Tumour Classification and Ellipsification for Breast Cancer in Mammogram Images using Image Processing in MATLAB

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Abstract

Recent advances in using quantitative ultrasound (QUS) methods have provided a promising framework to non-invasively and inexpensively monitor or predict the effectiveness of therapeutic cancer responses. One of the earliest steps in using QUS methods is contouring a region of interest (ROI) inside the tumours in ultrasound B-mode images. This contouring is done by manual segmentation which is a very time-consuming and tedious process where as auto-contouring is also an extremely difficult task for computers due to the poor quality of ultrasound B-mode images. For the prediction of cancer response cell, a rough boundary of the tumours as an ROI is only needed. In this work, a semi-automated tumours localization approach is proposed for ROI estimation in mammogram B-mode images acquired from the patients with locally advanced breast cancer (LABC). The proposed approach consist of some different modules, including 1) feature extraction using keypoint descriptors, 2) adding the feature descriptors with the distance of the keypoints to the user-input pixel as the center of the tumours, 3)a support vector machine (SVM) to classify keypoints as "tumours" or "non-tumours", and 4) ellipse as an outline of the ROI representing the tumours. These process with the B-mode images from LABC patients yielded promising results with an accuracy of about 80 to 90% using random functions. These results demonstrated that the proposed method can be used as the first stage in a computer assisted cancer response prediction system for semi-automated contouring of breast tumours.

Keywords - *Image Enhancement, Image Segmentation, Image Classification.*

I. INTRODUCTION

In this technique the tumor cells are identified by using classification and ellipcification process. The main aim of this process is to predict a means to assess the individual report to treat them early by this approach.There are several functional imaging modalities such as Magnetic Resonance Imaging (MRI), Diffuse Optical Spectroscopy (DOS), and Positron Emission Tomography (PET) that can provide imaging at a microscopic level to detect dead cells. The two main drawbacks of these imaging technologies include: (i) the requirements for a large capital investment and an external agent (ii)The latter is also expensive, and may cause some side effects and allergic reactions. In contrast, Quantitative UltraSound (QUS) methods in mammogram images provide a portable, non-expensive, and noninvasive means for a rapid acquisition of functional images that can be used for an early assessment of cancer cells. Moreover, in QUS methods, the endogenous contrast – generated by the process of cell death which is employed in treatment assessment, which reduces the requirement for injecting external agents. The applications of QUS methods have recently been extended from cancer response monitoring the tissue characterization (or) visualization using 3-D Automated Breast UltraSound (ABUS) scanners. The first major step in the implementation of each of these applications is to contour a Region of Interest (ROI) inside the tumours in frames with identifiable tumours areas. This step is currently performed manually as there is no automated software to segment an ROI in ultrasound B-mode images. The manual segmentation of tumours is a very time-consuming task. With the availability of 3-D scanners such as ABUS technologies, the problem will be even more severe to be contoured in each patient. Therefore, designing an automated segmentation method can save a significant amount of expert's time and efforts. In this work, a semi-automated supervised tumours localization method was proposed for ROI estimation in B-mode images gethered from patients with Locally Advanced Breast Cancer (LABC) and determining their accuracy of the cancer cells.

II. BACKGROUND

Several segmentation techniques has been tried for different mammogram images.Different classification techniques were applied on some expressive features have been employed to extract segments from the images.These classification techniques include some methods like FAST,SURF,BRISK and some simple methods like k-means and Fuzzy c-means(FCM).

k-mean algorithm

k-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed apriority.

Fuzzy c-mean algorithm(FCM)

FCM is a method of clustering which allows one piece of
data which belongs to two or more clusters

III. METHODOLOGY OF PROPOSED WORK

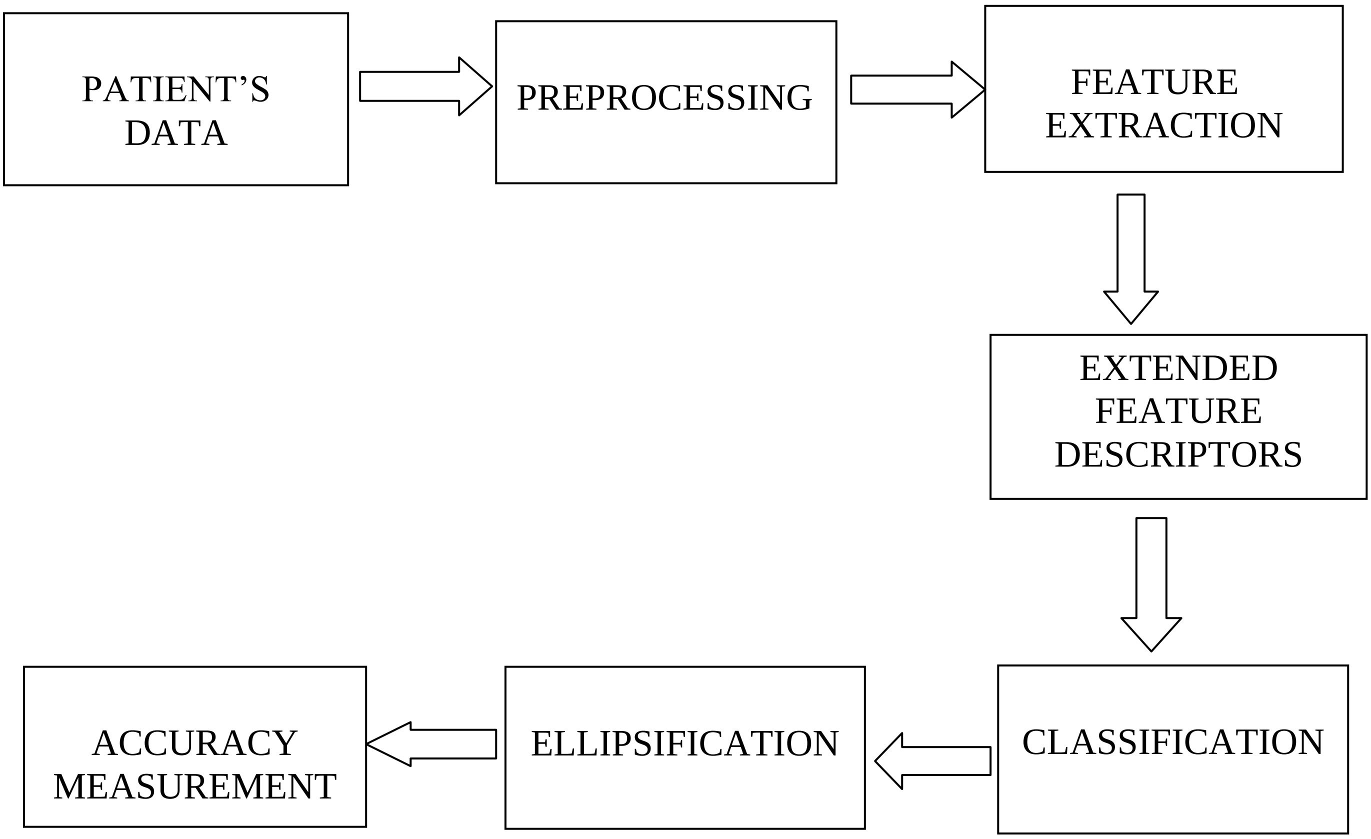


Fig.1: BLOCK DIAGRAM OF THE PROPOSED WORK

A. Proposed work and Developments

Patient Data

This work involved collection of Locally Advanced Breast Cancer (LABC) patients with tumours sizes between 5 and 15 cm or without tumours cells. The data acquisition was performed in accordance with the clinical research. A biopsy is used as the good standard test to confirm the cancer cases. In order to measure the size of tumours, all patients were imaged using MRI. Also, all patients were imaged using ultrasound before the start of chemotherapy ("pre-treatment").

B. Preprocessing

The quality and the contrast of B-mode images are increased during this process before going tofeature extraction, each and every images were pre-processed by applying Fuzzy histogram Hyberbolization [8].As well as 3×3 median filter was applied to each image [6] to remove the unwanted noises.

C. Feature Extraction

The features of the preprocessed image were extracted from the key points for the submission of extracted features to the classifier .The three main feature extracted algorithms are SURF, FAST, and BRISK.SURF is a feature detection method[9]. BRISK detector is used to find the scale of each keypoint in a continuous scale space [10]. FAST is a corner detection method [5]

D. Extended Feature Descriptors

After applying the feature extraction , a feature descriptor of size m for each key points was applied to characterize the image. This method describes the elementary characteristics of the key points. In above two methods, we did not obtain the strong correlations between the tumours and the feature points[3].

E. Classification

Classification is done by using a Support Vector Machine (SVM) with a radial basis function (RBF) kernel was used to classify the keypoints in each images as "tumours" or non-tumours pixels based on the extended feature descriptors. In addition, the k-

Mean and Fuzzy C-Means (FCM) [4] were also used for classification of the key points in the similar way for the purpose of comparison with the SVM performance.

After classification of all the key points as tumours and non-tumours pixels. The images are ellipsed by using ROI (Region of Interest).Consider that there are n points in the image. For ellipcification, first find position of all the n points in vertical and horizontal direction. This vertices is used as a boundary of ROI for representing the tumours.

F. *Accuracy Measurement*

The accuracy of the classification result was measured by using Dice Coefficient calculation. The Dice coefficient is given by,

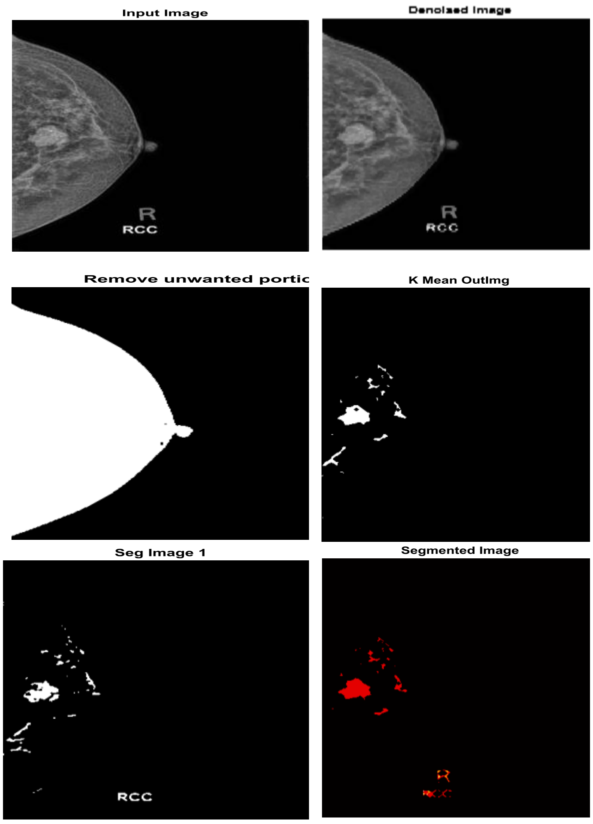
A= (b11-a11)*rand (1, 1,'double')+a11

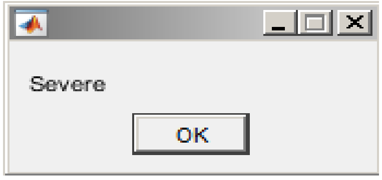
Where b11 is the fitted ellipse image and a11 is the ground-truth. It can be interpreted as a measure of overlapping the estimated and correct classes [11].

Result

The below figure shows the classified and ellipsified image.In this result the comparison between the preprocessed,denoised images and the original images shows the improvement in the quality of the B-mode image after preprocessing.

IV. RESULT





. **Fig 2: Preprocessed, Ellipsified and Classified image**

V. CONCLUSION

The results of ellipsification using the dice measure on all the B-mode images for various feature descriptors and classifiers are used for this work. The highest accuracy is of about 80% with the standard deviation of 17.5% using the SURF features and SVM classifiers. This classifier improves the features of the B-mode images. Depending upon tumours cells the accuracy can vary from 70% to 80%.The original mammogram images exhibits very poor quality. The proposed work produces a promising results of the mammogram images.

In future work, a large image dataset will be used for this process. This will increase the chances of adding the images of different size and shapes, which will help to be completely automate the approach.

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