transformed images are depicted in *Figure 5 (a1)-(a4).*

As the transformed images are produced with the inclusion of breast tissues, suppression of those tissues is done by dividing the each pixel by its number of occurances in the image. Those breast tissues suppressed images are shown in *Figure 6 (a1)-(a4).* As, the resultant suppressed image still contains the pectoral muscle, the removal of pectoral muscle is done with the help of region properties of the image. The pectoral removed images are given in *Figure 7 (a1)-(a4).*

After the suppression of pectoral muscle, still some non tumor artifacts remain in the resulting image. Those are removed by the application of morphological operation opening using the cross-shaped structuring element whose diameter is three. This results in the detection of mass, the images of which are depicted in *Figure 8 (a1)-(a4).*

Finally, region growing is applied on the detected images to segment the tumor region. Those tumor detected images are depicted in *Figure 9 (a1)-(a4).*

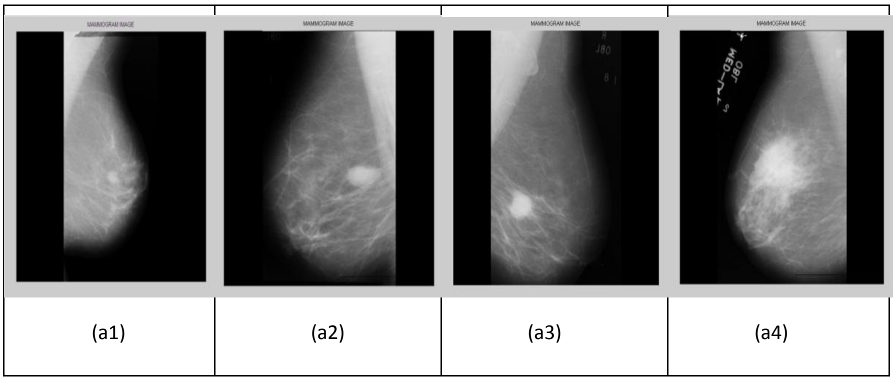

Fig 2: (a1) mdb010.pgm (a2) mdb025.pgm (a3) mdb028.pgm (a4) mdb081.pgm

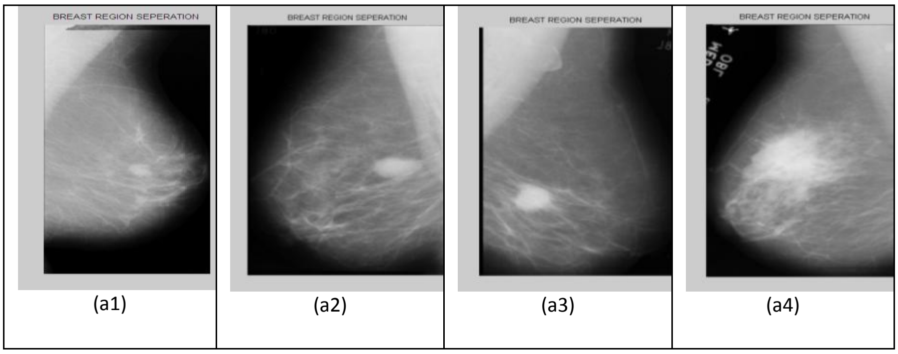

Fig 3*:* (a1)-(a4) Breast region extracted images of Figure 2 (a1)-(a4)

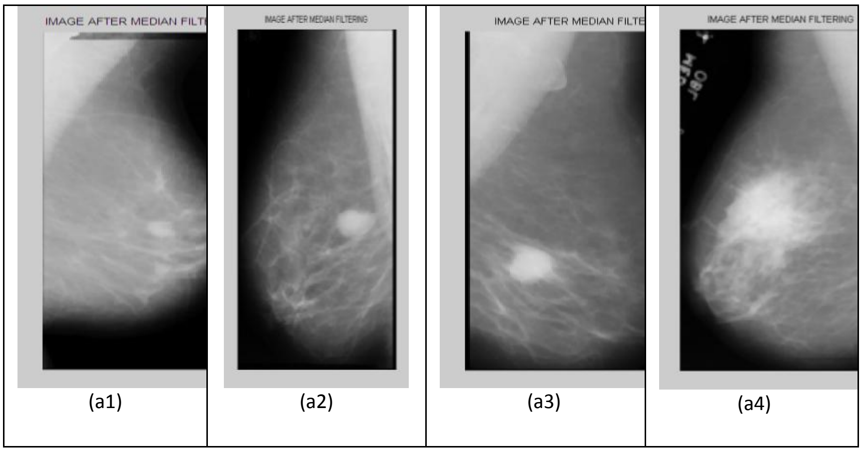

Fig 4: (a1)-(a4) Median filtered images of Figure 3 (a1)-(a4).

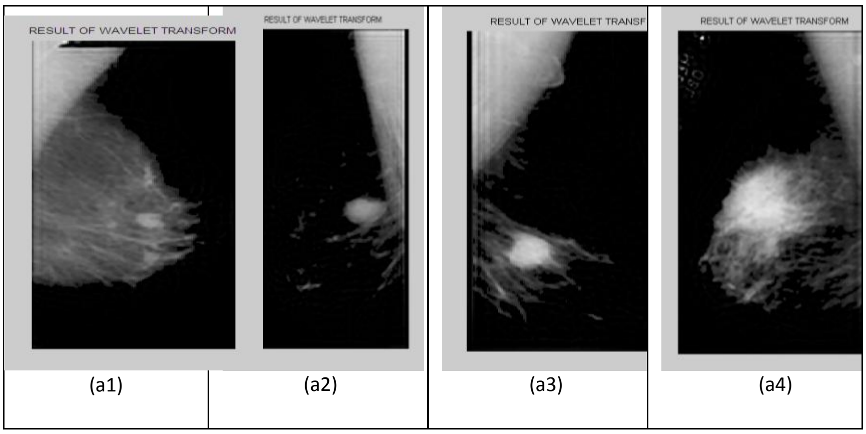

Fig 5: (a1)-(a4) Wavelet transformed images of Figure 4 (a1)-(a4)

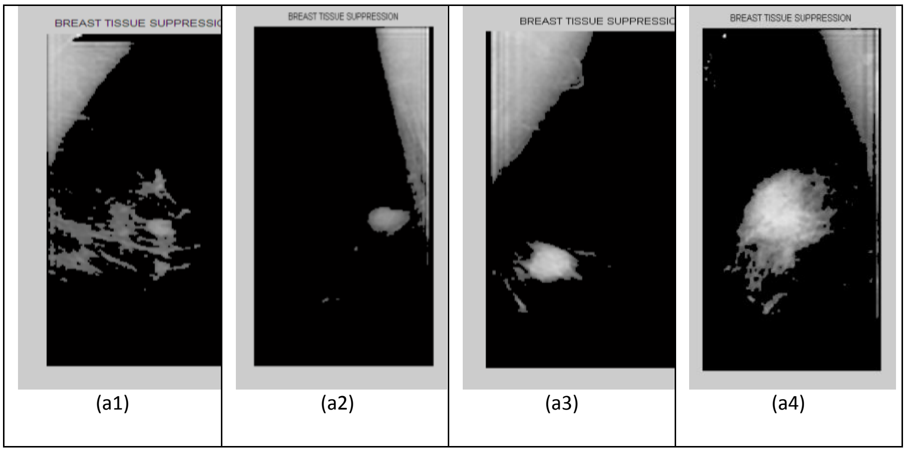

Fig 6: (a1)-(a4) Breast tissue suppressed images of Figure 5 (a1)-(a4)

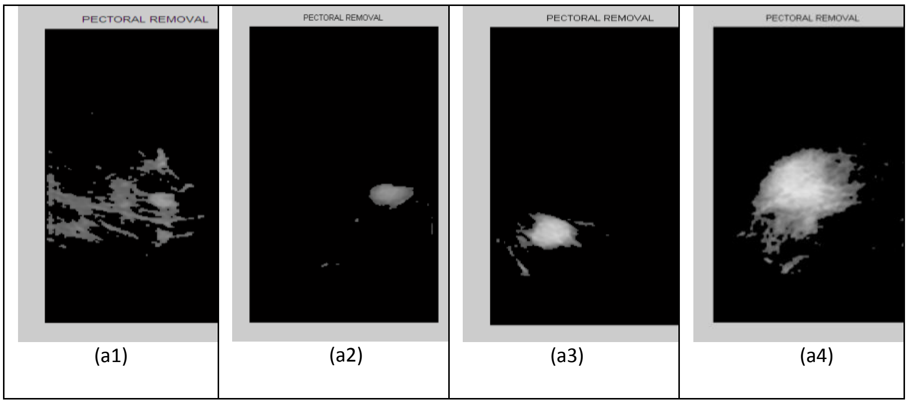

Fig 7: (a1)-(a4) Pectoral muscle removed images of Figure 6 (a1)-(a4)

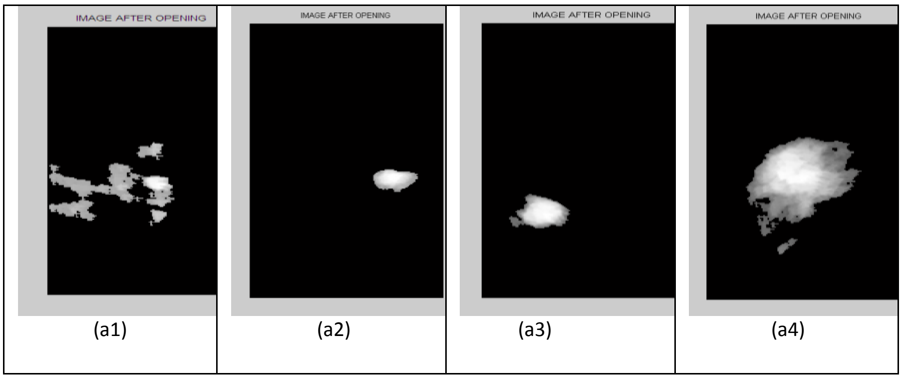

Fig 8: (a1)-(a4) Elimation of protrusions from the images of Figure 7 (a1)-(a4)

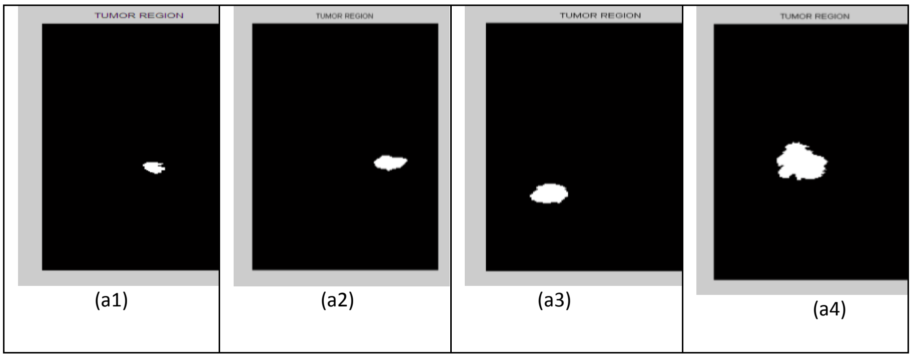

Fig 9: (a1)-(a4) Final detected tumor mass of Figure 8 (a1)-(a4).

5. CONCLUSIONS

The proposed paper WTBDM aims at the detection of masses from mammogram images using wavelet transformation that enables the early detection of breast cancer. The devised algorithm is developed using Matlab 9.0 which helps the radiologists in accurate prognosis. The complexity of this technique is found to be comparatively less. The potential ability of the proposed technique is that it could detect the suspicious tumor region exactly, which may prevent the need for biopsy. The future scope of the present study lies in the classification of those detected masses into either benign or malignant.

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