ENHANCEMENT OF MICROCALCIFICATIONS IN DIGITAL MAMMOGRAMS

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ABSTRACT

Microcalcifications are an important early sign of breast cancer development. Because of that computer aided detection systems (CADe) for detection of microcalcifications can be very useful and helpful for breast cancer control. In order to perform detection and classification of microcalcifications it is necessary to achieve accurate detection. To be able to perform accurate detection it is necessary to remove background influence. In this paper we propose a method for contrast enhancement of microcalcifications. The proposed method improves microcalcifications' contrast solely, while background is being suppressed. For background suppression we use combination of wavelet filtering and grayscale morphology. The results of the proposed method are significant improvement in background suppression and contrast enhancement of microcalcifications.

Index Terms— Digital Mammograms, Computer Aided Detection, Microcalcifications

1. INTRODUCTION

Computer aided detection (CADe) of microcalcifications is important in digital mammography because it helps radiologists reach their diagnosis with less false negative results. Although there have been many approaches to develop as good as possible detection algorithm, development of a method which will be completely accurate and with no false positive (FP) and false negative (FN) results still remains a challenge. For accurate detection of microcalcifications radiologists need to have very well captured mammograms with very high resolution and low noise. Typical size of a microcalcification is between 0.1 mm and 1 mm, and the average is about 0.3 mm [1]. Modern digital mammography devices offer spatial resolutions of 50 μm to 70 μm. Therefore, each calcification will occupy area of 5×5 pixels in average. This property of more or less known microcalcification size can be useful in detection of microcalcifications because it is possible to filter smaller and larger bright objects from the image.

In this paper we propose a method which should provide contrast enhancement only for microcalcifications. The method which we propose uses wavelet decomposition and subband suppression. On filtered images we are using grayscale morphology to emphasize objects with dimension similar to dimension of microcalcifications. The goal we set is to suppress all the surrounding breast tissue and boost the intensity of each individual microcalcification. This procedure should provide good results for standalone microcalcifications as well as for clusters of microcalcifications. Detection of standalone microcalcifications is often easier but clinically less important because clustered microcalcifications are often an early sign of a developing tumor. Standalone microcalcifications are usually larger and therefore brighter with higher contrast in comparison to surrounding tissue while clusters of microcalcifications are often consisted of physically smaller and scattered calcium deposits with much lower contrast to the background.

1.1. State of the art

There have been many different approaches to microcalcifications detection. Almost all of them are based on detection of bright objects with specific size. Enhancement of microcalcifications is a process which should produce good results for both manual and automatic detection and segmentation process. One of the most popular methods is contrast enhancement by histogram equalization [2]. There are many contrast enhancement techniques, but one of the most widely used, named contrast-limited adaptive histogram equalization (CLAHE), was proposed by Pizer et al. [3]. This technique was recently used in conjunction with redundant discrete wavelet transform [4]. Another approach is image filtering using unsharp mask filter which amplifies high frequency details but is not sensitive solely to microcalcifications [5]. Besides direct contrast enhancement and image filtering, it is possible to apply feature based contrast enhancement techniques which will allow enhancement of objects with certain morphological characteristics. One of these methods is multiscale image analysis [6]. Multiscale image analysis provides possibility to filter out or suppress objects with

dimension that do not correspond to the possible size of microcalcification. Usage of wavelet transform for multiscale analysis in microcalcification detection was presented by Strickland and Hahn in [7]. Besides their work, many other authors used wavelet analysis which proved to be one of the most widely used methods in microcalcification detection process. Using wavelet decomposition for image enhancement in mammography was presented by Mencattini et al. [8] but their work aimed at mass contrast enhancement and segmentation. Some recent approaches in microcalcification enhancement use multifractal analysis and mathematical morphology [9].

This paper is organized as follows. In Section II the contrast enhancement procedure is explained and contrast enhancement results are shown. Section III draws the conclusion.

2. CONTRAST ENHANCEMENT AND EXPERIMENTAL RESULTS

The image contrast enhancement method which we have chosen consists of discrete wavelet transform (DWT), subband filtering and grayscale morphology. DWT is commonly used transform for decomposing an image into frequency subbands while maintaining knowledge of spatial position of the pixel in the image. Using DWT it is possible to suppress certain objects which correspond to a group of frequencies in a subband. This property gave us the possibility to remove background objects that usually have lower spatial frequency. The method we propose uses wavelet decomposition of the third level on a patch with size of 128×128 pixels. This dimension of a patch gives a good compromise between expected size of microcalcifications and background objects while maintaining the size of 2^n. Fig. 1 shows dyadic wavelet decomposition up to third level which we used for the purpose of background removal. On the left side frequency subbands are shown according to the filtering of the corresponding level.

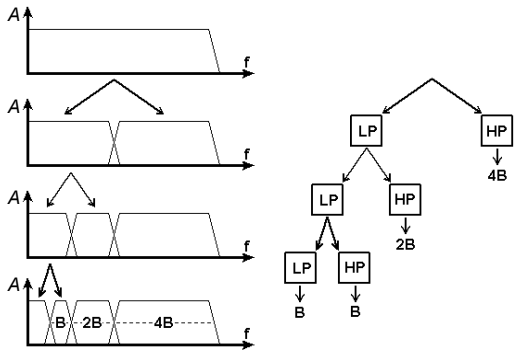
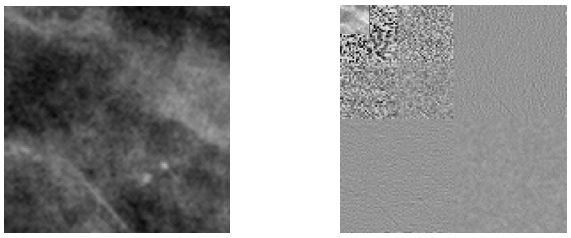


Fig 1. Dyadic wavelet decomposition up to third level.

By decomposing image up to third level, we shrink the width of the approximation or low frequency subband to 1/8 of the original frequency band. This means that new approximation subband can contain maximal spatial frequency of 1/8 of the original image, meaning that all objects smaller than 128/8 pixels are not contained in the approximation band if the image size is 128×128 pixels. Example of the third level decomposing of a patch containing calcifications is shown in fig. 3.



(a) (b)

Fig 2. Original patch containing calcifications; (b) Third level wavelet decomposition of the same patch

From fig. 2 it is visible that different decomposition subbands contain different details regarding their spatial frequency. Therefore it is possible to remove subbands which contain objects that are of no interest for the contrast enhancement purpose. Since we want to keep only objects with size of 5×5 pixels it is necessary to choose the frequency band sensitive to objects having corresponding spatial frequencies. By examining the fig. 2(b) it is obvious that objects which we want to enhance are not visible in the images of first level decomposition. Therefore we have chosen to remove first level detail as well as approximation image of the third level decomposition. Removing approximation image will result in suppression of uneven background caused by intensity variations due to different tissue type in the projection. Fig. 3 shows the reconstructed patch with removed approximation coefficients and first level details.

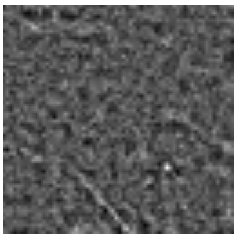


Fig 3. Reconstructed patch with removed approximation and first level details.

The same patch after reconstruction with suppressed frequency bands has visibly suppressed uneven background but also suffers from reduction of details due to lack of information contained in the filtered image. Since we cannot produce perfect filtering, some compromises concerning masking of low contrast calcifications needed to be made. After filtering by means of removing frequency subbands, we used grayscale morphology operator. It was necessary to chose appropriate structuring element for closing operation.

Morphological closing is defined as dilation followed by erosion with the same structuring element [10]. Closing can be expressed as:

$$A \bullet B = (A \oplus B) \ominus B \tag{1}$$

where A represents an image object and B represent a structuring element. Erosion is defined as:

$$A \ominus B = \{z | (B)_z \subseteq A\} \tag{2}$$

which means that B translated by z is contained in A. Dilation is defined as:

$$A \oplus B = \left\{ z | (\hat{B})_z \cap A \neq \emptyset \right\} \tag{3}$$

From (1) we can conclude that we have to choose an appropriate structuring element B which is similar in size to microcalcification which we want to emphasize. Therefore we have chosen our structuring element to be a square with dimensions 5×5 pixels. After grayscale closing with the proposed structuring element we get the result shown in fig. 4.

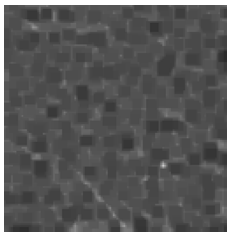


Fig 4. Patch after grayscale closing operation.

Morphological closing allows further background suppression and gives possibility to increase microcalcifications contrast in combination with original image. To achieve higher contrast of bright pixels on the dark background, we used simple multiplication operation:

$$X = A * (A \bullet B) \tag{4}$$

X represents output image of element by element multiplication of input image A with the same image A closed by structuring element B. The result of this multiplication is shown in fig. 5.

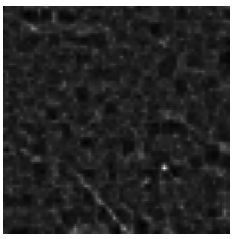


Fig 5. Patch after element by element multiplication of reconstructed patch and closed patch.

Even though these images offer contrast improvement visually, it will be good to quantize this gain. For representing the contrast improvement, we have used variance (5) and contrast (6) measures.

$$\mathrm{Var}(X) = \sum_{i=1}^{n} p_i \cdot (x_i - \mu)^2 \tag{5}$$

In (5) p_i represents probability mass function, in our case 1/(2^8) for each pixel, x_i is a sample value and μ is the expected value which in our case is the mean value of all pixels in the observed patch. We have chosen to define contrast gain as:

$$CG = \frac{\frac{max(X_2)}{min(X_2)}}{\frac{max(X_1)}{min(X_1)}} \tag{6}$$

where $\max(X_1)$ is the intensity of the maximal element in the original image, $\min(X_1)$ is the minimal element in the original image, $\max(X_2)$ is the maximal element in the enhanced image and $\min(X_2)$ is the minimal element in the enhanced image. Contrast gain calculated on a patch extracted from the breast tissue does not suffer from division-by-zero problem because breast tissue always consists of pixels with positive intensities. Using (5) and (6) we can express gain in visibility of bright objects against surrounding. These bright objects may not be micro-calcifications but objects of similar properties which should be discarded in later false positive reduction process. Variance gain is defined as ratio of variance of the enhanced patch and variance of the original patch. The expected result from these operations is smaller variance gain in the presence of microcalcifications, because of more uniform background and high contrast gain because of multiplication of corresponding bright pixels. Contrast gain in our example should be higher for the patches which contain micro-calcifications because of the existence of bright pixels which will produce higher final intensities with squared dependency. We have calculated variance and contrast gains for 10 patches. 5 patches do not contain microcalcifications and 5 patches contain microcalcifications. Patches which contain microcalcifications are shown in fig. 6(a) and those which do not contain calcification are shown in fig. 6(b). These patches are randomly chosen from the same mammogram and are very similar visually. After contrast enhancement of microcalcifications, variance gain and contrast gain should show some regularity. Table I shows variance and contrast gains for corresponding patches shown in fig. 6.

TABLE I. Variance and contrast gains for the patches shown in fig. 6

Patch No.	**1**	**2**	**3**	**4**	**5**
Var. gain	75141	16268	29756	64928	51470
Cont. gain	18643	5830	13932	18624	12533
Patch No.	**6**	**7**	**8**	**9**	**10**
Var. gain	13403	13017	18492	10363	10400
Cont. gain	20900	16240	18335	16929	14620

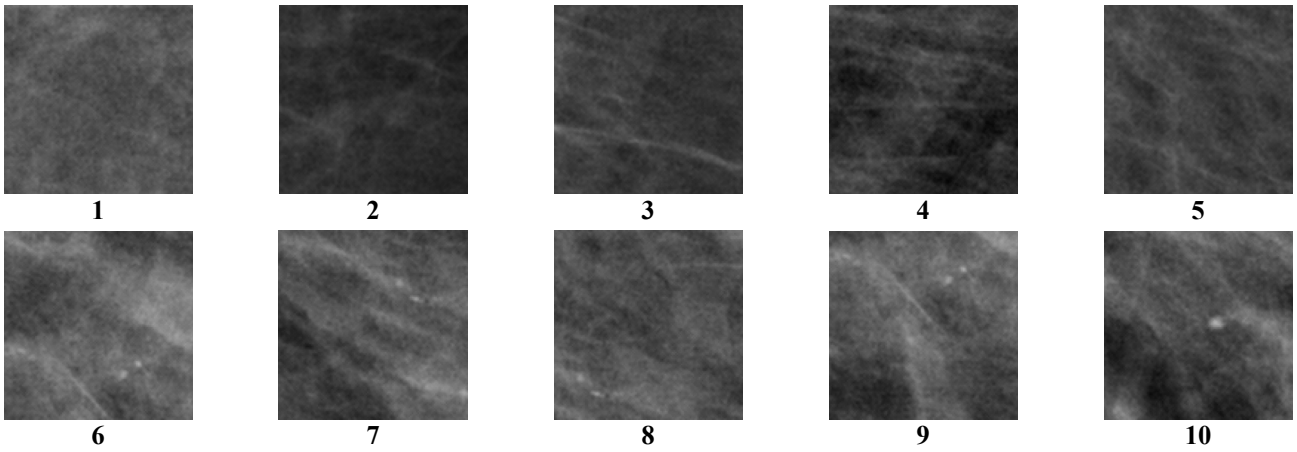


Fig 6. Patches which do not contain microcalcifications (1-5); (b) Patches which contain microcalcifications (6-10).

3. CONCLUSION

In this paper we have presented a method for contrast enhancement of microcalcifications. The proposed method uses combination of subband suppression of images decomposed using wavelet transform and grayscale morphological operators. Resulting images have suppressed tissue intensity variations and emphasized bright objects which are of the same dimension as expected calcifications. Variance and contrast gains achieved using the proposed method show that variance gain is much more uniform in the presence of microcalcifications and overall contrast gain of patches containing calcification is slightly higher. Microcalcification detection on enhanced patches gives much better results because of higher difference between bright objects and background. Our further work will include individual microcalcification detection and segmentation which will be based on maximizing sensitivity and reduction of false positive results in order to develop a CADe system for detection of low visibility clusters of microcalcifications.

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4. REFERENCES

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