A Novel Morphological Band Pass Filtering Technique for Detection of Breast Microcalcifications

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Abstract

Microcalcifications are early signs of breast cancer which emerge as minute vivid marks in the images of mammogram. As these mammogram images are small in size and shape, they are complicated to get detected. Morphological Band pass Filter (MBF) is proposed in this research work to detect microcalcifications. Morphological band pass filter is implemented by applying morphological operations with structure elements of different shapes and sizes. Multiple MBFs are modulated in succession for detection task. Finally, the output binary image contains the detected microcalcifications. The proposed method yields high percentage of accuracy in locating and detecting the microcalcifications.

Keywords: Microcalcifications; Morphological band pass filters; Structuring element; Mammogram Image; Morphological operators

Introduction

Mathematical morphology follows shape-based procedure in the domain of image processing. In the recent years, numerous shape representation schemes for morphology have been proposed. Among other issues in image processing, shape representation is a significant one as it affords major foundation for algorithms development in the domain of shape processing.

Applications of mathematical morphology

The field of image processing embraces a wide range of mathematical operators from set theory. The operators are useful for the analysis of binary images and the usages include the following

- Edge detection,
- Contrasting and filtering,
- Image enhancement and
- Image segmentation

Among many frequently used operations in image analysis, edge detection is commonly used. There are also many algorithms for detecting and enhancing edges in literature. Brightness of a pixel with respect to other pixels, form the basis for image contrast. Filters are used to alter image contrast within it. Kernel is an array which is multiplied and added to every pixel within the image, represents a filter. Improvement in the quality of an image is set as an enhancement by reducing noise, enhancing edges and contrast.

Literature Survey

Mammography is the broadly used technique in all imaging modality, particularly in breast imaging. Earlier CAD systems for breast cancer diagnosis are not fully computerized, in spite of higher accuracy [1]. There is a high increase in false-positive mammogram screening cases which leads to over-diagnosis of breast cancer and harmful overtreatment with huge expenses.

Increase in recent cancer research reveals that there is no noticeable difference reported, when a mammogram screening result is declared with and without CAD systems. So, the performance of CAD system for mammogram screening has to be advanced to make it completely automated in future.

Contrast upgrading, noise attenuation, texture inquiry and portioning algorithm are the image processing methods in this research paper [2]. These methods are intended to enhance and whet the

intensity of the image and reduce noise. Backdrop tissues and breast lesions types form the basis for the augmentation of assortment factor. So better upgrading of lesions depends on their density.

Averaging and thresholding techniques are used in this approach for the detection of cancerous tissues in mammogram [3]. Detection phase is tracked by segmentation of the tumor section in mammogram image. Max-Mean and Least-Variance techniques are also used for tumor recognition.

One of the systematic methods for detection and segmentation of microcalcifications in mammogram is presented. This technique is used to conserve shape and size of the individual calcifications accurately [4]. In this work, both rates of false positive and true positive for consistent diagnosis and found to be extremely low. A two-stage algorithm is anticipated for spot discovery and shape extraction. A weighted difference of Gaussian filter is applied for detecting the spots with the invariant noise and size. Second stage employs a morphological filter to replicate the shape of the spots. Conditional thickening operation is combined with the results of both the filters. Preservation of size and shape of the individual calcification is the main advantage of using this algorithm. Structures of interest, namely calcifications are separated from the tissue background.

Segmenting lesions is an important step in many computerized mass-detection schemes for digitized mammograms. First one is based on a Radial Gradient Index (RGI), which is single featured and the next one is based on simple probabilistic models to part accumulated lesions [5]. These methods are commonly called as seeded segmentation algorithms. RGI method is implemented by creating a series of image partition using gray-level information and prior knowledge of the shape of the typical mass lesions. Maximizes RGI is selected from the series of image partitions. RGI utility function is employed in this lesion segmentation that describes the shape of the lesions. RGI is the measure of average proportion of the gradients directed outward. An RGI of one indicates that all gradients just about the edges are pointing straightly outward down the radius vector and -1 signifies that all gradients just about the margin are pointing directly toward the centre of the partition inwardly [6].

Another method is based on probabilistic model, which is implemented by partitioning the image using probability function. Maximum probability is selected for avoiding the complexity of an optimization problem.

Pectoral muscle in MLO (Medio Lateral Oblique) view of mammograms is identified in this work using Gabor wavelets [7,8]. Piecewise-linear structure in ROI, which is used for detection of pectoral muscle, is enhanced by Gabor filters. Limitation of the straight-line representation is met out by this algorithm.

Motivation

Breast cancer detection depends on the accuracy and quality of the mammogram image. Mammogram images are low contrast and contain noise. MCs are very small in size. Detecting MCs are challenging one for human vision. Improving the contrast and removing noise is difficult one. Morphological operation is suitable for detection microcalcifications. Mathematical morphology is used in image processing and comprehending, on the basis of set theory, which is a powerful tool in the geometric morphological analysis, based on DWT. This morphological band passes filter method, which also verifies its feasibility and validity [9-11].

Mathematical Morphology AND Multi-Scale Structure Element

Morphology is the study of the forms and things. In general, the morphological operators transform the original image into another image. They are Binary Erosion, Binary Dilation, Binary Opening, and Binary Closing. An essential part of the morphological dilation and erosion operations is the structuring element used to probe the input image. A structuring element is a matrix that identifies the pixel in the image being processed and defines the neighborhood used in the processing of each pixel. The transformation of the original image is done through the interaction with the structuring element of certain shape and size. The structuring element has geometric feature that is they are similar in shape and size, whereas other features are suppressed. Thus, morphological operations clarify the image data by sustaining their shape characteristics and eliminate the irrelevancies only. In the application point of view, morphological operations are employed for many purposes, that we have already seen edge detection, segmentation, and enhancement of images and so on.

Binary erosion and Binary dilation are the two most basic operations in mathematical morphology. The input of these two operators is two: First one is an image to be eroded or dilated, and second one is the structuring element. The structuring element is also known as a kernel. The original image and the kernel are treated as representing sets of coordinates in a way that is slightly different for binary and gray scale images [12].

Mathematical operations

An image of a mammography can be determined as an (amplitude) function of two coordinate variables a (x,y) or two discrete variables a [m,n]. The other definition of an image can be established on the conception that an image comprised of a collection of either continuous or discrete coordinates. In this regard the set corresponds to the points or pixels that belong to the objects in the image. This is illustrated in Figure 1. There are two sets A and B in the figure. Note that we are in need of the coordinate system. And also we are considering the pixel values as binary.

$$A = \{\alpha \mid property(\alpha) = \ TRUE\} \qquad (1)$$

As an example, object B consists of {[0,0], [1,0], [0,1]}. A^c is the background of A (A's complement) which is defined as the elements that are not in A: Background

$$A^c = \{\alpha \mid \alpha \notin A\} \qquad (2)$$

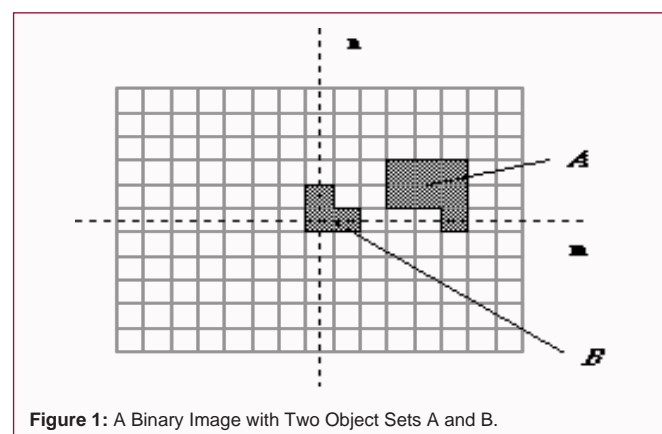The concept of neighborhood connectivity is shown in Figure

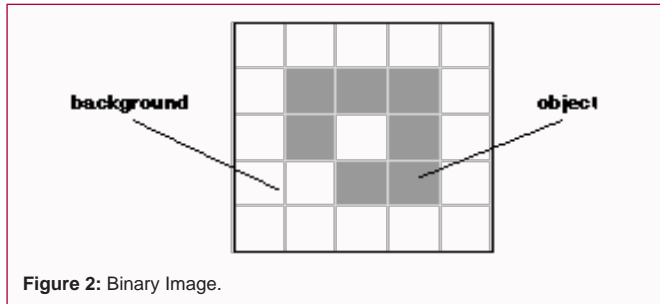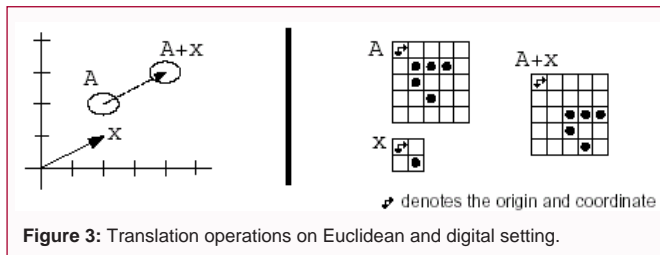**Figure 1:** A Binary Image with Two Object Sets A and B.

Figure 2: Binary Image.

Figure 3: Translation operations on Euclidean and digital setting.

Figure 4: Dilation on Euclidean and Digital Setting.

Figure 5: Erosion on Euclidean and digital setting.

2. Next we should recognize that whether an object A is defined on the basis of C-connectivity (C=4, 6, or 8) or not and then the background A^c has a connectivity given by 12-C. The necessity for this recognition of the connectivity is illustrated for the Cartesian grid in Figure 2 binary mathematical morphology is based on set theory from mathematics. In binary images, the complement set is known as background and the set points are known as foreground. Furthermore the usual set-theoretic operations of union and intersection are replaced by morphology pivots extensively on the translation operation. For convenience, $\cup$ denotes the set-union, $\cap$ denotes set intersection and + inside the set notation refers to vector addition in the following equations (Figure 3) [13].

Given an image A, the translation of A by the point X, denoted by A_X, is defined by

$$A + x = \{a + x : a \in A\} \qquad (3)$$

Binary dilation: Dilation is a shift-invariant operator, equivalent to Minkowski addition. If B has a centre on the origin, then the dilation of A by B can be understood as the locus of the points covered by B when the centre of B moves inside A. This is denoted by $A \oplus B$, is defined as

$$A \oplus B = \{a + b / \text{ for } a \in A \text{ and } b \in B\} \qquad (4)$$

From equation (4), dilation is equivalent to a union of translates of the original image with respect to the structure element

$$C = A \oplus B = \bigcup_{b \in B} (A)_b \qquad (5)$$

Intuitively, the structure element plays the role of a template. Dilation expands the image pixels i.e. it is used for expanding an element A by using structuring element B. Dilation adds pixels to object boundaries. The value of the output pixel is the maximum value of all the pixels in the neighborhood. In Figure 4, we obtain the modified image. The modification has been done in terms of the shape of structure element. The small hole has been removed, the dilation operation usually uses a structuring element for probing and expanding the shapes contained in the input image.

Binary erosion: Binary erosion is a mathematical morphology operation used for image processing. Structuring element used for the erosion. Non-zero el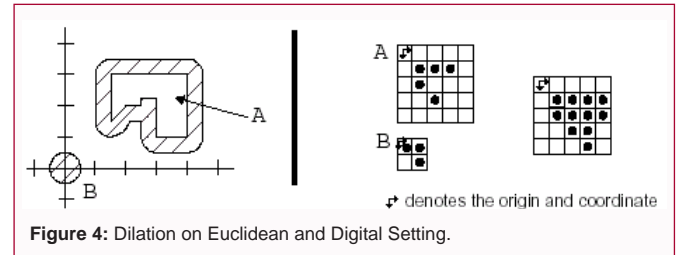ements are considered true. If no structuring element is provided, an element is generated with a square connectivity equal to one. Binary erosion of an image A by structure element B is established by $A \Theta B$ is defined as:

$$A \Theta B = \{ p / p + b \varepsilon A \forall b \varepsilon g \} \qquad (6)$$

Union translates represent dilation and intersection of the negative translates represent erosion as:

$$C = A \Theta B = \bigcap_{b \varepsilon B} (A)_{-b} \qquad (7)$$

–b is the scalar multiple of the vector b by -1.

Template translation is used to intuitively describe the structure element as dilation of the original image. The template is moved across the original image. For a given foreground pixel, put the centre of the template onto it, i.e. translate the template to that pixel. If the translation of the template is a sub image of the original image, that pixel is activated in erosion; otherwise it is not activated (Figure 5).

Binary opening: Opening of binary image A by structure element B, denoted by A∘B, is defined as

$$A \circ B = (A \Theta B) \oplus B \qquad (8)$$

From the definition, the original image is eroded first and then dilated. Therefore, it can spontaneously consider as "undulating the constructed or structure element with respect to the inner boundary of the image". The following definition gives a rigorous set – theoretic characterization of this "fitting" property. By stating that the opening of A by B is attained by considering the combination or union of all translates of B into A.

Opening of a binary image A by structure element B, denoted by A∘B is also defined as $A \circ B = \bigcup \{B + x / B + x \subset A\}$ (9)

Figure 6 shows how this original image is smoothed and the spot-like noise is removed because the disk can't fit into them. It is worth noticing that smoothing effect of the object boundary highly depends on the shape of the structure element.

Introduction to Segmentation

Partitioning a digital image into multiple set of pixels is termed as segmentation. Simplification of image representation to extract meaningful analysis is the ultimate goal of segmentation. Image segmentation stands for locating typically the objects and its boundaries. The set of region that collectively covers the whole image
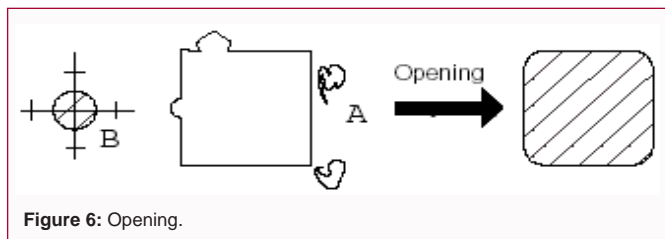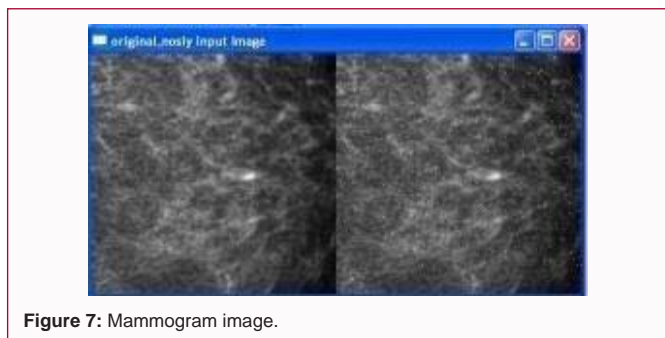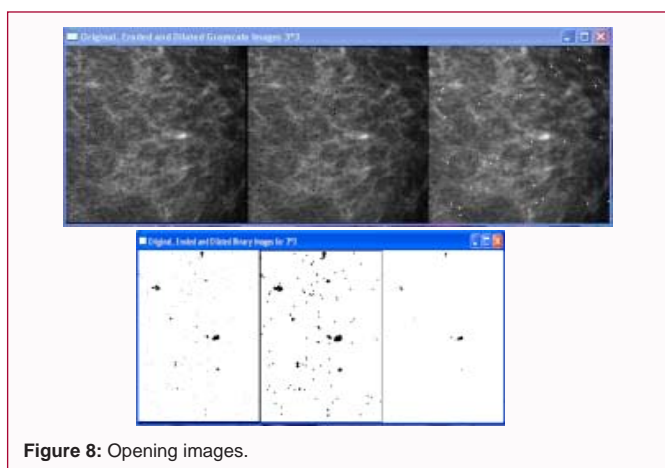
Figure 6: Opening.
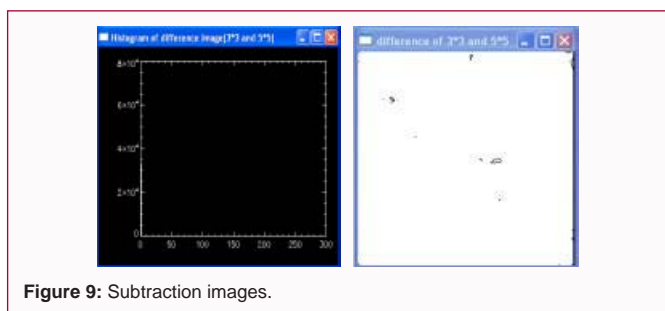

Figure 7: Mammogram image.

Figure 8: Opening images.

Figure 9: Subtraction images.

Figure 10: Resultant output image.

Figure 11: Input Image & Output image.

is the effect of image segmentation. Each of pixels in an area is same in some property like color, intensity and texture. Nearby regions are considerably dissimilar to the same characteristics respectively. Some practical applications of image segmentation are

- Medical imaging
- Locate tumors and other pathologies
- Measure tissue volumes
- Locate objects in satellite images
- Fingerprint recognition
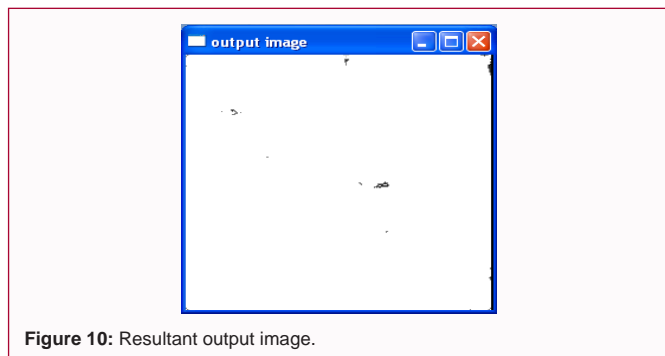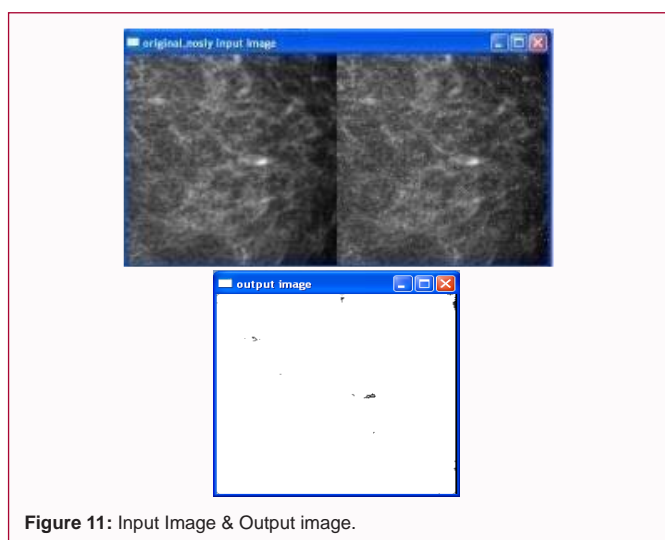- Automatic traffic controlling system

Several general purpose algorithms and techniques have been developed for image segmentation.

Proposed System

Morphological filters can be defined by basic morphological operations are dilation and erosion, other operation like open and close operation can be derived from the dilation and erosion operations. It is implemented by multilevel open operations. The multilevel open operation is just like a low pass filter, it eliminates those structures of the image that are smaller than the structuring element.

Morphological band pass filter is defined as the difference of two multilevel open operations with two different structuring elements. Steps are repeated until to detect all microcalcifications. Then compute weight of the image which is used to improve the enhancement of the image. It shows accurate results in the detection of microcalcifications.

Discrete wavelet transform method can decompose the image into sub images through sub-band decomposing filter bank. The sum of detail bands gives an image containing microcalcification detected in each direction. It gives could not provide accurate result, because it has the problem of locating as small detail objects (microcalcifications) that have small size in only one direction. It does not suppress the noise.

Proposed Plan of Work

1. Mammography is a technique, popular for all cancer detections, particularly for breast cancer. Mammogram images are low contrast

and contain noise. MCs are very small in size. Detecting MCs are challenging one for human vision. Figure 6 shows the mammogram image of breast having some microcalcifications [14,15].

Discrete Wavelet Transform method can decompose the image into sub images through sub-band decomposing filter bank. The sum of detail bands gives an image containing microcalcification detected in each direction. It gives could not provide accurate result, because it has the problem of locating as small detail objects (microcalcifications) that have small size in only one direction. It does not suppress the noise.

2. For the above Figure 7 I apply morphological binary opening as stated earlier with smallest structuring element 3×3 (J) and also with another structuring element 5×5 (K).

Figure 8 shows selecting different shape structuring elements in a fixed scale and using it to process a gray-scale image with erosion algorithm. Then, calculate the times of different shape structuring elements filled into a gray-scale image.

3. In the next step, I subtract K from J to get current Region of Interest (ROI). Finding ROIs with high accuracy can be very important for correct diagnosis. Figure 9 shows that subtracting the morphological opening image K from the morphological opening image. The Region of interest is attained when the threshold is applied along with this.

4. The steps 2 and 3 are repeated until to detect all microcalcifications to result Morphological Band pass Filter (MBF). Finally we get the current Region of Interests (ROI) which are required microcalcifications with accurate shape and size [16].

Experimental Results

Input image

The input image is implemented by the morphological band pass filter algorithm. The morphological opening is applied first with 3×3, 5×5 and 7×7 structural elements as stated in the proposed plan of work. Then they are subtracted with each other to get the final resultant image (Figure 10) [17].

The output image is the output image using different structuring elements are obtained (Figure 11).

Conclusion

Mathematical morphology is an important branch of image signal processing, and it provides useful tool for solving many image processing problems. In this paper, the method based on mathematical morphology shows effective results in detecting Microcalcifications (MCs) in the mammogram images. Moreover, morphological band pass filter is easy to understand and operate. Implementation of our algorithm reduces noise and improves the accuracy of microcalcifications. This method overcomes the limitation of Discrete Wavelet Transform Method (DWT). It produces more accuracy in terms of size and shape of microcalcifications. When compared to other existing algorithms, this is very faster in detection. The accuracy of location and detection of microcalcifications in terms of position and size is more.

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