Application of Gabor Filters for Detection of Dense Tissue in Mammograms

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Abstract - Determining breast density in mammograms is important both in diagnostic and computer-aided detection applications. Knowing the right breast density and having knowledge of changes in breast density could give a hint of a process which started to happen in a patient. Mammograms are projection images and suffer from problem of overlapping tissue which results in possibility of inaccurate detection of tissue types. The main problem is the fibroglandular tissue which has rather high attenuation of x-rays and is visible as brighter area in the resulting image. Small blood vessels are usually the most common interfering objects in mammograms. In this paper we try to suppress scattered structures which do not represent glandular or dense tissue in order to divide mammograms more accurately in two major tissue types, fatty and dense tissue. For suppressing blood vessels we have used Gabor filters of different size and orientation to detect edges of blood vessels and subtract them from the original image. Obtained results show much more homogenous areas which could be used for easier discrimination between tissue types.

Keywords - CAD; Gabor Filter; Breast Density; Blood Vessel

I. INTRODUCTION

Computer-aided diagnosis (CAD) systems are being developed more and more each day. Their aim is to help radiologists especially in screening examinations when a large number of patients are examined. Mammograms are x-ray breast images of usually high resolution and high bit-depth which makes them suitable for capturing fine details. Because of the large number of captured details, computer-aided detection (CADe) systems have difficulties in detection of desired microcalcifications and lesions in the image. Since mammograms are intensity projection images, it is difficult to automatically differentiate types of breast tissue because different tissue types can have same or very similar intensity. To overcome that problem different authors have came up with different solutions. Some used statistical feature extraction and classification of mammograms into different categories according to their density. Other approaches used filtering of images and then extracting features from filter response images. Among methods which use extraction of statistical features, Oliver et al. [1] obtained very good results. They have used combination of statistical features extracted not directly from the image, but from gray level co-occurrence matrices, which were later classified into four different density categories, according to BI-RADS [2]. Authors who used image filtering techniques tried to divide, as precisely as possible, breast tissue into two main types: dense and fat tissue. Knowing the amount of dense tissue in breast it would be possible to quantify the results of breast density classification. However, the task of defining the appropriate threshold for dividing breast tissue into two categories is far from simple. Many parameters affect intensity of each different mammogram. Different mammograms suffer from different intensities for the corresponding tissue. Reasons for that, if we neglect usage of different imaging equipment, are difference in actual breast size, difference in compressing force applied to breast during capturing process, different exposure time and anode current. Having all this in mind authors tried to overcome this problem by applying different techniques which should minimize influence of capturing inconsistencies. Muhimmah and Zwiggelaar [3] presented an approach of multiscale histogram analysis having in mind that image resizing will affect histogram shape because of detail removal when image is being downsized. Petroudi et al. [4] used Maximum Response 8 filters [5] to obtain a texton dictionary which was used in conjunction with support-vector machine classifier to classify breast into four density categories.

In this paper we present a method which should make possible to divide breast tissue between parenchymal tissue and fatty tissue without influence of blood vessels and fine textural objects which surround fibroglandular disc using region growing method. Our goal is to remove tissue which interferes with dense tissue and makes classification of breast according to densities less accurate. Gabor filters proved to be efficient in extracting features for breast cancer detection from mammograms because of their sensitivity to edges in different orientations [6]. Therefore, for the removal of blood vessels we have used Gabor filter bank which is sensitive to brighter narrow objects. Output of the entire filter bank is an image which is created of superimposed filter responses from different orientations. Subtraction of the image which represents vessels and different tissue boundaries from the original image produces a much cleaner image from which it is easier to distinct dense tissue from fat. The proposed method has been tested on mammograms from mini-MIAS database [7].

This paper is organized as follows. In Section II we present the idea behind image filtering using Gabor filter bank. In Section III we present results of filtering with the appropriate filter and discuss the results. Section IV draws the conclusions.

II. GABOR FILTERS

Gabor filters are linear filters which are most commonly used for edge detection purposes. Each filter can be differently constructed and it can vary in frequency, orientation and scale. Gabor filter in complex notation can be expressed as:

$$G = \exp\left(-\frac{(x\cos\theta + y\sin\theta)^2 + \gamma^2(y\cos\theta - x\sin\theta)^2}{2\sigma^2}\right) \cdot$$
$$\cdot \exp\left(i\left(\frac{2\pi(x\cos\theta + y\sin\theta)}{\lambda} + \psi\right)\right), \quad (1)$$

where θ is orientation of the filter, γ is the spatial aspect ratio, λ is the wavelength of the sinusoidal factor, σ is the sigma of the Gaussian envelope and ψ is the phase offset. Varying any of the stated parameters will result in creation of a different filter which will inherently produce a different response. Figure 1 shows different filters created using (1). Orientations of the filters are 0, 45, 90 and 135 degrees, respectively.
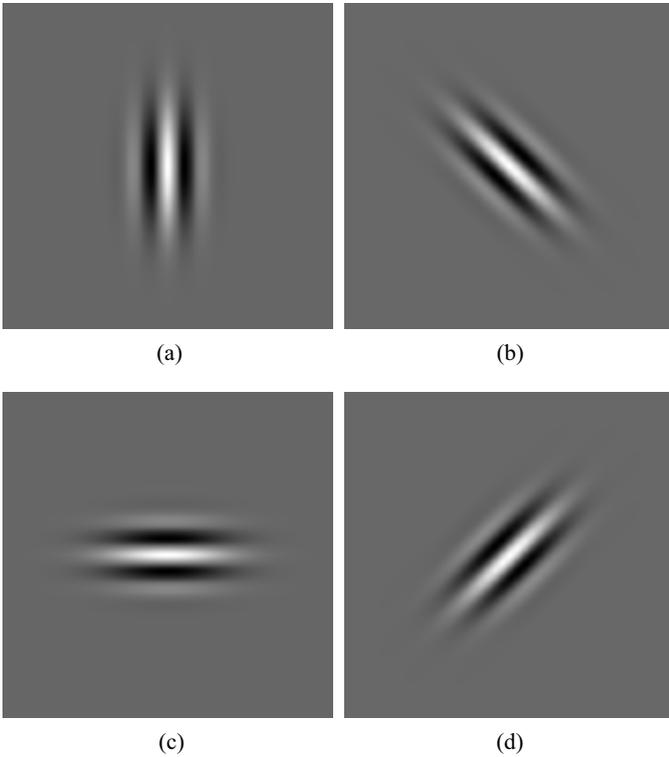
Figure 1.   Gabor filters of the same scale and wavelength with different orientations: (a) 0°; (b) 45°; (c) 90°; (d) 135°.

Besides the orientation angle, one of the most commonly changed variables in (1) is the sinusoidal frequency. If the chosen filter contains more wavelengths, filtered image will correspond more to the original. In the case of smaller number of wavelengths, filtered image will contain highly visible edges. This is somewhat expected because in that case Gabor filter will be similar to Sobel edge detector. Figure 2 shows different wavelengths of Gabor filter with the same orientation.
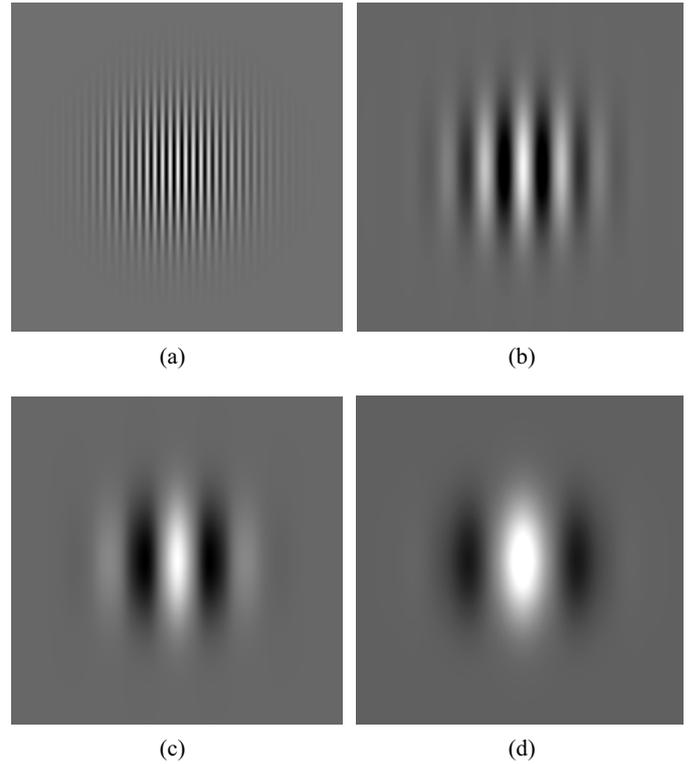
Figure 2.   (a)-(d) Gabor filters which contains larger to smaller number of sinusoidal wavelengths respectively.

There is of course another aspect of the filter which needs to be observed and that is the actual dimension of the filter. Dimension of the filter should correspond well with the desired object which we want to filter out and the image size.

III. IMAGE FILTERING

Before filtering we need to preprocess original images. Preprocessing steps include registration of images, background suppression with the removal of artifacts and pectoral muscle removal. For this step we have used manually segmented masks drawn for all images in mini-MIAS database. These masks were drawn by an experienced radiologist and can be treated as ground truth with no mistake in segmentation accuracy. Mask extraction process has been described in [8]. After these preprocessing steps we have to locate the position of fibroglandular disc in each breast image. Fibroglandular disc is the region containing mainly two tissue types, dense or glandular and fat. These two tissue types differentiate one from another mainly in intensity and in relative position towards edge of the breast. Since fibroglandular disc is our region of interest, only that part of the image was extracted. Entire preprocessing step done for all images in the mini-MIAS database is shown in Fig. 3.
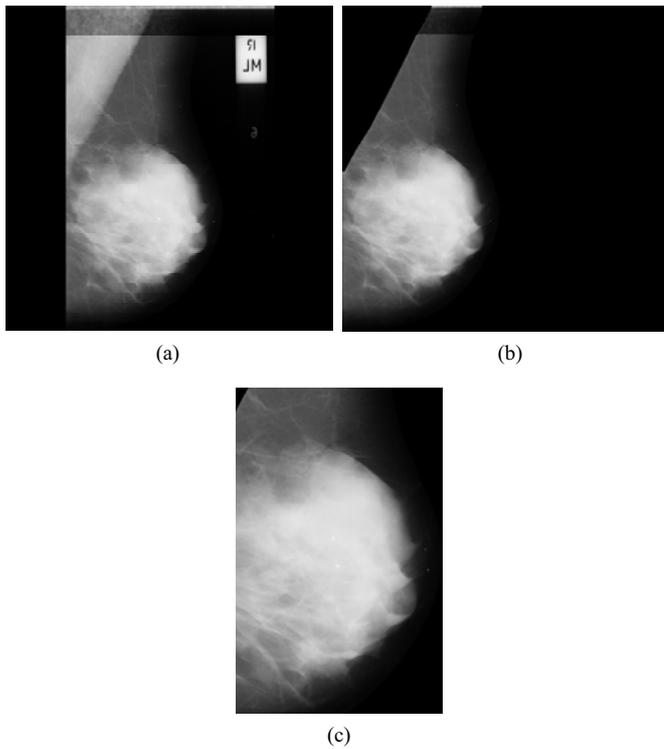
Figure 3. (a) Original mini-MIAS image "mdb002"; (b) Registered image with removed background and pectoral muscle; (c) Extracted ROI from the same image which will be filtered using Gabor filter.

Mini-MIAS images have the same initial size of 1024×1024 pixels. Depending of the actual breast size, which varies from image to image, resulting ROI has different dimensions for each image. To create ROI we have extracted part of the image according to the maximum breast tissue dimensions as shown in Fig. 4.
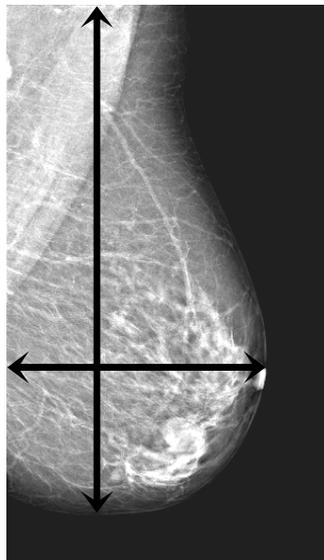
Figure 4. Defining maximal breast tissue dimension for ROI extraction.

Actual ROI boundaries are chosen to be V and H for vertical and horizontal coordinates respectively.

$$V = \left[\frac{\max(horizontal)}{2} : \frac{\max(horizontal)}{2} + \max(horizontal) \right]$$
$$H = \left[\frac{\max(vertical)}{3} : \max(vertical) \right]$$
(2)

where max(*horizontal*) is the vertical coordinate of the maximal horizontal dimension, and max(*vertical*) is the horizontal coordinate of the maximal vertical dimension. For determining which settings of Gabor filter should be used we decided to use the same ROI from "mdb002" which is a case of a dense breast with visible blood vessels which should be removed in the final image. Original ROI on which we have applied Gabor filter is shown in Fig. 3 (c). To give the idea of different results with different filter settings we have used filters shown in Fig. 2 to filter the same ROI. Output images show superposition of eight filter responses per image, where each filter response is achieved with different orientation while keeping all other parameters intact. This makes filters sensitive to edges in all orientations. Figure 5 (a)-(d) shows application of filters shown in Fig. 2 (a)-(d) respectively on the ROI shown in Fig. 3 (c).
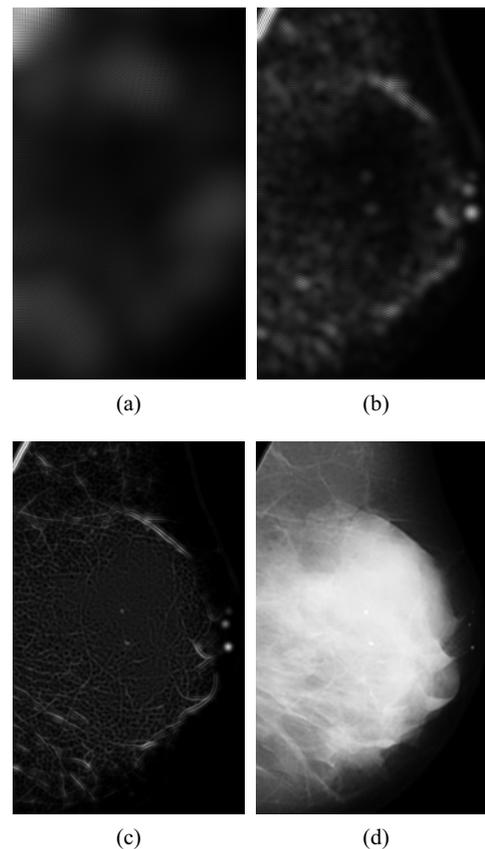
Figure 5. (a)-(d) Application of filters shown in Fig. 2 (a)-(d) on ROI shown in Fig. 3 (c) respectively.

From Fig. 5 it is clearly visible that the best results in blood vessel removal has been achieved using filter setup similar to the one shown in Fig. 3 (c). If we remove detected blood vessels and smaller linear shaped objects from the image by subtraction, resulting image will look as shown in Fig. 6 (a). This image however contains "holes" at positions of removed objects. To fill those holes we have to use morphological closing with a relatively small structuring element. Result of morphological closing with a square structuring element of 5×5 pixels is shown in Fig. 6 (b).

(a)	(b)
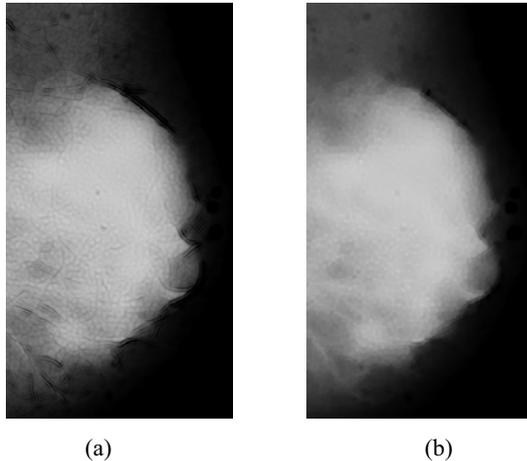
Figure 6.   (a) Removed linear shaped objects from the ROI by subtraction; (b) Morphologically closed image with 5×5 structuring element.

After filtering we have applied region growing which is one of widely used approaches in segmentation of two different regions with poorly defined boundaries. The major problem which occurs when using region growing method is the appropriate threshold setting as well as determining the appropriate seed point from which region growing would start. If we are able to create a more homogenous image according to intensity and further reduce bit depth, region growing should give better results because stopping condition as well as seed point position will not affect the final result as much as in non-filtered image. With the proposed filtering method using Gabor filter we have obtained improvement in segmentation of dense tissue using region growing algorithm. Results of application of the same region growing method with and without image filtering are shown in Fig. 7 (b) and (c) where Fig. 7 (a) shows the original region of interest from "mdb006".

(a)	(b)	(c)
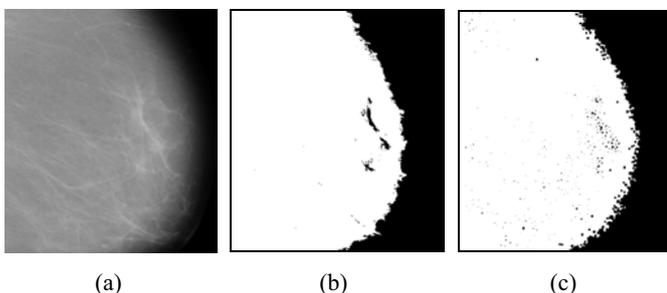
Figure 7.   (a) Original ROI from "mdb006"; (b) Result of region growing with stopping factor of 0.1 from original image; (c) Result of region growing with stopping factor of 0.1 from filtered image.

IV.   CONCLUSION

In this paper we have presented a method for mammographic image filtering using Gabor filters. Filtering images using Gabor filter with certain parameters has given us a possibility to remove blood vessels from mammograms and make a better distinction between fat and dense tissue. For this purpose we have decided to use Gabor filter with smaller number of wavelengths which is more sensitive to smaller objects and edges. The advantage of Gabor filter application over classical edge detectors is in easy orientation changing and possibility to cover all possible orientations by superpositioning of resulting filter responses. Usage of Gabor filter improves region growing performance when segmenting dense tissue in mammograms because it removes some false positive segmentations caused by superposition of fibrous tissue and blood vessels. Our future work in this field will be development of automatic segmentation algorithms for dense tissue in order to achieve quantitative breast density classification by knowing the exact amount of dense tissue.

REFERENCES

[1]   A. Oliver, J. Freixenet, R. Martí, J. Pont, E. Pérez, E.R.E. Denton, R. Zwiggelaar, "A Novel Breast Tissue Density Classification Methodology", IEEE Transactions on Information Technology in Biomedicine, Vol. 12, Issue 1, January 2008, pp. 55-65.

[2]   American College of Radiology, "Illustrated Breast Imaging Reporting and Data System (BI-RADS) Atlas", American College of Radiology, Third Edition, 1998.

[3]   I. Muhimmah, R. Zwiggelaar, "Mammographic Density Classification using Multiresolution Histogram Information", Proceedings of the International Special Topic Conference on Information Technology in Biomedicine, ITAB 2006, Ioannina - Epirus, Greece, 26-28 October 2006, 6 pages.

[4]   S. Petroudi, T. Kadir, M. Brady, "Automatic Classification of Mammographic Parenchymal Patterns: a Statistical Approach", Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Cancun, Mexico, Vol. 1, 17-21 September 2003, pp. 798-801.

[5]   M. Varma and A. Zisserman, "Classifying images of materials: Achieving viewpoint and illumination independence", Proceedings of the European Conference on Computer Vision, Copenhagen, Denmark, 2002, pp. 255–271.

[6]   Y. Zheng, "Breast Cancer Detection with Gabor Features from Digital Mammograms", Algorithms 3, No. 1, 2010, pp. 44-62.

[7]   J. Suckling, J. Parker, D.R. Dance, S. Astley, I.Hutt, C.R.M. Boggis, I. Ricketts, E. Stamatakis, N. Cernaez, S.L. Kok, P. Taylor, D. Betal, J. Savage, "The Mammographic Image Analysis Society Digital Mammogram Database", Proceedings of the 2nd International Workshop on Digital Mammography, York, England, pp. 375-378, 10-12 July 1994.

[8]   M. Mustra, M. Grgic, R. Huzjan-Korunic, "Mask Extraction from Manually Segmented MIAS Mammograms", Proceedings ELMAR-2011, Zadar, Croatia, September 2011, pp. 47-50.