

Various Applying of Wavelet Transform in Digital Mammograms for Detecting Masses and Microcalcifications

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Abstract

Clusters of Microcalcifications and masses are the signs of breast cancer. They have different shapes and sizes. Globally, clusters and masses have different frequency characteristics. Due to small size of microcalcifications and high intensity of them with compared to their neighbour pixels, microcalcifications correspond to high-frequency components of the image spectrum. On the other hand, masses are in the larger scales in comparison with microcalcifications, so masses correspond to low-frequency components. On the bases of above, in this paper we propose two algorithms, one of them for detecting microcalcifications and the other for detecting masses in digital mammograms. In the first algorithm, one wavelet transform block is added before last methods for detecting microcalcifications, in which mammogram is decomposed into different frequency subbands, the low-frequency subband is suppressed, and the mammogram is reconstructed from the subbands containing only high frequencies. In the second algorithm, a new method based on suppressing high frequency subband, calculating energy image and mapping intensity of the pixels, for detecting of the masses is proposed. Results show that two proposed algorithms are more accurate in detection of positions and sizes of microcalcifications and masses.

1 Introduction

Breast cancer is the main cause of death for women between the ages of 35 and 55. It has been shown that early detection and treatment of breast cancer are the most effective methods of reducing mortality [1].

The high number of mammograms requires computer aided diagnostics. The main goal is to ease the work of radiologists by filtering out the truly negative cases, therefore only suspected positive cases need to be examined by a human expert. This means that the detection ratio of positive cases must be as high as possible. A secondary goal is to keep the ratio of false positive detections at a low level to avoid unnecessary examinations. Basically three types of abnormal tissues are distinguished: masses, architectural distortions and microcalcifications [2].

Architectural distortion is defined in BI-RADS [3] as follows: "The normal architecture (of the breast) is distorted with no definite mass visible. This includes spiculations radiating from a point and focal retraction or distortion at the edge of the parenchyma". Focal retraction

is considered to be easier to perceive than spiculated distortion within the breast parenchyma [4].

A microcalcification cluster is commonly defined as three or more microcalcifications present in 1 cm on a mammogram [5]. These clusters are often difficult to detect due to their small size and their similarity to other tissue structures [6].

In this paper we use various applying of Wavelet Transform to propose two algorithms, one of them for detecting microcalcifications and the other for detecting masses in digital mammograms.

The organization of the paper is as follows: Section 2 presents 2D wavelet transform for image processing. Proposed algorithms for detecting microcalcifications and masses are described in section 3 and 4 respectively. Finally experimental results and conclusions are given in section 5.

2 2D wavelet transform for image processing

The wavelet transform is defined as follows:

$$W_k^j = \int f(x) \psi \left(\frac{x}{2^j} - k \right) dx \quad (1)$$

Where ψ is the transforming function and is called the mother wavelet. $f(x)$ is the original signal and j and k are scale and translation parameters respectively. Figure 1 shows a layer presentation of 2D WT for an image. W_V^j , W_H^j and W_D^j represent the detail component in the vertical, horizontal and diagonal directions at level j , respectively. S_j refers to the scaling (approximation) component at level j . In spatial frequency domain, the approximation and detail component correspond to the low-frequency and high-frequency components, respectively. If an image is decomposed to level max , level 1 contains the component of the highest frequency in the image, and level max contains the low frequency component in the image. The DWT coefficients of the respective frequency bands contain the localization information of original image [7].

It is known that the Fourier Transform (FT) gives what frequency components exist in the image. The coefficients obtained from the FT only provide frequency information. They do not give space localization information for a certain image pattern (edge or noise). For example if the edge and the noise have the same frequency, when enhancement operation applies to the coefficients of the frequency component, both the edge and the noise are enhanced. In contrast, the DWT gives both the frequency information and localization information. In general, those DWT coefficient having greater values represent edges.

On the contrary, those DWT coefficient having small values represent the noise [8].

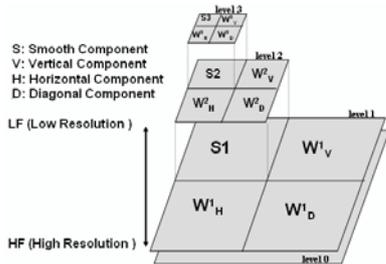


Figure 1: Layer presentation of 2D wavelet transform

3 Algorithm for detecting microcalcifications

Proposed algorithm for detecting microcalcifications is shown in Figure 1. It contains wavelet transform and morphological operations. Here a short description of algorithm is given.

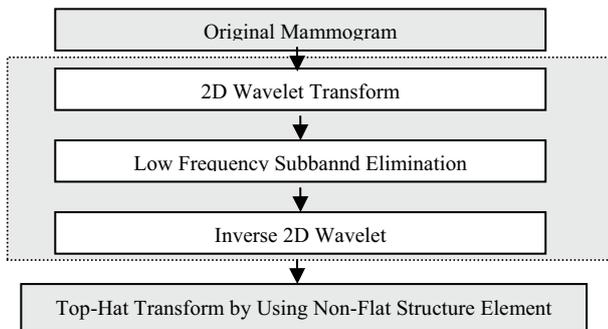


Figure 2: Proposed algorithm for detecting microcalcifications in mammograms

3.1 Low-pass frequency subband elimination

Due to small size of microcalcifications and high intensity of them with compared to their neighbour pixels, microcalcifications correspond to high-frequency components of the image spectrum [9], so we proposed decomposing mammogram into three frequency subbands, suppressing the low -frequency subband in level three, and then reconstructing the mammogram from the subbands which contain only high frequencies.

3.3 Top-hat transform

At the next stage, for better extraction of microcalcifications, proposed method in [10], which is based on morphological operations, is used.

Morphological contrast enhancement is based on the notion of morphological top-hats which were first proposed by Meyer [11]. A top-hat is a residual filter which preserves those features in an image that can fit inside the structure element and removes those that can not. Morphological contrast enhancement is derived by calculating the dual area top-hats in parallel. By performing a structural opening, the high-intensity regions of image that can not accommodate the structure element are removed. The top-hat by opening, γ_{TH} , is defined as

the difference between the original image, I_0 , and its grayscale opening, γ_B , using the structure element B :

$$\gamma_{TH} = I_0 - \gamma_B \quad (2)$$

Similarly the dual top-hat by closing, ϕ_{TH} , is the difference between the grayscale closing, ϕ_B , using the structure element B and the original image, I_0 :

$$\phi_{TH} = \phi_B - I_0 \quad (3)$$

The top-hat by opening, yields an image that contains all the residual features (i.e. peaks and ridges) removed by the opening. Adding these residual features to the original image has the effect of accentuating high-intensity (light) structures. The dual residual (i.e., valleys and troughs) obtained by using the top-hat by closing, is then subtracted from the resulting image to accentuate low-intensity (dark) structures:

$$\kappa = I_0 + \gamma_{TH} - \phi_{TH} \quad (4)$$

A structure element is a small set used to probe an image. Morphological analysis has traditionally been performed using flat structure elements, which have two dimensions in the case of two-dimensional images. Conversely non-flat structure elements are 3D structure elements, used to probe the intensity "shape" of features in the image, in addition to simply shape [10].

Microcalcifications found in digital mammograms have a cone shape with local maximum gray level values and they are appeared as local peaks on the mountains. Due to mammogram's inhomogeneous, there are noise and all kinds of isolated structure in it, which can be removed by a smaller structure element. Therefore by using suitable non-flat structure elements on the basis of the resolution of the image, deep valleys are exhibited and the peaks of the microcalcifications are separated. The structure elements used in this work are "ball-shaped" structure elements with radiuses: 3, 5, 7 and 9 pixels. So by calculating image resulted from equation (4) for mammograms, microcalcifications are extracted.

4 Algorithm for detecting masses

Proposed algorithm for detecting of masses is shown in Figure 3. It contains wavelet transform, morphological operations, calculating energy image and mapping intensity of the pixels. Here a short description of algorithm is given.

4.1 High frequency subband elimination

Masses are in the larger scales in comparison with microcalcifications, so masses correspond to low-frequency components. Therefore in proposed algorithm after decomposing mammogram into three frequency subbands, the high -frequency subband is suppressed and then the mammogram is reconstructed from the subbands containing only low frequencies.

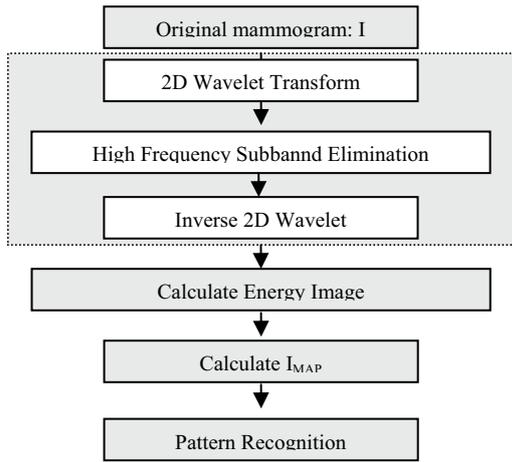


Figure 3: Proposed algorithm for detecting masses in mammograms

4.2 Energy image

Since in the regions which are containing masses, the density of the intensity of pixels are more than the density of the other regions, in the next stage, energy image is calculated and then it is normalized according to the below equation:

$$I_E(i, j) = I_M^2(i, j)$$

$$m = \frac{256}{\max(\max(I_E)) - \min(\min(I_E))} \quad (5)$$

$$c = -m * \min(\min(I_E))$$

$$I_{EN} = m * I_E + c$$

4.3 Non-Linear Map

Since in this process regions with high density are searched, we used non-linear mapping on the normalized energy image. Proposed map is shown in figure 4.

$$I_{map}(t, k) = b_i \quad \text{if } I_{EN}(t, k) \in [a_i, a_{i+1})$$

$$i = 1, 2, \dots, 7 \quad \dots(6)$$

$$b_i \in \{2, 3, \dots, 8\}$$

$$[a_i, a_{i+1}) = [256(1 - \sum_{j=i}^8 \frac{1}{2^j}), 256(1 - \sum_{j=i+1}^8 \frac{1}{2^j})$$

In the above equation I_{EN} is the normalized image and I_{map} is the mapped image. Clearly by using this non-linear mapping, pixel with more gray value is more highlighted. Therefore in the mapped image better segmentation of the pixels with higher density is achieved.

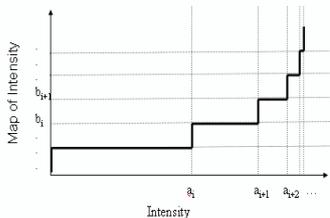


Figure 4: Proposed map

4.4 Pattern recognition

After calculating of the mapped image, for finding the position of the masses, space to space patterns like Figure 5 are searched. In this pattern the intensities are decreased from centre to the other directions. Values of X, Y and Z which are used for implementation in this work are $\{X, Y, Z\} \in \{(4,5,6), (5,6,7), (6,7,8)\}$.

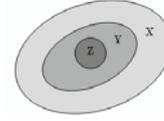


Figure 5: Space to space pattern

If one region with this pattern is recognized, such position is extracted and it shows the presence of mass in that position.

5. Experimental Results and Conclusions

The MIAS (Mammographic Image Analysis Society) database of digital mammograms used in this work [12]. In this database, abnormalities have been marked by the veteran diagnostician. Each image in the database has the resolution of $50\mu\text{m}$ with 256 gray levels. 25 images (200×250 pixels) that contain microcalcifications are selected for the first algorithm. Figures 6 illustrate the results of adding proposed block before the method based on top-hat transform by using non-flat structure element.

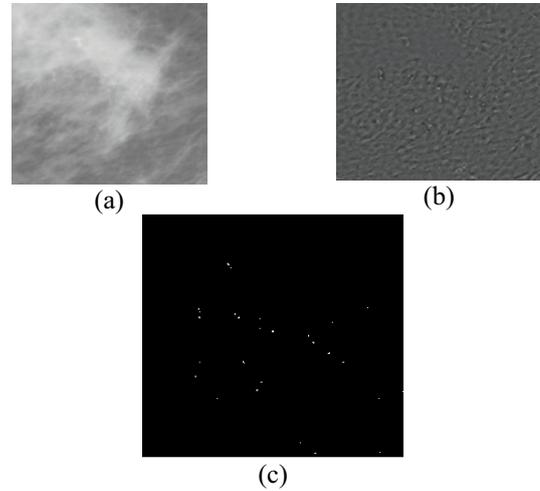


Figure 6: (a) Original mammogram mdb241 contain microcalcifications, (b) Resulted image after using top-hat transform with non-flat structure element, (c) Extracted microcalcifications by thresholding

The performance of the proposed method is evaluated by the receiver operating characteristics (ROC) curve [13]. For evaluating different methods same images are used. Figure 7 clearly shows that adding the proposed block before the method in [10] causes more accuracy in detection of positions and sizes of microcalcifications.

20 images (250×300 pixels) that contain masses are selected for the second algorithm. Figures 8 illustrate the results of proposed method for detecting masses.

Figure 9 shows the ROC curves of three algorithms for detecting masses by proposed method and two previous methods. One of the previous methods is based on radon transform [14] and the other is based on phase image [15]. The results show that our method outperforms other methods.

As it can be seen combining wavelet transform with morphological operation can improve accuracy of results in detecting suspicious regions. We are evaluating combining wavelet transform by other methods such as neural networks which have been used for detecting microcalcifications to see if this method can also improve their accuracy.

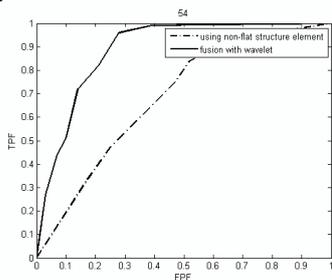
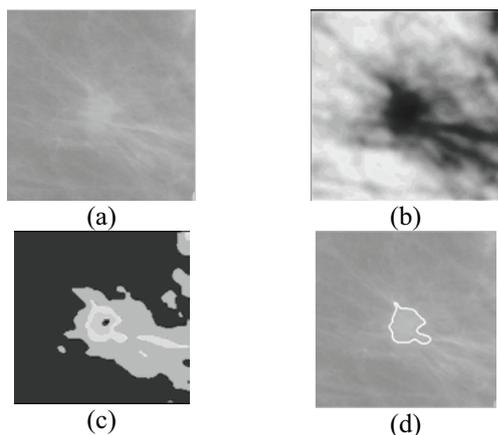


Figure 7: ROC curve for method by top-hat transform with non-flat structure element and fusion method with wavelet



Figures8: (a) Original mammogram mdb202 from MIAS database, (b) Energy image, (c) Non-Linear Mapping, (d) Showing the border of the detected mass on the original mammogram.

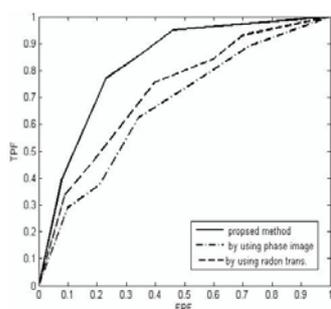


Figure 9: ROC curve for different methods for detecting masses

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