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Denoising and Automatic Detection of Breast Tumor in Ultrasound Images

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Abstract: Over the past three decades, Breast cancer has been the leading cause of death. Detection of breast cancer at the early stage is a critical procedure. So far Mammography is used for screening and detection, but this method is actually found to be uncomfortable among young woman. Whereas ultrasound can be the best replacement for mammography as imaging of human organs and soft tissue can be done much more easily in ultrasound without much pain and it is cost effective as well. In the ultrasound, the only drawback is its poor quality which is affected by speckle noise which in turn makes the segmentation and classification of interested lesion problematic. Usually, active contour segmentation technique is used which is proved to be ineffective when we go for automatic detection and more over it usually causes improper segmentation and classification. So in order to escape improper segmentation and classification we have developed a scheme which capable to locate region of lesions automatically. This method involves Tetrolet Transform speckle reduction method followed by statistical features of the lesion region and K-Nearest Neighbor (KNN) classifier. This technique is tested over 110 lesion images of breast. The accuracy of this method is around 91.51% and Sensitivity is around 94.42%. The Dice similarity which is found to be 91.27% is obtained between segmented ROIs and ground truth images. Hence, the automatic segmentation of lesion region is made possible. This method will help the radiologist to detect the lesion boundary automatically.

Key words: Breast ultrasound image, speckle noise, texture analysis, image segmentation, active contour, tetrolet transform

INTRODUCTION

In the entire world Breast cancer is found to be the foremost reason of death for many women (Siegel *et al*., 2013). Mammography is effective for detecting and diagnosing the breast cancer. Since this method involves ionizing radiation and its also difficult for young women with dense breast, there is a necessity for alternate procedure. Ultrasound is a widespread method for imaging soft tissues in the body because of its non-invasive, real time, suitable and cost effectiveness. However, these images are degraded with noise which is challenging for the Radiologist to identify the abnormal region. Eliminating speckle noise is still an issue in various tissues. The breast ultrasound images are very complicated, as the altering sizes and locations of these tissues make it challenging to find the region of interest. Speckle reduction methods are based on mean and median filtering (Windyga, 2001; Prabhakar and Poonguzhali, 2014; Telagarapu and Poonguzhali, 2014). The other useful filters are Lee (1980), the Frost *et al*. (1982) and the SRAD Filter (Yu and Action, 2002). While the present despeckle filters are called as “edge preserving” and “feature preserving”, these arise major limitations in their filtering methods. Even after smoothing and blurring the edges, the existing filters does not improve at all. Moreover, the despeckle filters are not directional to overcome these limitations. In the past years, several approaches have been recommended to expand the behavioral of geometric positions like Curvelets, Shearlets (Starck *et al*., 2002; Lim, 2010). Related to the current multiscale geometry study, for instance, the Curvelets, Shearlets are ideally best in signifying images and have the ability to completely capture directional and geometrical features. Moreover, it can be simply implemented. This study focuses on developing filtering techniques for speckle reduction. An automatic active contour procedure to detect the breast lesion is implemented.

So far various efforts have been taken for breast ultrasound image segmentation (Noble and Boukerroui, 2006). In the last few years, a large number of segmentation approaches have been suggested. For example, histogram thresholding or region-growing algorithm can find the initial lesion boundaries (Madabhushi and Metaxas, 2003; Joo *et al*., 2004).

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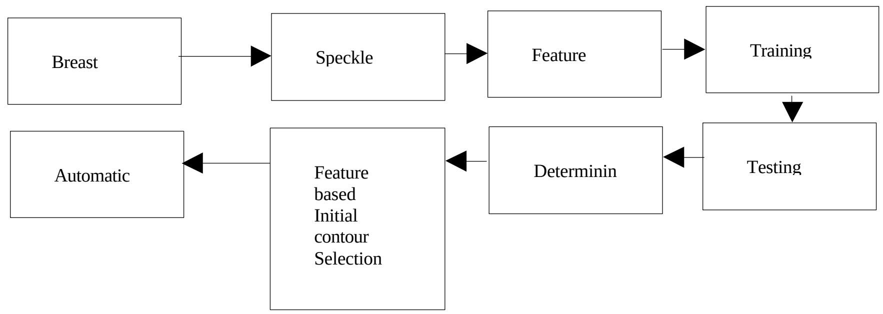

Fig. 1: The block diagram of automatic segmentation process

Though these techniques are very fast it cannot assure exact boundary detection moreover they are relatively sensitive to noise. They can serve as a midway step to deliver a rough contour (Madabhushi and Metaxas, 2003) or can be collective with post-processing processes such as morphological operations (Joo *et al*., 2004) and disk expansion (Yeh *et al*., 2009). Filtering methods are also developed for lesion detection. A radial gradient index filtering method for breast lesion detection was established (Drukker *et al*., 2002) and a nonparametric wavelet model based on order statistics was utilized to differentiate tumor and normal tissue regions (Mogatadakala *et al*., 2006). Filtering procedures are decent at distinguishing the rough location of a tumor region, but are not worthy at detecting the precise boundary of a lesion. Machine learning methods (Kotropoulos and Pitas, 2003; Zhan and Shen, 2006; Wu and Lu, 2007) can produce reasonable lesion contours. The drawback of machine learning approach is its training procedure is quite time-consuming and the performance depends on whether the test images and training images come from reliable stage. Watershed-based methods have exposed capable performance for ultrasound image segmentation (Ikedo *et al*., 2007) here a canny edge detector is used to identify the uneven location of the tumor and then employ the watershed algorithm to additionally segment the lesion. The main challenge of these approach is over segmentation; to report this difficulty, marker controlled (Huang and Chen, 2004; Gomez *et al*., 2010) and cell competition (Chen *et al*., 2005; Cheng *et al*., 2010) watershed methods are established. Nevertheless, they cannot resolve the over-segmentation problem completely. Poonguzhali and Ravindran, 2006) Suggested an automatic segmentation technique based on an automatic seed point selection. In this process, the seed point was automatically selected from the abnormal region based on examination of textural features. A region growing process was formerly agreed, according to the selected point. Model-based methods have robust noise resistant capabilities and are somewhat stable. Frequently used models include level set, (Chang *et al*., 2005; Liu *et al*., 2009) active contours, (Madabhushi and Metaxas, 2003; Chang *et al*., 2003; Chen *et al*., 2003; Cui *et al*., 2009; Prabhakar and Poonguzhali, 2014) Markov Random Fields (MRF), (Boukerroui *et al*.,2003; Xiao *et al*., 2002), etc. For model-based methods, an energy function is expressed and the segmentation difficulty is changed as finding the minimum (or maximum) of the energy function. Computing energy functions and reformulating the models are time-consuming, in addition, numerous models respond to pre-labeled (regions of interest) ROI or manually initialized contours. Further, most of the earlier work is focused only on manual segmentation of lesion in breast ultrasound images. In order to overcome the current problems in widespread segmentation approach, this study focuses on developing filtering techniques using Curvelet, Shearlet and Tetrolet for speckle reduction and an automatic active contour procedure to detect the breast lesion is implemented.

MATERIALS AND METHODS

In this study, the proposed algorithm is tested on 110 cases, these images are acquired with an ultrasound scanner using linear transducer arrays. In this study an automatic segmentation with region based active contour model and global segmentation is implemented with a selective binary and Gaussian filter regularized level set method. The success of the active contour method depends on the selection of initial contour and the minimized fitting term. In the existing method the user should give initial contour with a prior knowledge. In this work, the initial contour is automatically selected from the image using statistical features. The block diagram of automatic segmentation process is shown in Fig.1.

Speckle reduction: The ultrasound images are low contrast and affected by speckle noise. Hence speckle noise should be reduced without destroying any features.

Here the filtering techniques are implemented using curvelet transform, shearlet transform and tetrolet transform.

The curvelet transform (Candes *et al*., 2006) is an improved variant of the Ridgelet transform. It represents curve singularities much more efficient than the ridgelet transform. Curvelet transform has better directional characteristics. Here curvelet coefficients are obtained by irregularly sampling the Fourier coefficients of an image. It is observed that the curvelet transform covers whole frequency spectrum so that there is no loss of information.

The Shearlet transform (Lim, 2010; Easley *et al*., 2008) combines the multiscale and direction analysis separately. At first Laplacian pyramid is used to decompose the noisy image into high and low-frequency components, then direction filtering are used to get different subbands and different direction shearlet coefficients. Direction filtering is achieved using shear matrix.

A new adaptive Haar wavelet Transform is called Tetrolet Transform (Krommweh, 2010). In this algorithm the input image can be divided into 4x4 blocks to obtain the sparsest tetrolet representation in each block, then rearrange the low and high-pass coefficients of each block into a 2x2 block for storing the tetrolet coefficients (high-pass part) and finally apply the above process to the low-pass image as well.

Automatic selection of initial contour

Feature extraction: The statistical features are obtained from the breast lesion region as well as from the normal region. The features like Mean, Standard Deviation and Entropy are extracted from both normal and abnormal images and used for training the KNN Classifier. Features are obtained from every 18*18 pixels of the test image. These features are fed as input to the trained network. Then the network classifies the normal and abnormal regions based on the features. Hence the initial contour point can be found effectively within the lesion region. The mean of the 3*3 pixel block with the initial contour point acting as the center of the block is found. Depending upon this mean value, the active contour grows in the surroundings of initial contour pixel

$$\text{Mean}(\mu) = \frac{\sum X}{N} \tag{1}$$

Where:

$\sum X$ = The sum of all values

N = The number of samples

$$\text{SD}(\sigma) = \sqrt{\frac{\sum (x_i - \mu)}{N-1}} \tag{2}$$

Where:

X_i = Value of i

μ = The mean and

'N' = The number of samples

$$\text{Entropy(H)} = -\sum_i P(x_i)\log_2 P(x_i) \tag{3}$$

Values $\{x_1 \dots x_n\}$ and the probability function P (xi)

K-Nearest Neighbour classifier (KNN): K-nearest neighbour classifier is a familiar nonparametric learning technique used to classify the features set into different classes. All available data in the training is considered by the measure of distance while classifying the new instance. Features in the training set is for the cluster with the centre point as Centroid based on Euclidian distance. Its feature set is X and the class is represented by Y then the training set is represented by $\{(X_1, Y_1), (X_2, Y_2) \dots (X_n, Y_n)$.Where each X is a dimensional feature vector. When an unknown feature set (X_{new}, Y_{new}) is applied, k closest training points to ?is calculated by Euclidean Distance (ED). X_j is closest point:

$$\text{ED} = \sqrt{\left[\left(X_j^{(1)} - X_{new}^{(1)}\right)^2 + \dots + \left(X_j^{(d)} - X_{new}^{(d)}\right)^2\right]} \tag{4}$$

New feature is assigned to cluster with minimum distance. For each instance of test data, all the training data set is considered for the classification.

Active contour model with global segmentation: Active contour model (Chan and Vese, 2001) with global segmentation is a region based model and it is implemented with a Selective Binary and Gaussian Filtering Regularized Level Set method. Here the seed points act as initial contour with the help of a region-based Signed Pressure Force (SPF) function (Zhang *et al*., 2010) it can control the directions. The contour shrinks when it reaches outside the object, or expands when it is inside the object.

RESULTS AND DISCUSSION

The algorithm is implemented and tested on 110 breast ultrasound lesion images. Here the program runs on Intel Core i5-4200M CPU @ 2.50GHz processor. The developed algorithm successfully identifies the lesion boundary automatically.

Speckle reduction: Different filtering methods are employed like Curvelets, Shearlets and Tetrolets Transform techniques to reduce the speckle noise in

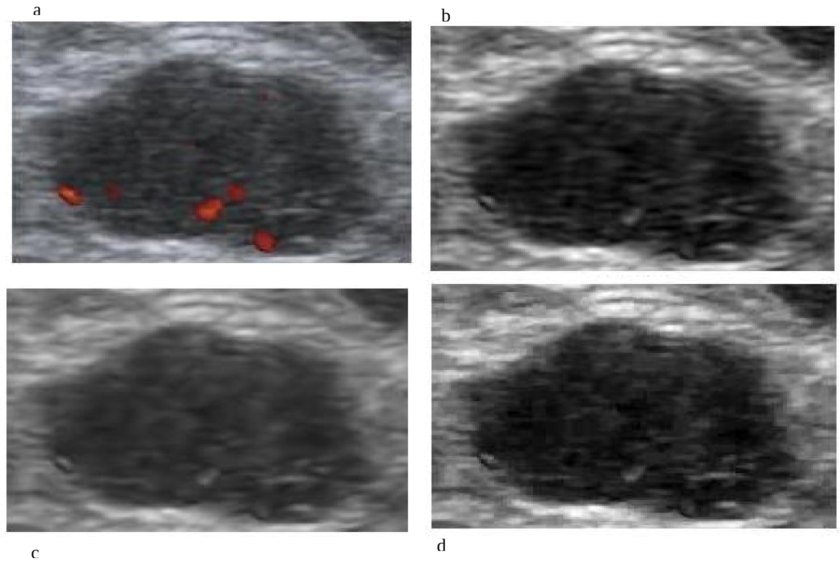

Fig. 2: Speckle noise reduced by several filter techniques; Breast ultrasound tumor image, Curvelet filter, hearlet filter, Tetrolet filter

breast ultrasound image. The output of different filters is shown in Fig. 2. After filtering, performance measurement is done by using SNR and PSNR:

$$\text{SNR} = 10\log_{10}\frac{(1/KL)\sum_{k=0}^{K-1}\sum_{l=0}^{L-1}\left(I_{org}\right)^2(k,l)}{\text{MSE}} \quad (5)$$

Where:

I_{org} = The reference image

K and L = The number of rows and columns

$$\text{PSNR} = 20\log_{10}\left[\frac{2^n - 1}{\sqrt{\text{MSE}}}\right] \quad (6)$$

'n' is the number of bits used in representing an image pixel. The calculated SNR and PSNR value for the different filtering techniques are and shown in Table 1. It is observed from Table 1 that the Tetrolet filter offers the best denoised output. Indicating that the curvelet, Shearlet and Tetrolet filters (Fig. 2) eliminates speckle noise without forming any distortion on test image. The Tetrolet Filter presents best performance and gives high SNR and PSNR values. From the image, it is seen that the filter preserved the original edges as compared to the other filters. This filter is used for the further processing.

Active contour model with global segmentation: From the filtered image, the features are extracted and classified using KNN classifier. Based on the classification results, the seed points are automatically extracted and these oints given as initial contour for further segmentation. After the completion of automatic initial contour selection process, the lesion region is automatically segmented using active contour model with global segmentation.

Table 1: Comparison of different de-noising filters

Filter	SNR (dB)	PSNR (dB)
Curvelet	11.72	32.6
Shearlet	12.13	33.55
Tetrolet	12.45	34.33

The various stages of the segmentation methods are shown in Fig. 3 and 4. Figure 4, it is observed that more seed points are extracted after filtering and it is very useful for accurate segmentation. The seed point will act as initial contour and the active contour algorithm segments the lesion region accurately.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$
$$\text{Sensitivity} = \frac{TP}{TP + FN}\text{Specificity} = \frac{TN}{TN + FP}\text{Jaccard(JC)} = \frac{|A \cap B|}{|A \cup B|} \quad (7)$$
$$\text{Dicesimilarity} = \frac{A \cap B}{|A| + |B|}$$

The segmented image; B-the ground truth image:

- True Positive (TP) is the number of pixels that are correctly segmented as ROI region

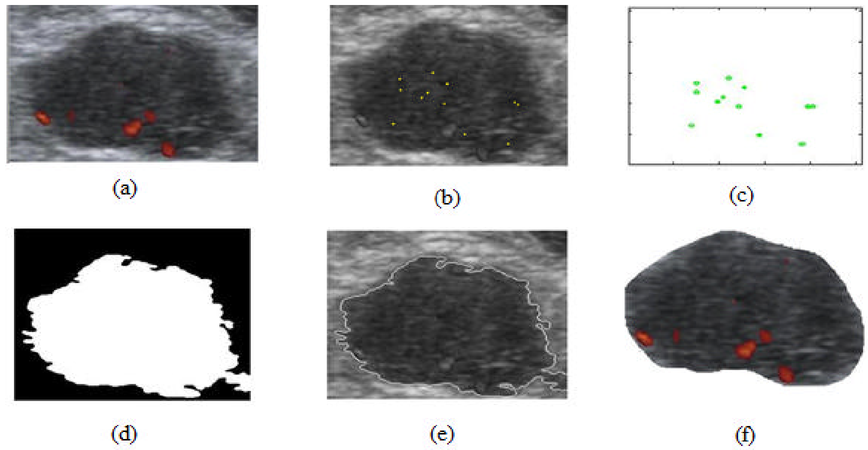

Fig. 3: Various stages of Breast ultrasound image segmentation (without filter); Breast ultrasound tumor image, Automatic seed points, seed points as initial contour, binary image, automatic segmented output, Tumor cropped by the Radiologist

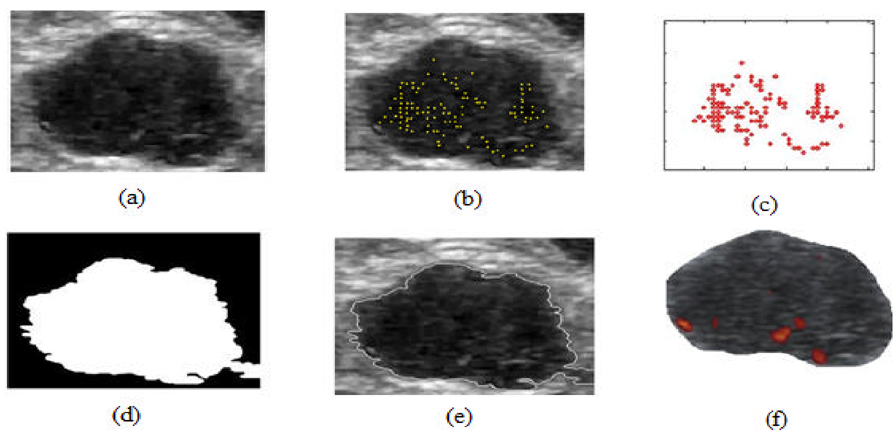

Fig. 4: Various stages of segmentation (with Tetrolet filter); Breast ultrasound tumor image; Automatic seed points; Seed points as initial contour; Binary Image; Automatic segmented output; Tumor cropped by the radiologist

- True Negative (TN) is the number of pixels that are correctly segmented as non-ROI region
- False Positive (FP) is the number of pixels that are incorrectly segmented as ROI
- False Negative (FN) is the number of pixels that are incorrectly segmented as non-ROI region

The performance of the segmentation algorithm is tested by evaluating the accuracy, sensitivity, specificity, Jaccard and Dice similarity. Table 2 shows the average measures of the segmentation algorithm tested on different ultrasound images. From Table 2, it is seen that the feature based active contour implementation on the Tetrolet filtered images gives the high performance. Hence, significant improvement in the performance is observed with accuracy, sensitivity, specificity, Jaccard (JC) and Dice Similarity (DS) measures, using proposed method.

Table 2: Performance comparison of segmentation output

	Metrics				
Method	Accuracy	Sensitivity	Specificity	Jaccard Index (JC)	Dice similarity (DC)
Without Filter	87.10	92.24	83.98	77.16	86.59
With filter (Tetrolet)	91.51	94.42	89.51	84.37	91.27

CONCLUSION

The aim of this research is to develop an algorithm for automatic segmentation of breast lesions from ultrasound image. In which the speckle noise is reduced using Curvelet, Shearlet, Tetrolet filters and breast lesions are segmented using feature based automatic active contour method. This method is implemented on filtered (Tetrolet) and without filtered images and these images act as input of segmentation in which the initial contour is identified by using features. The Tetrolet filtered images gives a high performance with its accuracy as 91.51%, Sensitivity as 94.42% and Dice Similarity as 91.27% when compared to without filtered images. The advantage of implementing this method is to identify the region of interest correctly. This approach could be helpful in detecting the breast cancer more accurately and this will help the radiologist to identify the lesion boundary automatically.

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