Segmentation And Characterization Of Masses In The Digital Mammograms

**Corresponding Author:**
Dr. Rash Dubey,
Professor, ECE Dept, Hindu College of Engg, Sonepat, 121003 - India

**Submitting Author:**
Dr. Rash B Dubey,
Professor, ECE Dept, Hindu College of Engg, Sonepat, 121003 - India

**Article ID:** WMC00726
**Article Type:** Research articles
**Submitted on:** 24-Sep-2010, 05:29:08 AM GMT   **Published on:** 24-Sep-2010, 05:29:25 PM GMT

**Article URL:** [http://www.webmedcentral.com/article_view/726](http://www.webmedcentral.com/article_view/726)

**Subject Categories:** BREAST
**Keywords:** Breast cancer, Malignant Breast Masses, Digital Mammograms, MGRMG and Watershed Segmentation.

**How to cite the article:** Dubey R, Hanmandlu M, Gupta S. Segmentation And Characterization Of Masses In The Digital Mammograms. WebmedCentral BREAST 2010;1(9):WMC00726

**Source(s) of Funding:**
Not applicable.

**Competing Interests:**
N.A.

**Additional Files:**
total manuscript
Segmentation And Characterization Of Masses In The Digital Mammograms

Author(s): Dubey R, Hanmandlu M, Gupta S

Abstract

Breast tumor segmentation is needed for monitoring and quantifying breast cancer. However, automated tumor segmentation in mammograms poses many challenges with regard to characteristics of an image. A comparison of two different semi-automated methods, viz., modified gradient magnitude region growing technique (MGMRGT) and watershed method is undertaken here for evaluating their relative performance in the segmentation of breast tumor. A set of 6 mammogram images is used to validate the effectiveness of the segmentation methods. The MGMRGT segmentation shows better results than those due to watershed approach. The present application is intended to assist the radiologist in performing an in-depth examination of the breast at considerably reduced time.

Introduction

Breast cancer is the most common female cancer and the second leading cause of cancer death among women in America. A mammogram is an X-ray examination of the breast. Mammography is the only effective and viable techniques to detect breast cancer. It is proved that early stages of breast cancer are well treatable. X-ray mammography is the current, clinical Gold Standard for the detection of breast cancer. It is a well understood and standardized procedure, it works fairly well in postmenopausal women and it is inexpensive [1- 3]. The early stages of breast cancer may only have subtle indications which can be varied in appearance, making physical examination ineffective and making diagnosis difficult even for experienced radiologist [4, 10].

A mammogram mainly contains two regions: the exposed breast region and the unexposed non-breast region. It is necessary to first identify the breast region for the reduction of the subsequent processing calculation and the removal of the non-exposed breast region. Bick et al. [5] have explored a segmentation method for the breast region based on the morphological gradient calculation and the modified global histogram analysis. Ball et al. [6] present an automated mammographic computer aided diagnosis system to detect and segment spicules. Mendez et al. [7] have described an automatic algorithm that computes the gradient of gray levels. Wirth et al. [8] make use of the snakes and fuzzy approach [9] for the purpose of segmentation. Elter and Horsch [11] focused their view on approaches for mass and micro-calciﬁcation diagnosis, covering the segmentation of region of interests for extracting shape and contour features and their posterior classiﬁcation [12]. In particular neural network have demonstrated their efﬁcacy in the clinical domain with diseases such as cancer where there is a weak relationship between the classes forming a benign or malignant diagnosis [13-14]. Hassanien [15] proposed a hybrid scheme that combines the advantages of fuzzy sets and rough sets in conjunction with statistical feature extraction techniques. An application of breast cancer imaging has chosen and hybridization scheme have been applied to see their ability and accuracy to classify the breast cancer images into two outcomes: cancer or non-cancer. Du et al. [16] presented a framework for improvement of mammogram classiﬁcation, which includes a new preprocessing methodology for segmenting, a unique associative rule discovery based algorithm for classiﬁcation and an evaluation of efﬁcacy of raw derived features using fuzzy K-nearest neighbor and agglomerative clustering of associative features. A co-occurrence analysis is applied to identify statistically signiﬁcant differences in pathology co-occurrence patterns between premenopausal and postmenopausal women [17, 18].

This paper explores the comparison of the MGMRGT and morphological watershed approach for segmentation.

Methods

Modified gradient magnitude region growing technique (MGMRGT)

In the first step proper threshold is chosen in order to distinguish the interior area from other organs in the MR image dataset. Then modified gradient magnitude region growing algorithm is applied, in which gradient magnitude is computed by Sobel operator and employed as the definition of homogeneity criterion. This implementation allowed stable boundary
Results
The mammograms that are positive for the malignant mass are collected for this study from the mammography image analysis (MIAS) database. The total number of cases is 6. Mammograms come up with labels and contain noise and irregularities that need to be eliminated prior to the segmentation. This can be achieved by using several denoising techniques, viz. morphological open-close reconstruction filter and morphological top and bottom hat filtering.

The algorithm is implemented on personal computer (1.8GHz CPU, 2GB RAM). The proposed algorithms have been tested on 6 mammograms containing malignant masses. Expert-segmented data in all the images are provided in Table 1. All images are semi-automatically segmented and the results are compared with the corresponding expert-segmented ones.

We introduce two segmentation approaches for mammogram images and investigate its application to the detection of region of interest (ROI), which includes both masses and the pectoral muscles. In the mammograms, masses are assumed to be distinctive regions that are relatively brighter than the surrounding background, while the pectoral muscles appear to be more uniformly bright making their presence at a predictable location. Different tumor area obtained after MGMRGT and watershed segmentation are tabulated in Table 3 and the results are validated with manually segmented expert radiologist.

Table 1: Comparison of tumor area with an expert radiologist.

Conclusion(s)

Two semi-automated approaches are presented for the segmentation of a tumor. These overcome the accuracy and sensitivity limitations of the current solutions. Our goal here is to compare two popular techniques: MGMRGT and watershed with an expert’s manual segmentation. Recently attention is being paid to the semi-automatic segmentation methods on tumor measurements in order to avoid the observer variability and therefore to increase the accuracy. In the study of the reliability of the breast tumor area measurements, we quantitatively compare the expert manual trace method with semi-automatic segmentation methods. The semi-automatic segmentation techniques require very less time to generate tumor area measurements than the manual method. Manual method is highly labor intensive and requires more concentration than the semi-automatic method. Both methods have been tested extensively and results are validated numerically. The result shows that MGMRGT segmentation better than the watershed approach.

Authors Contribution(s)

Tested two methodology

References

11. M. Etler and A. Horsch, “CADx of mammographic
detection and segmentation in mammographic images,
13. P. Lisboa and A. Taktak, The use of artificial
neural networks in decision support in cancer:
14. P. Lisboa, A review on evidence of health benefit
from artificial neural networks in medical intervention,
soft cluster neural network for the classification of
suspicious area in digital mammograms, Pattern
16. A Hassanien, Fuzzy rough set hybrid scheme for
breast cancer detection, Image and Vision Computing,
17. S. Du, H. Singh and H. W. Thompson, Associative
classification of mammograms using weighted rules,
Hooke, C. D. Sriver and M. N. Liebman,
Co-occurrence analysis for discovery of novel breast
cancer pathology patterns, IEEE Trans Inf. Technol in
19. M. Sato, S. Lakare, M. Van and A. Kaufaman, A
gradient magnitude based region growing algorithm for
accurate segmentation, in Proc. 2000 Int. Conf. on
20. S. Saraswathy, F. Crawford and S. J. Nelson,
Semi-automated segmentation of brain tumor lesions
21. L. Vicent, and P. Soille, Watersheds in digital
spaces: an efficient algorithm based on immersion
simulations, IEEE Transaction on Pattern Analysis and
Machine Intelligence, 13(6):583-598, 1991
22. R. Van, D. Boomgard and R. Van Balen, Methods
for Fast Morphological Image Transforms Using
Bitmapped Images, Computer Vision, Graphics, and
Image Processing: Graphical Models and Image
23. R. Adams, Radial Decomposition of Discs and
Spheres, Computer Vision, Graphics, and Image
Processing: Graphical Models and Image Processing,
24. R. Jones, and P. Soille, Periodic lines: Definition,
cascades, and application to granulometrie, Pattern
Illustrations

Illustration 1

Table 1: Comparison of tumor area with an expert radiologist.

<table>
<thead>
<tr>
<th>Sample No.</th>
<th>Expert radiologist Area (mm²)</th>
<th>MGMRGT Method Area (mm²)</th>
<th>WS Method Area (mm²)</th>
<th>Relative Error (%) (MGMRGT)</th>
<th>Relative Error (%) (WS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1000.00</td>
<td>1090.78</td>
<td>900.32</td>
<td>8.32</td>
<td>9.07</td>
</tr>
<tr>
<td>2</td>
<td>85.70</td>
<td>78.36</td>
<td>70.10</td>
<td>7.75</td>
<td>8.56</td>
</tr>
<tr>
<td>3</td>
<td>1000.60</td>
<td>989.76</td>
<td>900.54</td>
<td>1.08</td>
<td>10.06</td>
</tr>
<tr>
<td>4</td>
<td>20000.30</td>
<td>20758.66</td>
<td>18684.43</td>
<td>3.79</td>
<td>6.58</td>
</tr>
<tr>
<td>5</td>
<td>2800.89</td>
<td>2758.13</td>
<td>2271.19</td>
<td>1.53</td>
<td>18.91</td>
</tr>
<tr>
<td>6</td>
<td>900.00</td>
<td>855.08</td>
<td>805.00</td>
<td>4.99</td>
<td>4.91</td>
</tr>
</tbody>
</table>
Illustration 2

Fig. 1: (a) Original image, (b) segmented mage, (c) extracted tumor after MGMRGT and ROI.
Illustration 3

Fig. 2: Watershed line with catchment basins.
Illustration 4

Fig. 3 (a-k): Various steps involved during watershed segmentation.
Illustration 5

continue..
Illustration 6

continue..
Disclaimer

This article has been downloaded from WebmedCentral. With our unique author driven post publication peer review, contents posted on this web portal do not undergo any prepublication peer or editorial review. It is completely the responsibility of the authors to ensure not only scientific and ethical standards of the manuscript but also its grammatical accuracy. Authors must ensure that they obtain all the necessary permissions before submitting any information that requires obtaining a consent or approval from a third party. Authors should also ensure not to submit any information which they do not have the copyright of or of which they have transferred the copyrights to a third party.

Contents on WebmedCentral are purely for biomedical researchers and scientists. They are not meant to cater to the needs of an individual patient. The web portal or any content(s) therein is neither designed to support, nor replace, the relationship that exists between a patient/site visitor and his/her physician. Your use of the WebmedCentral site and its contents is entirely at your own risk. We do not take any responsibility for any harm that you may suffer or inflict on a third person by following the contents of this website.