Automated Breast Ultrasound Using Adaptive Threshold For Multi-Dimensional Tumor Detection

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Abstract— Research in the segmentation of medical images will strive towards improving the accuracy, precision, and computational speed of segmentation methods, as well as reducing the amount of manual interaction. Accuracy and precision can be improved by incorporating prior information from atlases and by combining discrete and continuous-based segmentation methods. Automated Whole Breast Ultrasound (ABUS) is becoming a popular screening modality for whole breast examination. Compared to conventional handheld ultrasound, ABUS achieves operator-independent and is feasible for mass screening. The medical images consist a general framework to segment curvilinear 2D objects. The proposed method based on Adaptive Threshold algorithm is traditionally applied on image domain. The Adaptive Threshold algorithm and clustering based applied to gather similar tissues around local minima to be homogeneous regions. The likelihoods of being tumors of the regions were estimated using the quantitative morphology, intensity, and texture features in the 2-D False Positive Reduction (FPR). And classification normal and abnormal analysis using neural network using Matlab.

Keywords: segmentation, interaction, ultrasound, adaptive, Abus-image, clustering, classification.

I. INTRODUCTION

1.1 Overview

Breast cancer starts in the breast cells of both women and men. It is the fifth most common cause of cancer death. According to the National Cancer Institute (NCI), an estimated 207,090 new cases and 39,840 deaths from breast cancer (only women) are expected to occur in the United States, despite recent advances in treatment. Although breast cancer has very high incidence and death rate, the cause of breast cancer is still unknown. No effective way to prevent the occurrence of breast cancer exists. Therefore, early detection is the first crucial step towards treating breast cancer and plays a key role in breast cancer diagnosis and treatment. For example, given such circumstances, the 5-year survival rate for patients with breast cancer decreases from approximately 96% for cancers treated at an early stage to 77% formed-stage cancers to just 21% for late-stage cancers that have spread to distant organs. For better survival odds and reduced use of treatments and therapies and, fewer side-effects, many imaging modalities are continually being developed to diagnose the breast cancer at early stage currently using modalities include mammography, breast ultrasound, magnetic resonance imaging (MRI) and so on.

Especially, ultrasound (US) is one of useful diagnostic tools to distinguish benign from malignant masses of the breast. However, breast US remains controversial for screening because interpretation of the US images is greatly influenced by the scanning techniques and the sonographic features of the suspected abnormality. Thus the breast US exam is widely recognized to be one of the more difficult imaging procedures to perform and interpret. There is a considerable overlap benignancy and malignancy in ultrasonic images and interpretation is subjective.

Proposed a fully automatic scheme for detecting mass. The Canny edge detector was used to detect edges followed by the classification of near-vertical edges or near-horizontal edges. The near-vertical edges were regarded as the positions of tumor candidates. Then, the adaptive threshold was adopted to segment the located positions and generated the tumor candidate regions. Developed a CADe system for detecting breast tumors in multi-pass automated breast US.

II. PROPOSED SYSTEM

2.1 Ease of Use

Hundreds of slices in an ABUS image volume are time-consuming. A computer-aided detection (CADe) system based on watershed transform was proposed in this study to accelerate the reviewing.
The watershed transform was applied to gather similar tissues around local minima to be homogeneous regions. The likelihoods of being tumors of the regions were estimated using the quantitative morphology, intensity, and texture features in the 2-D/3-D false positive reduction (FPR). The collected database comprised 68 benign and 65 malignant tumors. As a result, the proposed system achieved sensitivities of 100% (133/133), 90% (121/133), and 80% (107/133) with FPs/pass of 9.44, 5.42, and 3.33, respectively.

2.2 Block diagram

As a modification, statistical parameters like adaptive thresholding features can be estimated and the type of tumor classified.

III. BASIC OPERATION

3.1 Input – RGB image:

RGB color model is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue. The main purpose of the RGB color model is for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography. Before the electronic age, the RGB color model already had a solid theory behind it, based in human perception of colors.

3.2 Gray conversion image

Grayscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white (also called bi-level or binary images). Grayscale images have many shades of gray in between.

3.3 Gray scale imaging single and multi coloring

Color images are often built of several stacked color channels, each of them representing value levels of the given channel. For example, RGB images are composed of three independent channels for red, green, and blue primary color components; CMYK images have four channels for cyan, magenta, yellow and black ink plates, etc.

The reverse is also possible: to build a full color image from their separate grayscale channels. By mangling channels, using offsets, rotating and other manipulations, artistic effects can be achieved instead of accurately reproducing the original image.

3.4 Clustering

Image-based pattern classification methods typically assume that the neurological effects of a disease are distinct and well defined. This may not always be the case. For a number of medical conditions, the patient populations are highly heterogeneous, and further categorization into sub-conditions has not been established.
A threshold map does not need to be generated pixel by pixel. Interpolation or least-squares methods can be used alternatively to create smoother threshold maps. The original image was subdivided into 36 (6 x 6) tiles, and in each tile, the pixel with the minimum intensity was located. A parabolic intensity function was chosen and the unknown parameters were determined using a least-squares fit. This intensity function, evaluated for each pixel, resulted in the threshold. In the special case of Figure 5.10B, the smooth threshold map with its fairly rigid parabolic function is not able consistently to separate the features from the background. The type of map that shows superior performance needs to be determined experimentally for each application.

3.6 Segmentation using adaptive k-mean clustering

Traditional statistical image segmentation algorithms, as simple as Thersholding or as complicated as K-mean and even fuzzy K-mean clustering, all classify the pixels into clusters based only on their intensity values. Each cluster is usually characterized by a constant intensity and no spatial constraint is imposed. Segmentation since the number of clusters is usually known for images of particular regions of human anatomy. In biomedical applications, the spatially varying intensity change of a biomedical structure is usually caused by inhomogeneity in the process of image acquisition.

In homogeneous distribution of the magnetic field gradient in MR imaging. It has been shown that such intensity change can be updated locally during the segmentation process through a maximum a posteriori (MAP) estimation scheme.

Table 3.1 Distinguishing between masses and FPs.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Wilk’s lambda</th>
<th>F value</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.965</td>
<td>201.910</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Ad</td>
<td>0.989</td>
<td>62.895</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>PCD</td>
<td>0.993</td>
<td>40.957</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>DAD</td>
<td>0.967</td>
<td>188.868</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>DWR</td>
<td>1.000</td>
<td>0.504</td>
<td>0.478</td>
</tr>
</tbody>
</table>

3.7.1 Feature Extraction

To generate the description of the scene or for image understanding, we usually need to recognize each of these regions. One of the
prerequisites of identification and recognition is feature extraction. By the term feature extraction, we mean determining various attributes as well as properties associated with a region or object.

3.7.2 Artificial neural networks

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows setoff instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do. Neural networks process information in a similar way the human breast does. The network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable. On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks that are more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks require systems that use a combination of the two approaches (normally a conventional computer). Statistical parametric mapping or SPM is a statistical technique created by Karl Freestone for examining differences in breast activity recorded during functional neuroimaging experiments using neuroimaging technologies such as MRI or PET. It may also refer to a specific piece of software created by the Welcomes Department of Imaging Neuroscience (part of University College London) to carry out such analyses. Unit of measurement, Experimental designs, Image pre-processing, Statistical comparison.

3.7.3 Image pre-processing

Images from the breast scanner may be pre-processed before any statistical comparison takes place to remove noise or correct for sampling errors. A study will usually scan a subject several times. To account for the motion of the head between scans, the images will usually be adjusted so each of the voxels in the images corresponds (approximately) to the same site in the breast. This is referred to as realignment or motion correction, see image realignment. Functional neuroimaging studies usually involve several participants, who will have slightly differently shaped breasts. All are likely to have the same gross anatomy, but there will be minor differences in overall breast size, individual variation in topography of the gyred and sulk of the cerebral cortex, and morphological differences in deep structures such as the corpus callous. To aid comparisons, the 3D image of each breast is transformed so that superficial structures line up, a process known as spatial normalization. Such normalization typically involves not only translation and rotation, but also scaling and nonlinear warping of the breast surface to match a standard template. Standard breast maps such as the Talairach Tournoux or templates from the Montréal Neurological Institute (MNI) are often used to allow researchers from across the world to compare their results.

IV. ULTRASOUND CAD

4.1 Ultrasound Breast Cad

It is not always easy for a human observer to provide objective evidence of the benignity or malignancy of the tumor. Although performance can often be improved by having two sinologists review US images, this strategy is not easily available. On the other hand, computer vision techniques may help detecting some of them and supplying numerical measurements of the presence and relevance of abnormal factors.

CAD has been developing fast in the last two decades. The main idea of CAD is to assist radiologists in interpreting medical images by using dedicated computer systems to provide second opinions.

<table>
<thead>
<tr>
<th>Table 4.1 BI-RADS US Descriptors</th>
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<tr>
<td><strong>Descrip</strong></td>
</tr>
<tr>
<td>Shape</td>
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<td>Orienta</td>
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</table>
Parametric Mapping algorithm for classification using MATLAB. The neural model considered hereby refers to classification MRI Image only with the same size of the breast medical images slice. Distinguish between normal and abnormal of the breast medical images. Extract the region of abnormal tissues using image processing tool in MATLAB. Analyzing the artificial neural networks model performance accuracy. Involves the artificial neural networks model coding, simulation, adaptation and training of the neuron using the MATLAB. This project starts with converting the Breast medical images into a form of data using MATLAB.

V. SOFTWARE SIMULATOR

5.1 Matlab
MATLAB is high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical.

MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non-interactive language such as C or FORTRAN.

VI. CAD SYSTEM

The proposed CAde system based on the analysis of regions composed of various tissues. The toboggan-based watershed was performed on the transverse planes of 2-D slices instead of using time-consuming 3-D segmentation for tissue segmentation. The acquired ABUS passes were composed of 318 slices. For a better efficiency, every five slices with slight variation in composition were overlapped in the transverse direction to reduce the number of slices.

4.2 Trans-Rectal Ultrasound Imaging

Trans-rectal ultrasound (TRUS) imaging is a procedure, in which a probe is inserted into the rectum. It emits high energy sound waves, which penetrate internal tissues or organs and produce echoes. Those echoes create an image of organs in the pelvis. Trans-rectal ultrasound (TRUS) images are widely used for the screening of the prostate gland. TRUS images may reveal prostate cancer, benign prostatic hypertrophy, or prostatitis. TRUS images may also be used to help guide a biopsy of the prostate. Analyzing breast ultrasound image is preprocessing that suppresses the speckle noise. On the other hand, edge-enhanced method is needed not to lose the important information for object boundaries and detailed structures in ultrasonic images. Finally, CAD should locate all suspicious nodules, before segmenting and analyzing the nodules.

4.3 Scope Of Methodology

Convert the Breast medical images into a form of data using MATLAB. Process the Breast medical images using PCA. Develop the Statistical...
Figure 6.1 Results of the suspicious abnormality extraction (a) Original image with in tumor circled. (b) Result after applying watershed transform to (a), and (c) The extracted suspicious abnormalities.

To extract the target suspicious abnormalities, regions with hypo-echogenicity compared to other regions were considered. Regions in a slice were sorted according to their average intensity values in ascending order. In the experiment, equal to or smaller than were extracted for further analysis. That is, 50% of brighter regions were removed according to their hyper-echogenicities on each slice. After removing the hyper-echogenic regions, anatomical location was the other criterion to determine nontumor regions. A tumor is an abnormal growth of neoplastic tissues existed in the breast area surrounded by skin, muscle, and shadows [Fig. 6.1(b)]. Removing the regions connected to the image border was expected to be meaningful in decreasing nontumors. As shown in the left and right regions in (c) corresponds to the shadows in (b). So are the top (skin) and bottom (muscle) regions. After removing these border regions, the final result of the suspicious abnormality extraction.

6.1 2-D/3-D False Positive Reduction

The extracted suspicious abnormalities were the tumor candidates in the further classification. Quantitative features were extracted from the tumor candidates and combined in a classifier for the distinguishing between tumors and nontumors. A 2-D/3-D FPR composed of applying 2-D FPR followed by 3-D FPR was used in the classification procedure. In 2-D FPR, the region characteristics were first described using the quantitative morphology, intensity, and texture features.

morphology and intensity features were extracted to remove regions with lower probabities than true tumor regions in 3-D FPR. Based on this approach, the spatial information of 2-D and 3-D spaces was modeled to filter out the regions with low likelihoods being tumors. The quantitative features are described in the following sections and are summarized.

6.2 Morphology Features

Morphology features extracted from tumor contour can provide useful information for tumor detection. Four morphology features including region size, compactness, size to bounding box ratio, and short to long axis ratio were implemented. The delineation of region boundary was obtained after the watershed transform. By calculating the region area [(2-D)] and region volume [(3-D)], noises or shadows with extremely small and large sizes can be distinguished and be removed.

A tumor is formed by an abnormal growth of neoplastic tissues. In other words, a tumor can be regarded a cluster of homogeneous region. The region size to bounding box ratio was used to describe the aggregation property of the region.
Table 6.1 Sensitivities of the cade system and the corresponding fps/pass.

<table>
<thead>
<tr>
<th>Sensitivity (%)</th>
<th>Mropology (n:4)</th>
<th>Intensity (n:4)</th>
<th>Te xture (n:16)</th>
<th>Mropology &amp; Intensity (N:8)</th>
<th>Mropology &amp; Texture (n:20)</th>
<th>Intensity &amp; Texture (n:24)</th>
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<tr>
<td>60</td>
<td>28.1</td>
<td>9.2</td>
<td>12.0</td>
<td>2.56</td>
<td>3.44</td>
<td>4.6</td>
</tr>
<tr>
<td>70</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>2</td>
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<td>4</td>
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<tr>
<td>80</td>
<td>39.1</td>
<td>11.1</td>
<td>20.0</td>
<td>4.43</td>
<td>5.83</td>
<td>6.6</td>
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<td>90</td>
<td>0</td>
<td>89</td>
<td>90</td>
<td>7.05</td>
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<tr>
<td>100</td>
<td>51.0</td>
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<td>1.37</td>
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<td>36</td>
<td>62</td>
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<td></td>
<td>124</td>
<td>19</td>
<td>25</td>
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<tr>
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<td>47</td>
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<td>106</td>
<td>127</td>
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<td>01</td>
<td>.11</td>
<td>.52</td>
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VII. RESULT AND SIMULATION
The proposed technique is applied to 2D TRUS images and can be extended to 3D TRUS images, where it may help in obtaining new valuable information from the images. Classification can be done through Artificial Neural Network (ANN) algorithm for normality and abnormality of the cancer.

8.1 Future Enhancement

In future work to increasing efficiency of detection of very minute part of breast tumour using removal of minute noise and algorithmic performance near to 99.5% accuracy.

REFERENCES


