Detection of Breast Asymmetry by Active Contour Segmentation Technique

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Abstract - *A method for the detection of the breast boundary in mammograms is provided. The approach started with adjustment of the original image's contrast. A binary technique was then applied to the image, and an approximate contour of the breast was found using the active contour algorithm in Matlab. Finally, the identification of the true breast boundary was carried out using the estimated contour as the input to a specifically tailored active contour model algorithm for this purpose.*

Key Words: **Active contour algorithm, Matlab, Breast Asymmetry, contour segmentation, segmentation techniques**

1. INTRODUCTION

Breast cancer among women around the world is the most common type of cancer. Recent statistics suggest that breast cancer affects one in ten women in Europe and one in eight women in the United States [1]. More specifically, the second most common type of cancer is breast cancer and Nishikawa's fifth most common cause of cancer death [2]. Potentially fatal disease is nothing but breast cancer among women who have reached 40 years. The breast cells continue their growth and develop irregular breast tissue shapes that lead to cancer. It is not exactly known the cause of the disease. Many of the women's lives have been ravaged by the disease when they are not diagnosed early. Early detection is therefore the key to reducing breast cancer death rates and increasing a patient's lifespan. Clinically advised early detection successful tool that discloses breast cancer tissues up to two years before a patient or physician can feel or see some breast symptoms is mammography [1, 2].

Masses, calcifications, architectural distortion and observed bilateral asymmetry are considered in mammographic images as abnormalities. In various forms such as round, oval, speculated, nodular lobulated and stellate, masses also occur. In the present work, however, we are focusing on finding the suspect area of obscure masses which is a very important early-stage intervention to eliminate breast cancer. While mammograms are an effective tool for early detection, the detection of mammographic lesions is difficult because all masses may not be cancer. The tissues that are tightly compacted can also conceal some of the cancerous masses, both look white and fatty tissue on black background looks almost black. Therefore, recognizing the area of early cancer detection to help radiologists survive as a still warm automation mission. We have built an appropriate framework in the proposed method to address the difficulties addressed [3].

First, in the proposed study, each section is analyzed using different segmentation techniques to understand the foreground (breast region) and background (background) area.

2. RELATED WORK

Micro calcification is one of the most important symptoms of early breast cancer detection. image is acquired from the mini mias repository and performs various steps such as image enhancement, extraction of features and classification. In image enhancement, images are enhanced using filters and features are extracted from the enhanced image using Gabor filter and micro calcification is classified using support vector machine to categorize the masses into benign, malignant [4].

A new model of effective contours for the identification of features in an image based on curve evolution techniques, Mumford–Shah for segmentation and level sets. The model will detect objects whose boundaries are not automatically described by gradient. It to reduce the energy that can be considered as a specific case of a minimum partition problem. The problem becomes a "mean-curvature flow"-like evolving the effective contour in the level set formulation which stops at the desired boundary. Nevertheless, as in the classical active contour models, the stop term does not depend on the gradient of the image, but rather is connected to a specific segmentation of the image. It will use finite differences to give a numerical algorithm. Ultimately, it will present different experimental results and in particular some examples for which the gradient-based classical snakes methods are not applicable. The initial curve can also be detected anywhere in the image, and internal contours are detected automatically [5].

A dynamic K-means clustering algorithm to find regions of interest (ROI) in mammograms. This method is used to divide an image into a set of regions (clusters or classes) automatically. this approach consists of three phases: firstly, preprocessing images using thresholding and filtering methods; secondly, generating array of clusters by using Local Binary Pattern (LBP) and applying k-means with its features to automatically generate the optimal number of clusters (hereafter k is the number of clusters generated);

thirdly, partitioning mammograms images into k clusters Using the adaptive k-means clustering algorithm, end up detecting regions of interest (ROI) in images of mammograms. Here, it uses the Mini-MIAS (Mammogram Image Analysis Society, UK) database of 322 mammograms to illustrate the findings of method. The quality of system is evaluated using ROC (FROC) Free Response curves. The results archived are 2.84 false positives per image (FPpI) and 85 percent sensitivity [6].

Digital mammography has become the most effective method of early detection of breast cancer. Digital mammogram takes and stores a digital image of the breast directly on a screen. The purpose of the study is to build an automated system to support virtual mammogram analysis. Computer image processing techniques are applied to improve images, accompanied by region of interest (ROI) segmentation. The textural characteristics will then be extracted from the ROI. The texture characteristics will be used to classify the ROIs as masses or non-masses. In this analysis, normal breast images are taken from the electronic mammogram database of the Mammographic Image Analysis Society (MIAS) with masses used as the standard input to the proposed system. Masses are classified into speculated, circumscribed and unknown in the MIAS list. Additional information includes the location of centers of masses and the mass radius. Using gray level co-occurrence matrix (GLCM), which are constructed in four different directions for each ROI, extracts the textural characteristics of ROIs [7].

3. METHODOLOGY

Image segmentation is a system in which an image is partitioned into sections or regions. This division into sections is often based on the image's pixel characteristics. For example, looking for abrupt discontinuities in pixel values, which typically indicate edges, is one way to find regions in an image. Such edges are able to define regions. Other ways of splitting the image into regions dependent on color or texture values. Here we segment the mammography images. In the proposed study, each section is analyzed using different segmentation techniques to understand the foreground (breast region) and background (background) area. Different segmentation techniques are classified as:

1. **Active contour:** Segment image with active contours (snakes) in the foreground and background.
2. **Gray threshes:** Global image threshold using Otsu's method.
3. **Multithresh:** Multilevel image thresholds using Otsu's method.
4. **Otsu thresh:** Global histogram threshold using Otsu's method.
5. **Adapt thresh:** Adaptive image threshold using local first-order statistics.

Active contour algorithm: Image processing is a technique used to extract photo data. Segmentation is an image processing segment designed to separate or segregate data from the image's appropriate target area. Various techniques are used to segment pixels of interest from the image. Active contour is one of the active models of segmentation techniques, using the energy constraints and forces in the image to distinguish the area of interest. Effective contour determines a different boundary or curvature for the segmentation regions of the target object. The contour depends on different constraints that classify them into different types such as gradient vector flow, balloon and geometric models. Active contour models are used primarily for medical image processing for various image processing applications. Dynamic contours are used in medical imaging in the segmentation of regions from different medical images such as brain CT images, MRI images of different organs, cardiac images and different regions of the human body pictures. For movement tracking and stereo tracking, effective contours can also be used. Thus, for specific image processing, the effective contour segmentation is used to distinguish pixels of interest.

4. RESULT AND DISCUSSIONS

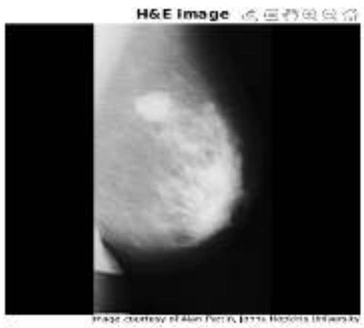

Fig -1: Original image

Fig 1 represents the mammographic image of original image with tumor present. It's a Malignant cell which represents final stage of breast cancer.

Fig -2: Initial contour and final contour

Fig 2 represents the mammographic image with active contour algorithm is applied. We can see that, two lines of figures present in it. It is the initial contour and final contour of the represntation.With the help of these represntation, fig 3 of ROI segmentation is obtained.

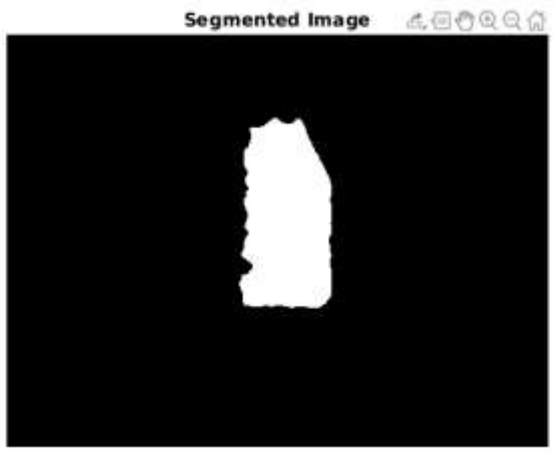

Fig -3: Segmented image

5. CONCLUSION

In this paper, we suggest a method for segmenting the ROI cell images of breast cancer collected through the mini-mias data set. The segmentation method takes advantage of prior knowledge that the leading protrusion of cancer cells is a distinct high-level characteristic of cell boundaries relative to other techniques. It performs Active contour technique to segment the Roi of Breast cancer cell. It is an effective method for segmenting the asymmetry portions of a mammography image.

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