

# Detection of the Regions of Interest in Mammographic Images by the Multiscale Product and Segmentation Using the Continuous Wavelet Transform

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**Abstract**—Breast cancer is the leading type of cancer among women worldwide, but it can be cured if diagnosed at an early stage. Mammography is the main means of screening for cancer and provides useful information on the signs of cancer, such as macrocalcifications, masses, architectural distortion and asymmetry. This information is not easy to distinguish because of certain defects in mammographic images, including low contrast, high noise, blurring and confusion. To solve this problem, a new region-of-interest detection strategy based on multi-scale product and segmentation has been developed. The aim of this strategy is to improve the visibility of microcalcifications in regions of interest for better detection and interpretation. Mammographic images are represented in a way that facilitates the detection of microcalcifications and the classification of healthy and cancerous images. Using Matlab software, the algorithms developed were used on images from the public accessible international database of the Mammographic Image Analysis Society (MIAS), which contains 322 images. The results obtained in terms of visual quality were satisfactory. Compared with the results of the literature, our results appear to be better.

**Keywords**—breast cancer, mammography, multi-scale product, region of interest, segmentation

## I. INTRODUCTION

More than 2.2 million cases of breast cancer were reported in 2020, making it the most common cancer. Nearly one woman on 12 will develop breast cancer in her lifetime. Breast cancer is the leading cause of cancer-related death in women [1].

Mammography is the main method used for breast cancer screening, as the images obtained by mammography can detect even small changes in the breast that cannot be detected by manual examination [2–4]. Nevertheless, analysing and interpreting mammographic

images remains a difficult task because of the noise, poor contrast and low limits [2, 5]. To overcome this problem, region of interest detection is necessary. This is the preliminary and main step in any processing application, which can be used to improve image quality [6].

Several works have been published by researchers on different techniques for detecting regions of interest in mammograms, including the discrete cosine transform (DCT) and the discrete wavelet transform (DWT) [7], numerical computation and space-time transforms [8, 9]. Each of these techniques has its own performances but also its limitations.

Recognizing the advantages of detailed time-frequency (scale) analysis, where precise localization of signal transients is possible, we propose in this work to use an approach for detecting regions of interest in mammographic images by combining the multiscale product and segmentation after the continuous wavelet transform.

The rest of the paper is organized as follows: Section II presents the material used and the method developed.

Section III presents the implementation of the proposed approach. Section IV presents the results obtained. Section V presents the discussions. Finally, the conclusion and outlook are presented in Section VI.

## II. MATERIALS AND METHODS

### A. Materials

We used the digital mammography database of the Mammographic Image Analysis Society (MIAS). MIAS is an organization of groups of researchers interested in work on mammography. It is based in the UK and has produced a database of digital mammograms [10]. The X-ray films in the database have been carefully selected from the UK National Breast Screening Programme and digitized using

a Joyce-Lobel scanning micro densitometer to a resolution of  $50 \mu\text{m} \times 50 \mu\text{m}$ ; each pixel being 8-bit coded. The database contains images of the left and right breast of 161 patients. In total, there are 322 images, of three types: normal, benign and malignant. There are 208 normal, 63 benign and 51 malignant (abnormal) images.

We used this database because it provides several pieces of information about the anomaly, namely the class of lesion, its location and size.

For our work, we used the Intel(R) Core (TM) i5 CPU, 4 GB RAM memory and Matlab R2017b software.

### B. Methods

We will first present a brief state of the art on the techniques for detecting regions of interest, Secondly, we will present our contribution for interest regions detection. Thirdly, we will test the approach we have developed on a few images from the MIAS database.

#### 1) Using continuous wavelet transforms

Micro-calcifications appear as small details in mammograms, making them difficult to recognised and highlight. Recognizing the advantages of detailed time-frequency (scaling) analysis where precise localization of signal transients is required, we use the continuous wavelet transform and the choice of wavelet is of crucial importance. We used a visual criterion and took into account certain wavelet characteristics that allow us to vary two parameters to modify the time and frequency spread. We carried out a visual analysis of twenty-one wavelets when we run the continuous wavelet transform algorithm. The Morlet wavelet was thus chosen. Once the choice of wavelet has been made, how many levels of image decomposition are there? According to the theory, an image may be analyzed up to  $J$  levels of decomposition for an image whose size is  $N \times N$  pixels' resolution where  $J$  is given in (1):

$$J = \log_2(N). \quad (1)$$

In practice, several researchers use different levels of decomposition from three to six decomposition levels. The authors of [11] carried out a study on the choice of the number of decomposition levels, based on the energy criterion of the image. In this study, interest was focused on the energy contained in the approximation because it is a coarse version of the image. It was found that for the images analyzed, almost all of the image energy remains concentrated in the approximation up to four decomposition levels. The variation in the energy of the approximation is very significant at the fifth decomposition level. This variation can be explained by the fact that at the fifth scale, information about the details of the image appears, i.e. the energy of the image is divided between the approximation and the details at the fifth scale. So, according to this study, our choice is five levels of decomposition.

#### 2) Multi-scale product

The multi-scale product consists of multiplying a coefficient by itself across scales, and in the case of our work, five scales are involved. This odd number of scales

has the advantage of preserving the sign of a given coefficient. The bright spots in the images, whether visible or hidden in the fat masses or adipose tissue, are stronger and appear very clearly. From a mathematical point of view, points of discontinuity (non-homogeneous zone) are manifested by coefficients with high absolute values, whereas points of continuity (homogeneous zone) are manifested by low absolute values. Thus, the product of a coefficient with a high absolute value by itself amplifies its value across the scales and that of a coefficient with a low absolute value makes it weaker and weaker across the scales. As microcalcifications are considered as points of discontinuity (isolated points) in mammographic images, the multi-scale product amplifies their values and makes them visible, thus contributing to their detection.

#### 3) Segmentation

Segmentation is a process whose aim is to group the pixels of the image studied into regions or classes or even subsets according to the predefined criteria such as color (or grey level), texture, gradient or even shape, which is often a criterion used [12]. Various segmentation approaches have been applied to lesions, such as segmentation using the fuzzy C-Means (FCM) algorithm [13], automatic OTSU thresholding based on the image histogram, manual thresholding [14] and mathematical morphology [15]. In our case, we used automatic OTSU thresholding. The idea is to only display pixels with values above a certain threshold.

### III. PROCEDURE FOR THE PROPOSED APPROACH

The mammographic images in the MIAS database have been processed to improve their quality using a set of techniques based on combinations of existing techniques. The aim is to put these images into a representation that would facilitate detection of the regions of interest. We then eliminated the artefacts (labels, markers, pectoral muscle, etc.) and the result obtained is considered to be the input image for the wavelet transform decomposition. The steps involved in decomposing the wavelet transform are as follows:

Continuous wavelet decomposition using the Morlet wavelet was performed in Matlab, for five levels [16, 17];

The wavelet transform coefficients were thresholded at each scale using the Donoho threshold;

The multi-scale product of these coefficients was calculated. We used a multiplication coefficient  $\alpha$  ( $\alpha=1099$ ).

For segmentation, the images obtained by the work presented in [18] are the inputs for the segmentation.

### IV. RESULTS AND DISCUSSION

#### A. Results Obtained

Six images from the MIAS database were used to evaluate our proposed method. Among the six images, three are normal, i.e. without anomalies (Figs. 1 to 3) and the three other have anomalies, i.e. they are malignant. The results obtained using the proposed method are shown in Figs. 1 to 6.

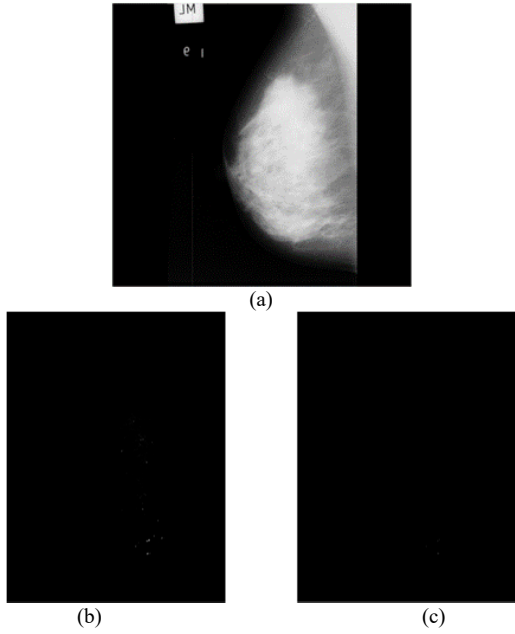


Figure 1. (a) original mdb003 image, (b) multi-scale product result, (c) segmentation result

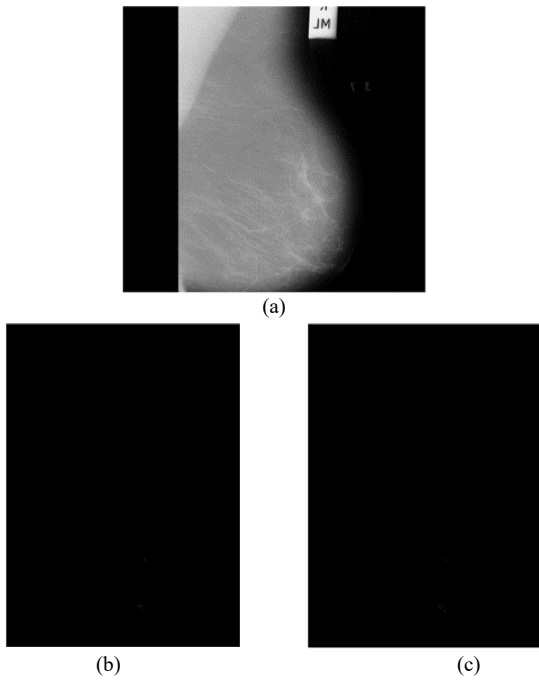


Figure 2. (a) original mdb006 image, (b) multi-scale product result, (c) segmentation result.

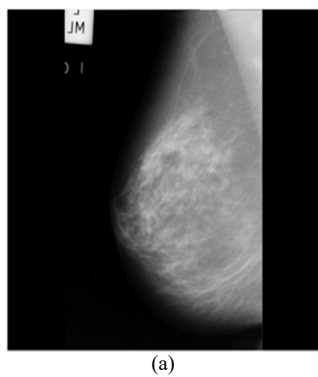


Figure 3. (a) original mdb007 image, (b) multi-scale product result, (c) segmentation result.

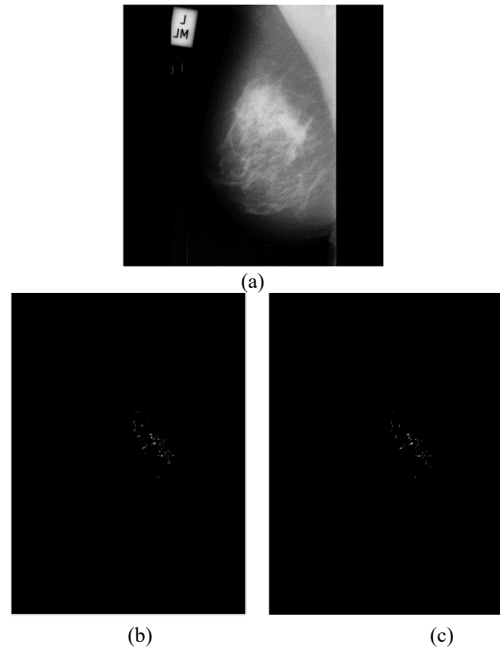


Figure 4. (a) original mdb209 image, (b) multi-scale product result, (c) segmentation result

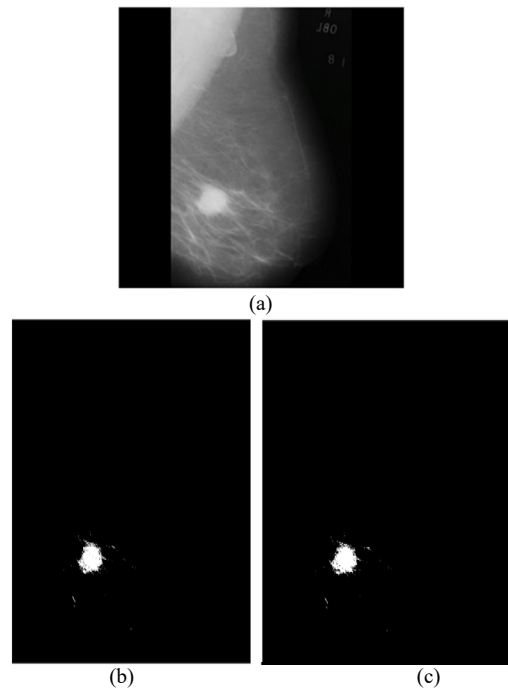


Figure 5. (a) Original mdb028 image, (b) multi-scale product result, (c) segmentation result.

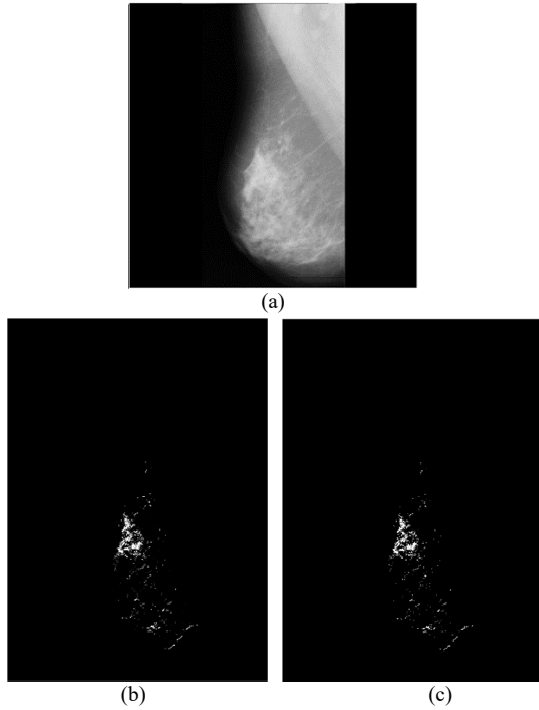


Figure 6. (a) Original mdb249 image, (b) multi-scale product result, (c) segmentation result.

### B. Discussion

The results obtained from the multi-scale and segmentation product, using images from the MIAS database, are encouraging. Firstly, we delimited the area of interest [18]. Secondly, we processed the area of interest obtained using the procedure described in Section III and the results obtained clearly show that the method increases the dynamic's intensity of the pixels, which represent the discontinuities, by highlighting the spatial information present in the mammographic images.

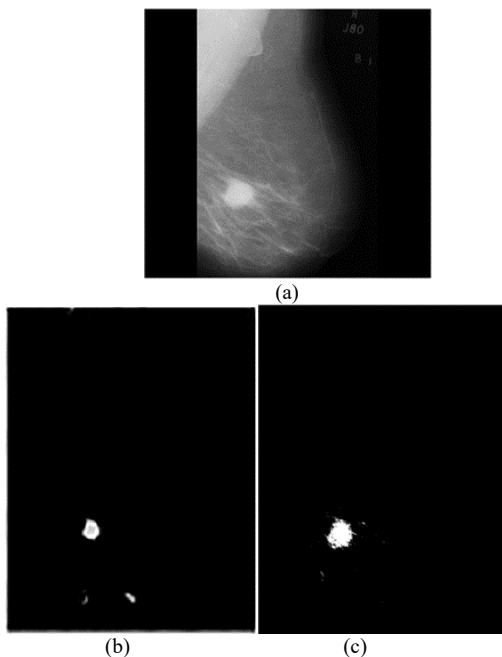


Figure 7. (a) Original mdb028 image, (b) result obtained in (Sh. Ekta and S. Vineeta, 2020), (c) result of our method.

Thus, the results obtained by our approach show that the images represented by Figs. 1, 2 and 3 have virtually no discontinuity points. These results confirm the classification by MIAS of these first three images in the category of images with no anomalies. The images shown in Figs. 4, 5 and 6 show areas of discontinuity that are likely to contain microcalcifications. These results once again confirm the classification of these last three images in the category of images with anomalies. These results, compared with those presented in [19, 20], are better. Figs. 7 and 8 clearly illustrate the difference between our proposed method and those of the literature. We can see that in Fig. 7(b), which is the result of Sh. Ekta and S. Vineeta, 2020, the volume of the detected mass is too small whereas the result obtained by our method shown in Fig. 7(c) keeps the volume of the mass of the original image. Also, in Fig. 8, the result of our method (Fig. 8(c)), shows that there are more points detected than the points detected by the method of M. A. GUERROUDJI, 2017 (Fig. 8(b)).

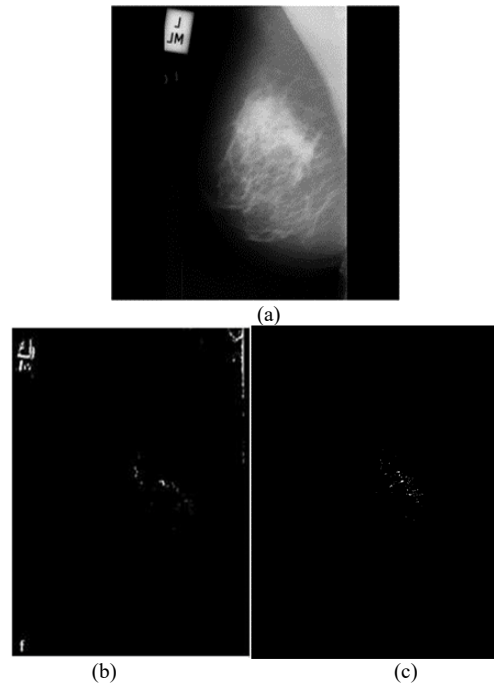


Figure 8. (a) Original mdb028 image, (b) result obtained in (M. A. GUERROUDJI, 2017), (c) result of our method.

### V. CONCLUSION

We have proposed a method for detecting regions of interest in mammographic images based on the multiscale product and segmentation.

The continuous wavelet transform was applied to the results of combination 2 [18]. The results highlight the areas likely to contain microcalcifications whose, if detected and characterized, will enable a decision to be made as to whether the tumour is benign or malignant. Compared to some results of the literature, the results obtained by our approach are better.

### CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

A conducted the research and wrote the paper; B supervised the research and C analyzed the data.

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