Application Of Contour Models For The Detection Of Cancer Tumors In Breast Tissue

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Abstract

This paper deals with a qualitative analysis to focus on the application of deformable models for mammogram image analysis. Also demonstrate the use of contour models for the identification of any cyst/tumor/lesions etc in the breast tissue from a mammogram. The images are obtained from the famous mini-MIAS mammogram image data base for conducting experiments. The active contour model software has been employed on the mammogram images which visually reveal tumors, lesions etc. and the results have shown better performance in the detection of boundary of any abnormalities. The results have been validated by visual inspection by an expert radiologist.

INTRODUCTION

There are several reasons why active contours offer an appropriate approach to the process of breast region extraction. The principal reason is that the breast is a well defined curve and as such is amenable to the curve approximation characteristics of active contours. In addition, the background in most mammograms is a low intensity, low gradient region, and as such can be avoided by the active contour in its search for a local minimum. However it is anticipated that there will be several issues to resolve before using active contours with mammograms:

- Medium intensity noise may inadvertently attract the active contour away from the breast region if it is too close to the initial contour.
- The breast-air interface is typically a medium gradient, so any energy functional based on edges will need some preprocessing.
- The initial contour will have to be placed relatively close to the desired breast contour.

PREVIOUS WORKS

A semi-automated method based on the concept of "united snakes" is described by Ojala et al. It uses an interactive boundary tracing technique called livewire to initialize the snake. The united snake compactly unifies the most significant snake variants, allowing the user to choose the most appropriate snake. The algorithm is tested on mammograms from mini MIAS database. The "basic" snake as defined by Kass etal .would give results to mark the breast tumor contours, however no mention is made of the extent of the testing, and the illustrated mammograms which contain visible contours. Ojala et al later describe an active contour method for smoothing breast contours in mammograms as part of a comparison with two other methods, namely Fourier smoothing and B-Spline approximation. The method described in the paper follows a traditional threshold and filtering pre-processing step prior to snake activation. First a method for finding the traditional "bend" in the threshold curve that signifies the transition from background to breast values is used. A window of histogram bins is used to measure discontinuity, the measure being a squared sum of differences. The discontinuity is used to determine the bend position, and hence the threshold intensity. Morphological filtering is then used to smooth the boundary of the binary image, and objects outside the breast region are removed. The only other known work incorporating the use of active contours for segmentation of the breast region is that of McLoughlin and Bones. They first derive an approximate separation of the breast region and background using a global threshold applying the algorithm of Otsu. Pixels below this threshold are used to obtain a model of the background of the mammogram using Poisson approximation. The threshold found by the Poisson model is used to form a binary mask from which an initial contour can be extracted and is smoothed using the greedy snake algorithm. The algorithm reports acceptable results when tested on 40 mammograms.

THE THEORY OF ACTIVE CONTOUR MODELS:

Active contours, or “snakes” were introduced by Kass et al. and are local minimum seeking contours. By placing the contour near desired image features, the snake essentially “slithers” to the points by taking a minimum energy measure of all possible points in an neighborhood surrounding each point. In general, the energy measure of a snake contains internal and external forces. The internal forces regulate the ability of the contour to stretch or bend at a specific point while preserving some degree of geometric smoothness. The external forces attract the contour to specific image features. The snake's general form, described by Kass et al represents a contour by a vector having the arc length, s. The equation for the energy measure is given as:

Figure 1

$$E_{snake} = \int (E_{int}(v(s)) + E_{ext}(v(s)) + E_{image}(v(s)))ds \qquad (1)$$

E_{int} represents the internal energy of the contour due to bending or discontinuities, E_{image} represents the energy from the image forces, and E_{ext} represents the optional external constraints energy. The internal energy that maintains the snake's structure and resists singular deformations and is given by:

Figure 2

$$E_{int} = 1/2(\alpha(s)|v_s(s)|^2 + \beta(s)|v_s(s)|^2) \qquad (2)$$

The values of α and β at a point determine the extent to which a contour is allowed to stretch or bend. If α is zero, discontinuities can occur at that point. If β is zero, curve discontinuities (i.e. a 90 °sharp corner) are permitted. Kass et al. approximate the derivatives in Eq.(2) using finite differences as :

Figure 3

$$\frac{dv_i}{ds} \cong |v_i - v_{i-1}|^2 + (y - y_{i-1})^2 \qquad (3)$$

Figure 4

$$\left|\frac{d^2 v_i}{ds^2}\right|^2 \cong |v_{i-1} - 2v_i + v_{i+1}|^2 = (x_{i-1} - 2x_i + x_{i+1})^2 + (y_{i-1} - 2y_i + y_{i+1})^2 \qquad (4)$$

However, there are several limitations to snakes based on variational principles:

- Sensitivity to initial contour position and internal parameters: The quantity of parameters and the sensitivity of the snakes to them makes its behavior unpredictable.
- Sensitivity to noise and weak edges: The snake is susceptible to being drawn towards undesired local minimums.
- Convergence of points: A suitable local minimum could be missed if a time-step is too large, or an oscillation could occur between two pixels surrounding a local minimum.
- Manual initialization: The initial contour should be placed near the desired contour.
- Lack of hard constraints: It is not easy to enforce a hard constraint such as keeping points a certain distance apart to avoid points on the contour converging. This initial method was significantly improved by Amini et al who converted the active contour into a dynamic programming problem. Their approach eliminates three of the problems (convergence, hard constraints, instability) and guarantees a global optimal solution for the neighborhoods surrounding the points, but suffers from time complexities. Given a contour of n points which are allowed to move to any point in a mm neighborhood at each iteration, this algorithm is rated at O(nm3). The snake described in this work is based on the ACM designed by greedy method of Williams and Shaw

This algorithm incorporates the improvements of the dynamic programming approach while improving the time complexity from O(nm3) to O(nm).This algorithm uses an energy measures of the form given by

Figure 5

$$E_{snake} = \int (\alpha(s)E_{int} + \beta(s)E_{image} + \gamma(s)E_{image} \qquad (5)$$

This equation is similar in form to Eq.(1). The first two terms represent the continuity and curvature terms corresponding to E_{int} in Eq.(1) which ensures that the contour does not shrink and remains smooth. The last term, E_{image} , measures some image quality such as intensity or edge strength, and is equivalent to the middle term of Eq.(1). The parameters α,$\beta$and γ are used to balance the influence of the three terms. The basic algorithm searches a 3X 3 neighborhood surrounding the current point vi . .The energy term is calculated for all eight positions in the neighborhood, and the previous point vi-1 and next point vi+1 are used for calculating continuity and curvature constraints. The point is moved to the lowest energy term in the neighborhood, and the next point is calculated.

THE PROPOSED SEGMENTATION ALGORITHM

Applying snakes to a mammogram is a trivial task. The uncertain location of the breast contour means that initial placement is critical. There are several observed properties concerning mammograms that can be used to help make snakes a viable method for mammogram segmentation:

1. the breast-air interface itself is a very low gradient and may be obscured by noise,
2. the uncompressed fat near the breast-air interface is a gradient, growing as the fat nears the centre of the breast,
3. the breast region is the largest feature in the mammogram. From observation (i) we see that the method will have to include some sort of noise removal to allow the snake to distinguish between the breast contour and the noise in the mammogram. Snakes are designed to fill in gaps which occur in contours, so are well suited to dealing with contour detail which is lost during the process of noise removal. From observation (ii), two points can be inferred. First a right-to-left edge detection will pick up the gradient of the breast as an edge when the breast is approaching “from” the left. In contrast, a left-to-right edge detection will not pick up the breast contour but will pick up noise and other artifacts. Secondly, a dual threshold will produce a difference in terms of the breast area detected. By taking this difference, one should be able to obtain an approximate location of the breast contour. The method uses this in association with a least squares fit of these points to achieve an initial placement of the contour. The last observation is useful in the threshold portion of the algorithm to determine which object is the breast. The fact that the breast region is usually the largest object makes this trivial. With these three observations, a method has been designed for segmenting the breast region in mammograms. Note that this applies to right-facing mammograms; directional dependencies are reversed for left-facing mammograms.
4. The steps include:
   a. Perform a dual threshold on the original mammogram to identify all possible initial placement points. The initial threshold is partially determined using the Unimodal threshold algorithm
   b. Run the initial placement points through an algorithm for a least-squares fit piecewise quadratic curve, and take points at intervals along this curve to get the initial placement points of the snake.
   c. Perform a right-to-left edge enhancement and equalization of the original mammogram to obtain the breast contour edge image. Perform a left-to-right edge enhancement on the original mammogram, perform grayscale erosion and use this as a noise mask on the breast contour edge image.
   d. The snake's image energy measure is defined as a right-to-left and down-to-up gradient functional. Start and end point movement of the snake is limited to make an open contour. A small factor is used on left neighbors of control points to favour the snake movement to the left, since in most cases the breast will be to the left of the initial placement.
   e. Generate a mask image from the final resting place of the snake points, and take this as the tumor contour.

EXPERIMENTAL RESULTS

The algorithm has been tested on 10 mammograms from the MIAS mammogram database. Each of the mammograms was manually segmented into breast- and background-regions, to facilitate quantitative analysis of the segmentation results. There were two types of quantitative errors classified. Pixels in the manually segmented mammogram that were identified as breast but were identified as background in the processed mammogram are dubbed “breast miss”. Similarly, pixels segmented as background in the manually segmented mammogram but identified as breast in the processed mammogram are dubbed "background miss" pixels.

Figure 6

Figure 1: Contor on mdb007

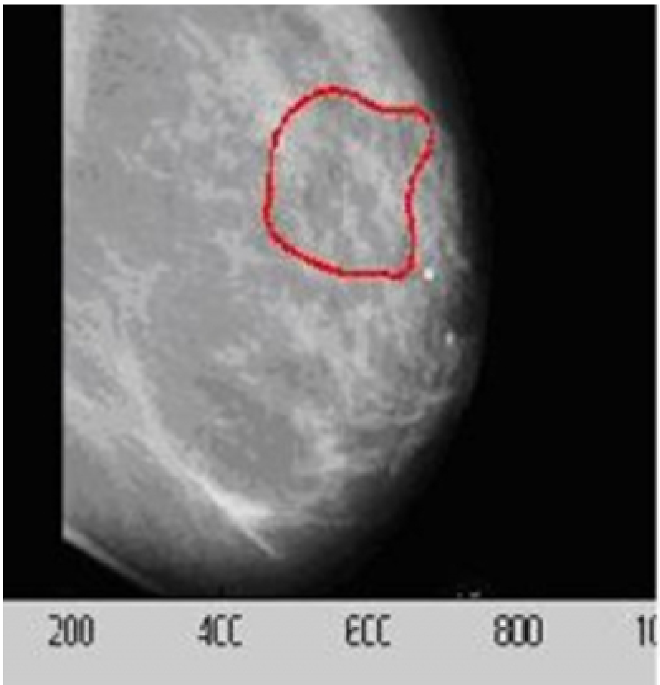


Figure 7

Figure 2: Contor on mdb032

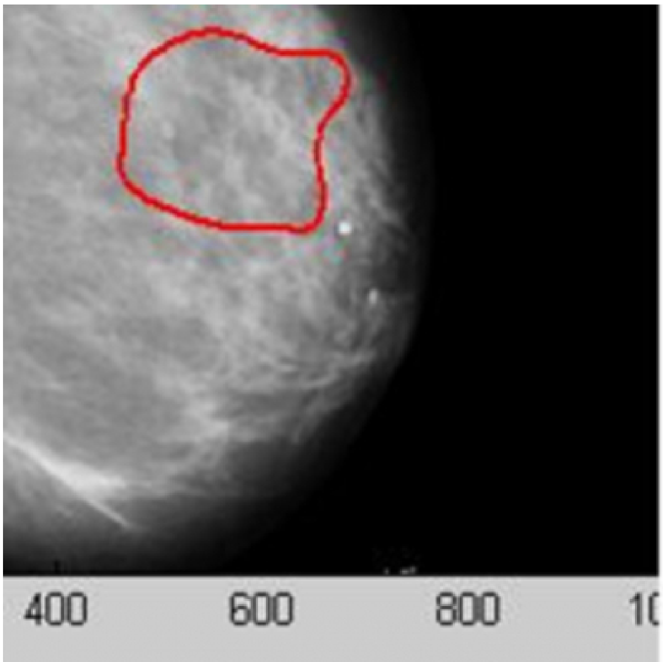


Figure 8

Figure 3: Contor on mdb0332

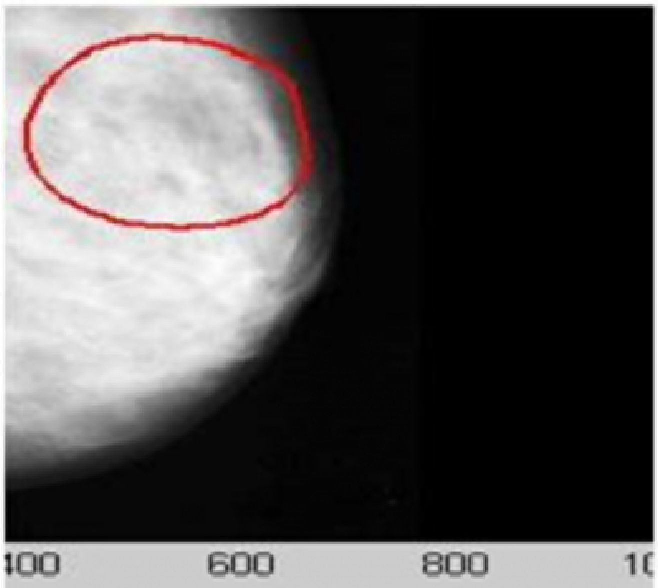
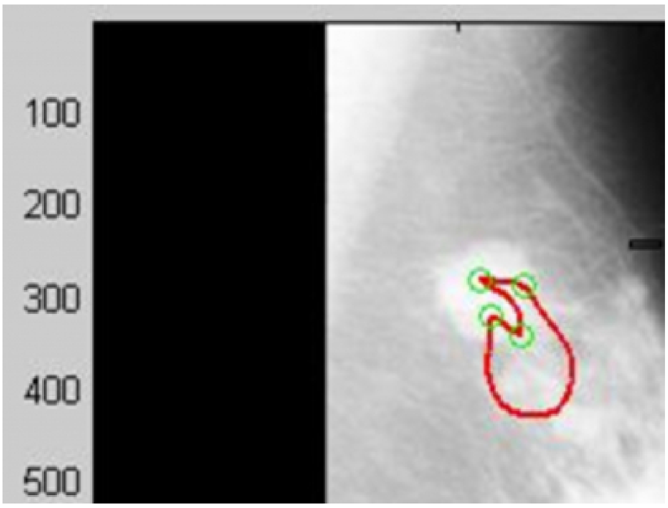


Figure 9

Figure 4: Contor on mdb028



ANALYSIS OF RESULTS

Four cases of the breast region segmentation performed on the MIAS mammograms are shown in the above figures. The images portray the original mammogram, the edge image generated, the extracted breast region represented by a binary image, and the contour superimposed on attenuated version of the original. In all the cases the active contour has closely approximated the breast contour, however the contours are slightly beyond the breast region, reflected in the high background .Several conclusions can be made from the above figures.

1. The amount of pixel error versus the amount of

background error varies significantly. It was observed that images with a large difference in the two errors primarily had errors in region detection. A large relative background classification error often resulted from the snake catching onto image noise outside the breast region. A large relative breast region classification error often resulted from the snake being unable to identify a gradient edge on the outside of the breast region and bringing the contour in too far.

2. On the average, breast error percentages were less than background error percentages: 1.6% on average for breast region, 1.1% for the background.

3. An attempt has been made to approximate the tumor size and found to be exact as identified by an expert radiologist.

ACTIVE CONTOUR ERROR

There exist some error in the active contour drawn by the snake and that drawn by an expert radiologist who visually observed the mammograms. It has been found that the error is negligible .This error may be due to the contour being pulled towards image noise. Increasing the alpha term can help to alleviate this, but in doing so, the remaining parameters have to be re-evaluated and adjusted. Weak breast gradient was found in 4 of the 10 images. This resulted in the breast being classified as background since the image functional was not strong enough. Increasing the gamma-coefficient would help this, but also aggravate noise problems. The algorithm fails to adequately segment the nipple when it is in profile in a mammogram.

As can be seen from the listed problems, parameters play a large part in how well the snake works. The primary parameters of concern are the gradient scaling factor present in the initial contour identification, and the left boost factor in the snake algorithm. The effect of how varying alpha affects the amount of error is shown in Fig.4. Lower values of alpha significantly increase the error rate, especially when curvature is ignored.

CONCLUSIONS

A method has been described for applying active contours to the task of segmenting the breast region in mammograms and extracting the breast contour. The method uses knowledge from the mammogram problem domain to automate the initial placement of the snake, and process the image into a suitable input for an active contour. Preliminary results indicate that, in terms of the amount of the mammogram classified as breast region, it is comparable to existing techniques. One of the significant shortcomings of this method is the inability of the snake to recognize when it is inside the breast. If such a situation occurs, the snake will segment on subcutaneous tissue instead of the breast contour. Future work will focus on tailoring snake parameters and extending the concept on active contours to exploit neural networks in a algorithm we term neural snakes.

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