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MRI Breast Skin-line Segmentation and Removal using Integration Method of Level Set Active Contour and Morphological Thinning Algorithms

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In the MRI breast Computer Aided Detection systems, skin-line segmentation and removal is a vital process. Similar intensity levels of the skin-line and the other parts of the breast image such as; dense tissue and tumor could possibly lead to faulty tumor segmentation if the skin-line is not removed correctly. In this study, a technique for skin-line segmentation and removal is presented. The approach integrates two algorithms. Level Set Active Contour algorithm is used to segment the breast skin border; the Morphological Thinning Algorithm is used to delete the detected breast skin-line. The approach is applied and tested on the RIDER breast MRI dataset and the results are evaluated using six measures. The evaluation results show high performance for the proposed approach with accuracy of 0.9607 for the skin-line segmentation stage and 0.9099 for the removal stage.

Key words: Breast MRI, computer aided detection, skin-line segmentation, skin-line removal, level set active contour, morphological thinning

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INTRODUCTION

Several of the commonly used medical screening techniques used for breast screening such are; mammography, ultrasound and Magnetic Resonance Imaging (MRI). Mammograms and ultrasound are difficult to interpret because of the sensitivity of screening is affected by the image quality and the radiologist's level of expertise (Rangayyan *et al*., 2007). While MRI images are clear and have better contrast between most of the breast regions. For that reason, MRI is used for breast screening. Although, some regions in MRI breast images have the same intensity values and that may affect the segmentation process.

Therefore, the MRI breast images are enhanced using computer techniques of image processing in Computer Aided Detection (CAD) systems that help radiologists in detecting the tumour regions.

The intensity level between the breast skin-line and the tumor regions is similar in the majority of MRI breast cases. Thus, segmenting and removing the breast skin-line region methods will be discussed in this study. Without this, segmentation errors may occur if not managed correctly (Solves Llorens *et al*., 2012). This process would be more importance in the next stage of the automatic tumor segmentation in CAD systems.

MATERIALS AND METHODS

The proposed approach of MRI breast skin line segmentation and removal consists of three main stages. These are: image pre-processing using the median filter, followed by skin line segmentation using Level Set Active Contour which is applied on the resultant image in the first stage. The last stage involves skin line removal using Morphological Thinning. The following is a detailed description of the processes involved.

Image pre-processing: As mentioned, the pre-processing phase is the first process that is executed. The median filter is applied in order to enhance the images' resolution and to reduce the presence of the salt and pepper noise.

Breast skin-line segmentation: To segment the breast skin line, Level Set Active Contour algorithm (Li *et al*., 2005) is used. Level set formulation without re-initialization (which is specially known as Chunming's algorithm) is included as one of the active contour's detection algorithms. Active contours are dynamic curves that move toward the mass border. An external energy moves the zero level curves toward the mass border using the edge indicator function g that is defined in Eq. 1:

$$g = \frac{1}{1+|\nabla G_\sigma \times 1|^2} \quad (1)$$

where, I is the image, G_σ is the Gaussian kernel with a standard deviation σ. By changing the σ parameter value and the number of the iterations N_{LS}, the resultant detection is changed. Figure 1 shows the different results after Level Set Active Contour algorithm with different values of σ and N_{LS} is applied.

Based on Fig. 1, it can be observed that the higher number of iterations N_{LS} gives better detection. Therefore, the best value for N_{LS} is 700 while the best value of σ is 1.5. These choices of the values are generic for all breast MRI images after resizing the image to be 288×288 pixels.

Breast skin-line removal: In order to delete the detected breast skin border, the Morphological Thinning Algorithm as described by Lam *et al*. (1992) is used. The image is divided into two distinct sub-fields. Then in the first sub-iteration, pixel p from the first sub-field is deleted if and only if the first three conditions as shown below are

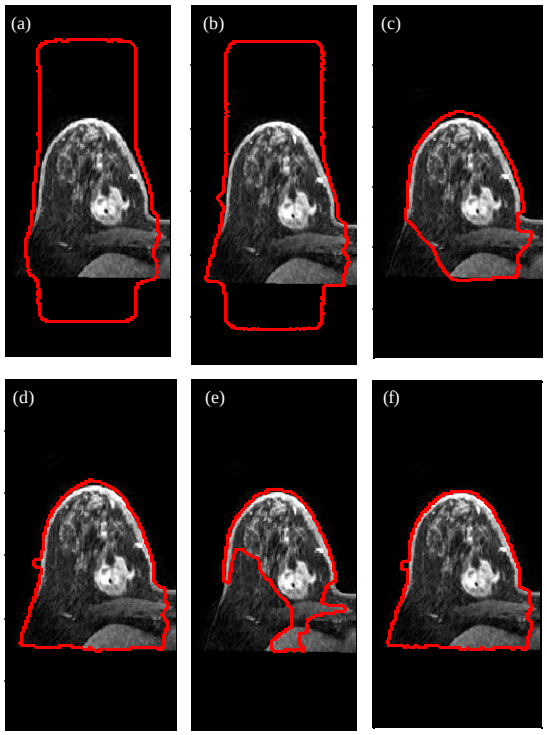

Fig. 1(a-f): Different results after the application of level set active contour algorithm with different values of σ and N_{LS}. (a) σ = 3, N_{LS} = 100, (b) σ = 1.5, N_{LS} =100, (c) σ = 3, N_{LS} = 300, (d) σ = 1.5, N_{LS} = 300, (e) σ = 3, N_{LS} = 700 and (f) σ = 1.5, N_{LS} = 700

true. In the second sub-iteration, pixel p from the second sub field is deleted if and only if, the first two and fourth conditions are true.

First condition:

$$X_H(p) = 1 \quad (2)$$

Where:

$$X_H(p) = \sum_{i=1}^{4} b_i \quad (3)$$

$$b_i = \begin{cases} 1, \text{ if } x_{2i-1} = 0 \text{ and } (x_{2_{2i}} = 1 \text{ or } x_{2_{2i}} = 1) \\ 0, \text{ otherwise} \end{cases} \quad (4)$$

$x_1, x_2, ..., x_8$ are the values of the eight neighbours of p, starting with the east neighbour and numbered in counter-clockwise order.

Second condition:

$$2 \leq \min\{n_1(p), n_2(p)\} \leq 3 \quad (5)$$

Where:

$$n_1(p) = \sum_{k=1}^{4} x_{2k} - 1 V x_{2k} \quad (6)$$

$$n_2(p) = \sum_{k=1}^{4} x_{2k} V x_{2k+1} \quad (7)$$

Third condition:

$$(x_2 \vee x_3 \vee \bar{x}_8) \wedge x_1 = 0 \quad (8)$$

Forth condition:

$$(x_6 \vee x_7 \vee \bar{x}_4) \wedge x_5 = 0 \quad (9)$$

The two sub iterations formulate the main iteration of the thinning algorithm. The thinning level depends on the number of iterations. Whenever the number of iterations is increased, there would be more shrinking of the image's border. The Morphological Thinning Algorithm only accepts a binary version of the image. Therefore, the resultant image after the Level Set Active Contour algorithm would be converted to binary image. Furthermore, after the thinning procedure, the binary image is reconverted into its original grey scale representation. Figure 2 shows the results after the Morphological Thinning algorithm is applied using three different iteration numbers (N_{Th} = 1, N_{Th} = 3 and N_{Th} = 7).

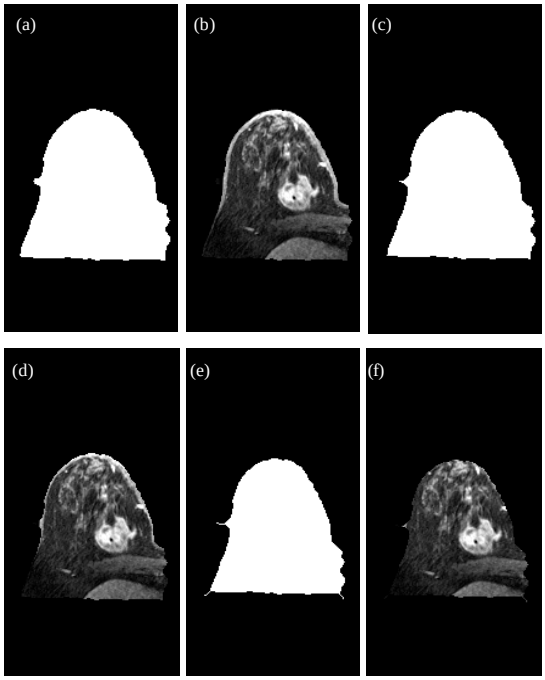

Fig. 2(a-f): Results after applying morphological thinning algorithm with three different iteration numbers on the resultant image of level set active contour algorithm (a) After applying thinning (N_{Th} = 1) on binary image, (b) After reconverting thinning image (N_{Th} = 1) to its original grayscale, (c) After applying thinning (N_{Th} = 3) on binary image, (d) After reconverting thinning image (N_{Th} = 3) to its original grayscale, (e) After applying thinning (N_{Th} = 7) on binary image and (f) After converting thinning image (N_{Th} = 7) to its original grayscale

From Fig. 2, N_{Th} =7 is the best iteration number which enables the thinning algorithm whereby the deleted amount of pixels equals the thickness of the breast skin.

Evaluation approach: To evaluate the results of the segmentation and the removal processes, pixel based evaluation approach (Rosin and Ioannidis, 2003) is used. This approach compares between pixels of processed image (R_t) and ground truth (R_g). The following measures are used in this work to build the comparison; Dice index, Jaccard index, True Positive Fraction (TPF), False Negative Fraction (FNF), False Positive Fraction (FPF) and True Negative Fraction (TNF). The calculations are made using the equations 10-15. (McNeil and Hanley, 1984; Metz, 1986; Chalana and Kim, 1997; Rosin and Ioannidis, 2003; Fenster and Chiu, 2005; Prasad *et al*., 2011):

$$\text{Dice} = \frac{2|R_t \cap R_g|}{|R_t| + |R_g|} \quad (10)$$

$$\text{Jaccard} = \frac{R_t \cap R_g}{R_t \cup R_g} \quad (11)$$

$$\text{TPF} = \frac{R_t \cap R_g}{R_g} \quad (12)$$

$$\text{FNF} = \frac{R_g - R_t}{R_g} \quad (13)$$

$$\text{FPF} = \frac{R_t - R_g}{R_g} \quad (14)$$

$$\text{TNF} = 1 - \frac{R_t - R_g}{R_g} \quad (15)$$

As the basis of measurements: for the Dice, Jaccard, TPF and TNF approaches, whenever the results are higher, the performance is better. Meanwhile for the rest of the basis of measurements which are MCR, FNF and FPF, the lower results indicate better performance.

RESULTS

The methodology explained earlier is applied and tested on the RIDER Breast MRI dataset which is downloaded from the National Biomedical Imaging Archive (NBIA)(US National Cancer Institute, 2007). This website belongs to the U.S. National Cancer Institute. The dataset includes breast MRI images for five patients. All images are Axial 288×288 pixels. Three sequences are selected for each patient to be used in the experiments as test images. Two Ground Truth (GT) images sets are prepared manually for the purpose of the evaluation; the first GT is to evaluate the segmentation process while the second GT set is to evaluate the removal process.

In the breast skin-line segmentation stage, the chosen parameters for Level Set algorithm are $\sigma = 1.5$ and $N_{LS} = 700$ while $N_{Th} = 7$ is the chosen parameter for the Thinning algorithm for the removal stage. The parameters have been selected using the Trial and Error method. Figure 3 shows five RIDER patients images and the processes of breast skin-line segmentation and deletion processes.

The proposed approach is applied on all the RIDER dataset images. Then the calculations are made by comparing these with the ground truth using the evaluation measures eq. 10-15. The results of the segmentation stage are tabled as in Table 1 while the results of the skin-line removal are tabled as in Table 2.

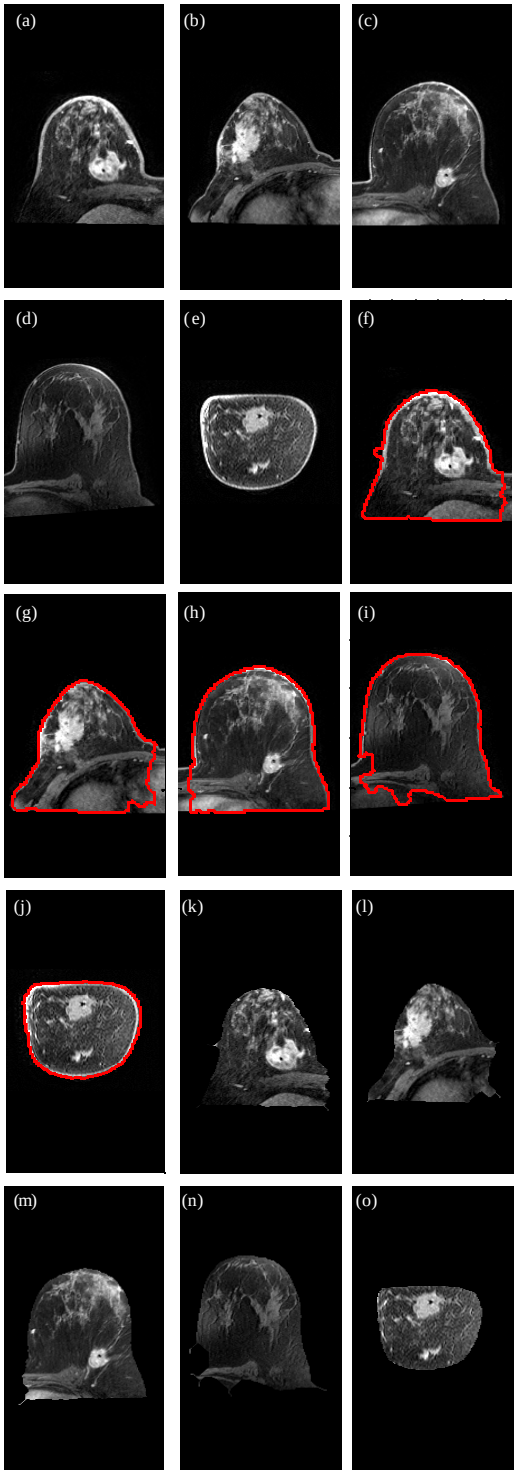

Fig. 3(a-o): (a-e) Breast skin segmentation and removal processes on the five RIDER images; original images (f-j) Five images after applying level set algorithm with $\sigma = 1.5$ and $N_{LS} = 700$ and (k-o) Then applying the Thinning Algorithm with $N_{Th} = 7$

Table 1: Results of skin-line segmentation for RIDER MRI breast images using evaluation measures (Dice, Jaccard, MCR, TPF, FNF, FPF and TNF)

Measure image	Dice	Jaccard	MCR	TPF	FNF	FPF	TNF
1	0.9771	0.9553	0.0003	0.9997	0.0003	0.0465	0.9535
2	0.9332	0.8748	0.0923	0.9077	0.0923	0.0376	0.9624
3	0.9389	0.8848	0.0800	0.9200	0.0800	0.0398	0.9602
4	0.9780	0.9570	0.0016	0.9984	0.0016	0.0433	0.9567
5	0.9817	0.9641	0.0000	1.0000	0.0000	0.0373	0.9627
6	0.9775	0.9561	0.0001	0.9999	0.0001	0.0458	0.9542
7	0.9763	0.9537	0.0035	0.9965	0.0035	0.0449	0.9551
8	0.9751	0.9514	0.0028	0.9972	0.0028	0.0481	0.9519
9	0.9741	0.9495	0.0030	0.9970	0.0030	0.0500	0.9500
10	0.9246	0.8597	0.1060	0.8940	0.1060	0.0398	0.9602
11	0.9229	0.8568	0.1067	0.8933	0.1067	0.0426	0.9574
12	0.9187	0.8497	0.1097	0.8903	0.1097	0.0478	0.9522
13	0.9801	0.9611	0.0130	0.9870	0.0130	0.0270	0.9730
14	0.9856	0.9716	0.0041	0.9959	0.0041	0.0251	0.9749
15	0.9833	0.9671	0.0082	0.9918	0.0082	0.0256	0.9744
Mean	0.9607	0.9275	0.0354	0.9646	0.0354	0.0401	0.9599
SD	0.0261	0.0466	0.0471	0.0471	0.0471	0.0083	0.0083

Table 2: Results of skin-line removal for RIDER MRI breast images using evaluation measures (Dice, Jaccard, MCR, TPF, FNF, FPF and TNF)

Measure image	Dice	Jaccard	MCR	TPF	FNF	FPF	TNF
1	0.9372	0.8818	0.0935	0.9065	0.0935	0.0280	0.9720
2	0.8671	0.7653	0.2159	0.7841	0.2159	0.0245	0.9755
3	0.8753	0.7782	0.2017	0.7983	0.2017	0.0258	0.9742
4	0.9491	0.9032	0.0905	0.9095	0.0905	0.0070	0.9930
5	0.9503	0.9054	0.0923	0.9077	0.0923	0.0026	0.9974
6	0.9493	0.9035	0.0908	0.9092	0.0908	0.0064	0.9936
7	0.9231	0.8572	0.1126	0.8874	0.1126	0.0353	0.9647
8	0.9275	0.8648	0.1056	0.8944	0.1056	0.0342	0.9658
9	0.9286	0.8667	0.1045	0.8955	0.1045	0.0332	0.9668
10	0.8664	0.7643	0.2199	0.7801	0.2199	0.0206	0.9794
11	0.8611	0.7561	0.2246	0.7754	0.2246	0.0256	0.9744
12	0.8588	0.7526	0.2275	0.7725	0.2275	0.0265	0.9735
13	0.9258	0.8619	0.1345	0.8655	0.1345	0.0042	0.9958
14	0.9298	0.8688	0.1287	0.8713	0.1287	0.0029	0.9971
15	0.9258	0.8619	0.1366	0.8634	0.1366	0.0018	0.9982
Mean	0.9099	0.8394	0.1453	0.8547	0.1453	0.0186	0.9814
SD	0.0355	0.0581	0.0554	0.0554	0.0554	0.0128	0.0128

DISCUSSION

From Table 1 and 2, it can be concluded that the proposed approached scored good results using the various measures. For the skin-line segmentation stage, the mean of results was high with (Dice = 0.9607), (Jaccard = 0.9275), (MCR = 0.0354), (TPF = 0.9646), (FNF = 0.0354), (FPF = 0.0401) and (TNF = 0.9599). For the skin-line removal stage the mean of results was high with (Dice = 0.9099), (Jaccard = 0.8394), (MCR = 0.1453), (TPF = 0.8547), (FNF = 0.1453), (FPF = 0.0186) and (TNF = 0.9814).

Then, Receiver Operating Characteristic (ROC) is applied to illustrate by drawing curve the True Positive Fraction compared with the False Positive Fraction as shown in Fig. 4 and 5.

From the curves, it can be observed that the Area under the Curve (AUC) for the segmentation stage is 0.9902 and AUC for the removal stage is 0.9507. The high AUC indicates improved segmentation performance.

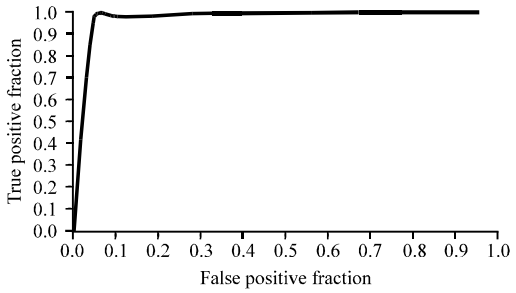

Fig. 4: ROC curve for MRI breast skin-line segmentation

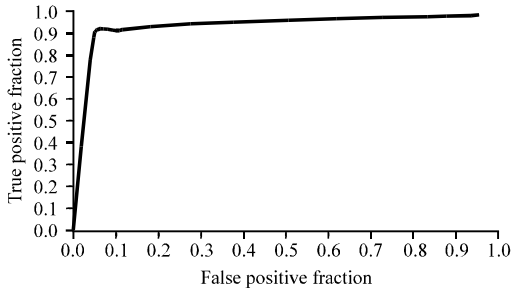

Fig. 5: ROC curve for MRI breast skin-line removal

CONCLUSION

An integration method of Level Set Active Contour algorithm and Morphological Thinning algorithm is presented in this work. The procedure for segmenting and removing the skin-line region from MRI breast images is a necessary process before the next level of the breast segmentation processes. The proposed approach is divided into three stages; pre-processing using median filter, skin-line segmentation using Level Set Active Contour which is then followed by skin-line removal using Morphological Thinning Algorithm.

The study is then tested by applying the methodology on the RIDER breast MRI dataset. The ground truth is manually prepared from the dataset as a benchmark. The evaluation statistic using six measures shows that the performance is significantly high compared with ground truth. The results of the segmentation stage are Dice = 0.9607, Jaccard = 0.9275, MCR = 0.0354, TPF = 0.9646, FNF = 0.0354, FPF = 0.0401 and TNF = 0.9599. While the results of the removal stage are Dice = 0.9099, Jaccard = 0.8394, MCR = 0.1453, TPF = 0.8547, FNF = 0.1453, FPF = 0.0186 and TNF = 0.9814. The proposed approach could also be implemented on other types of breast images such as the X-Ray mammogram images. However, it is necessary to take into account of changing the parameter values of the algorithms to fit specifications of the type of breast images.

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