SEGMENTATION OF BREAST CANCER MASS IN MAMMOGRAMS AND DETECTION USING MAGNETIC RESONANCE IMAGING

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Abstract
Breast cancer is one of the major causes of death among women. An improvement of early diagnostic techniques is critical for women’s quality of life. Mammography is the main test used for screening and early diagnosis. Contrast-enhanced magnetic resonance of the breast is the most attractive alternative to standard mammography. This paper presents a research on these two techniques and image processing techniques used for cancerous tumor mass segmentation. The processing techniques include fractal dimension analysis, image enhancement by filtering, morphological analysis and region growing algorithm.

I Introduction
Every two minutes a woman is diagnosed with breast cancer. Breast cancer has been one of the major causes of death among women since the last decades and it has become an emergency for the healthcare systems of industrialized countries. Breast cancer is the commonest cancer among women in Singapore [7]. Each year, about 700 women are diagnosed with this cancer. American statistics classify breast cancer as the second leading cause of death among women and the most common cause of death among women with an age between 40 and 55 years [12].

Breast cancer takes years to develop. It is commonly classified into four stages according to size of tumors and degree of cancer spread from the breast to other parts of the body. There is one pre-cancerous stage called ductal carcinoma in situ (DCIS) when a pre-cancerous lesion has not developed into a cancer tumor. In the first stage, a 0-2 centimeter tumor forms without spreading outside the breast. If the cancer is detected in this stage the five-year survival rate is 96% [12]. In the second stage, the cancerous cells form new malignant foci in positive lymph nodes or the tumor enlarges to 2-5 centimeter. In this stage, the survival rate drops to 73% [2]. In the third stage, a tumor is larger than 5 centimeters with positive lymph nodes, or a tumor has skin and chest wall involvement. The surgical intervention performed would be quite heavy; it may need partial or total breast removal and lymph nodes dissections. In the fourth stage, obvious metastases to other organs of the body, most often the bones, lungs, liver, or brain occur and the five-year survival rate drops to 20% [2].

Although breast cancer can be fatal, people have the highest chance of survival if cancer could be detected at the early stages. Early diagnosis and treatment play critical roles in increasing the chance of survival. My study involves a literature research on diagnostic techniques used for breast cancer and development of a computer-aided diagnosis tool using Matlab for breast segmentation in mammograms. Image enhancement techniques commonly used are spatial and frequency domain filters; moreover, fractal analysis could serve as a preprocessing stage before segmentation in mammograms. In order to extract boundaries of suspected tumor masses, region growing and morphological edge detection algorithms are implemented.

In this research, I use mammograms from the Digital Database for Screening Mammography (DDSM) established by University of South Florida [5] to evaluate effectiveness of the processing methods. The database contains approximately 2620 mammography exams. They are cataloged into normal, cancer and benign classes.

This paper is organized into five sections. In section II characteristics and limitations of standard examination, X-Ray Mammography is investigated. In section III I introduce the breast MRI examination. In section IV I describe several image processing methods used to enhance and segment the breast cancer mass for mammograms.

II. X-Ray Mammography
X-Ray Mammography is commonly used in clinical practice for diagnostic and screening purposes. Screening mammography has been recommended as the most effective method for early detection of breast cancer. Singapore Health Promotion Board (HPB) has launched BreastScreen Singapore (National breast cancer screening programme) on 17 January 2002 to encourage women aged 40 years and above to go for regular mammography.

Mammography provides high sensitivity on fatty breast and excellent demonstration of microcalcifications [2]; it is highly
indicative of an early malignancy. Due to its low cost, it is suitable for mass screening program.

Mammography has its limitations. It is less reliable on dense breast of young women or women underwent a surgical intervention in the breast because glandular and scar tissues are as radiopaque as abnormalities. Furthermore, there is low dose X-Ray radiation.

III. MRI of the Breast

Magnetic Resonance Imaging is the most attractive alternative to Mammography. MRI is sensitive for detecting some cancers which could be missed by mammography. In addition, MRI can help radiologists and other specialists determine how to treat breast cancer patients by identifying the stage of the disease. It is highly effective to image breast after breast surgery or radiation therapy. To be effective, contrast-enhanced breast MRI is carried out by injecting in the patient's body of a paramagnetic contrast agent. This method is based on the hypothesis that, after the injection of the agent, abnormalities enhance more than normal tissues due to their increased vascularity, vascular permeability and interstitial spaces [8]

MRI forms 3D uncompressed image. It can perform with all women including who are not suitable for mammography, such as young women with dense breast and women with silicone-filled breast implants. Since it uses magnetic fields, MRI has no harmful effects on human bodies.

However, MRI takes rather long time to perform and has high cost which is more than ten times greater than mammography. Its low resolution limits its application to very small lesions or microcalcifications.

IV. Image processing tools for tumor detection in Mammograms

Since screening mammography is currently the main test for early detection of breast cancer, a huge number of mammograms need to be examined by a limited number of radiologists, resulting misdiagnoses due to human errors by visual fatigue. In order to improve the diagnostic accuracy and efficiency, computer-aided diagnosis has been introduced into the screening process.

Currently, there are several image processing methods proposed for the detection of tumors in mammograms. Various technologies such as fractal analysis [10], discrete wavelet transform and Markov random field have been used [10]. In [11], a multiple circular path convolution neural network architecture has been designed for the analysis of tumor and tumor-like structures. In [3], Petrick et al. reported a two-stage adaptive density-weighted contrast enhancement (DWCE) algorithm for tumor detection in mammograms. These studies focus on two types of breast cancer: microcalcifications and masses. The performance of various methods reported in the literature in most cases has been measured on different data sets. The choice of database used by these researchers can influence the performance of their algorithms significantly [1]. Due to time limit, this paper aims to implement some conventional imaging processing techniques to detect mass in mammograms from DDSM of USF.

A. Spatial and Frequency Domain Filters

Spatial and frequency domain filters are widely used as tools for image enhancement. Low pass filters smooth the image by blocking detail information. Mass detection aims to extract the edge of the tumor from surrounding normal tissues and background, high pass filters (sharpening filters) could be used to enhance the details of images.

Sharpening spatial filters involved Laplacian and Gradient filters [6]. Convolution is the mathematical process involved. By changing the masks used during convolution, different types of filtering could be performed. For example, Laplacian of a Gaussian Filter (LoG) uses mask shown in fig 1[6].

\[
\begin{array}{ccc}
0 & 0 & -1 \\
0 & -1 & -2 \\
-1 & -2 & 16 \\
0 & -1 & -2 \\
0 & 0 & -1 \\
\end{array}
\]

(a)

(b)                    (c)
Filtering in the frequency domain makes use of Fourier transform. Input image is Fourier transformed before multiplying by a filter function. Gaussian and Butterworth filters are commonly used. Inverse Fourier transform is computed for the product and real part is obtained to construct the image. Fig.2 shows the results of second order Butterworth filtering and Gaussian filtering.

B. Fractal Analysis

Since for most mammograms, the image roughness of the regions containing masses are usually different form that of normal tissue, fractal technique could be used to detect these difference and remove the regions that do not contain tumors in the coarsest LL DWT subband image. Fractal analysis could improve the efficiency by processing segmentation on remained regions.

Mammograms are subdivided into 32×32 blocks and fractal dimension is calculated for each block. Fractal dimension D measures the roughness of the block. Since fractal dimension of a tumor involved region falls within a certain region, D could be used to locate the possible cancerous region. The area of fractal surface is given by equation (1).

\[
A_r = K \times r^{2-D}
\]  

where

- \(A_r\) surface area;
- \(r\) ruled area;
- \(K\) scaling constant;
- \(D\) fractal dimension indication the roughness of a given region.

Parameter D is computed by the Blanket Method [10]. Fig.3 shows the fractal processing result of a right breast mammogram.
C. Segmentation by Morphological Algorithm

Mathematical morphology is used as a tool for extracting image components such as boundaries in image segmentation. Since language of mathematical morphology is set theory, this segmentation approach is based on binary image. This algorithm includes two major steps: preprocessing and segmentation.

Thresholding is used to convert input image into binary image. Since tumor tissue tends to have maximum intensity in mammograms, normally closed to 1 in gray level, a global threshold could serve as the first cut in the process and convert the image into binary image.

Dilation and erosion are two basic morphological operations defined by equation (2) and (3) respectively [6].

\[ A \oplus B = \{ z \mid (\hat{B} \ominus z) \cap A \neq \emptyset \} \] (2)

\[ A \ominus B = \{ z \mid (B \ominus z) \subseteq A \} \] (3)

The simplest way to realize boundary extraction of a binary image A is given by equation (4) [6],

\[ \beta(A) = A - (A \ominus B) \] (4)

where B is a suitable structuring element. However, there could be noise present by this method, instead of using original binary image A; dilation of A, that is, \( A \oplus B \) could be used. Equation (5) is the resulting edge detection formula.

\[ \beta(A) = (A \oplus B) - ((A \oplus B) \ominus B) \] (5)

D. Segmentation by Region Growing

Region growing starts with a set of “seed” points and region grows by appending to each seed those neighboring pixels that have properties similar to the seed. Specific ranges of gray level are used as growing criteria.

This first procedure is determining the seed regions. When dealing with mammograms, it is known that pixels of tumor regions tend to have maximum allowable digital value (255 in uint8 images). Based on this information, thresholding is used to detect the possible clusters which contain masses. Image features are then extracted to remove those clusters that
belong to background or normal tissue as a first cut. Features used here include cluster area (total pixels involved in the cluster) and eccentricity. The centroid of the remaining clusters is used as seed.

There are two criteria for a pixel to be annexed to a region: (1) the gray-level difference between any pixel and the seed had to be less than a specified parameter $t$ which is 0.11 in this case. Parameter $t$ needs to be evaluated from experiments, (2) pixel is 4-connected to at least one pixel in the annexed region.

Fig.5. (a) The original image. (b) The output of region growing segmentation.

**V. Conclusions and future work**

In this paper I have characterized two techniques used for breast cancer detection. Mammography is widely used in diagnosis and screening. Besides Mammography, MRI could be studied further on its application to early stage detection of breast cancer. This paper also described some conventional image processing methods used for tumor mass detection in mammograms. These enhancement tools such as filters, fractal analysis, and segmentation algorithms like region growing and morphological operations could be applied to other image processing fields.

In future work, currently popular Artificial Intelligent techniques could be used into the segmentation and classification process to increase the efficiency and accuracy of computer-aided diagnosed tools. These techniques such as neural network could also be applied to segmentation and classifications of breast tumor in MRI images.

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**References**


