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Improved Segmentation of Suspicious Regions of Masses in Mammograms by Watershed Transform

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Abstract

Screening mammograms are powerful aids in early detection of breast cancer. This work deals with segmentation of suspicious region of anomalies known as masses in mammogram. The proposed method is based on watershed transform of morphologically reconstructed image. The suspicious mass regions are isolated and the results are compared with two current methods: thresholding of graph based saliency map of preprocessed mammogram and morphological extraction from saliency. Quantitative analysis and comparison of results are performed using similarity measures and classifier performance and found that the proposed method gives better results achieving 0.95 similarity measure and 83% of ROC area.

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Keywords: Mass;saliency;pectoral muscle;gradient magnitude;ROC curves;dice similarity

1. Introduction

With increasing awareness about breast cancer, thousands of mammograms are captured annually in screening centres. Due to mismatch between the number of experts available and the screening mammograms generated, the

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role of Computer Aided Detection systems to automate the diagnosis of screening mammograms has gained significance. This work deals with one of the commonly detected anomaly in mammogram known as mass. A mass is defined as a space-occupying lesion seen in more than one projection varying in size and shape[1]. Multi-lateral Oblique (MLO) view mammogram is captured from the side at an angle of a diagonally compressed breast to include more of breast parenchyma tissues. Detection refers to identifying the possible region of mass. A pre-processing stage is required to remove areas that are not related to the detection region. Pre-processing also intends to enhance the overall contrast of the image. Image segmentation is followed which is about extracting several, non-overlapping ROI (Region of Interest where the mass is expected) candidates from the background tissue[2]. The detection algorithms involve segmentation of the suspicious region and identifying the mass region by extracting features and classification.

2. Review of State of the Art

Several segmentation algorithms are proposed for mass detection in mammogram. The mammogram images are generally low on contrast and have noise in background such as tape markings and labels which may affect the segmentation results. J. Harel, C. Koch and P.Perona[2] proposed graph based visual saliency from a gray scale image for segmentation. The closeness of visual saliency model with human perception is analysed by A. Borji et al[3]. Along with breast tissue, pectoral muscles also appear in MLO view mammograms. These pectoral muscles have high intensity values in the mammogram which may be misinterpreted as mass. Therefore, algorithms generally involve removing the pectoral muscles or a segmentation step to suppress pectoral muscle region followed by detection. Praful Agrawal and Mayank Vatsa[4] suggested visual saliency based ROI segmentation for mass detection which avoids separate segmentation of pectoral muscles to remove it .

3. Proposed Method

In this work, segmentation of region of interest (ROI) for detection of mass is done after pre-processing the screening mammogram and obtaining the salient regions using graph based visual saliency method. This process gives salient regions including mass and some normal tissues. The thresholding of saliency map is done to isolate the ROI[4].The region is isolated but contains not the mass region alone. So, morphological operations on saliency map are done to improve the isolation. But the shape of ROI segmented varies considerably with that of mass region. The contribution of this work is obtaining the ROI by subjecting the pre-processed image to edge detection followed by watershed transform of morphologically reconstructed image with regional maxima. This method gives object boundaries to extract the ROI which shows an improved result of ROI segmentation. The performance metric used is ROC (Receiver Operating Characteristics) curves. A quantitative comparison is made by estimating the area of ROI extracted and the similarity measures.

3.1. Pre-processing

The pre-processing of mammogram is required due to low contrast and the contrast between objects and background is enhanced to distinguish the breast tissue structures better. The mammogram is pre-processed to remove the labels, background noise etc. and enhance the contrast. It includes sequence of steps such as masking, enhancement, blending and cropping.

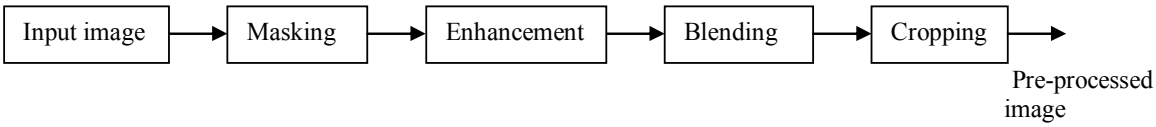

Fig. 1. Block diagram-Pre-processing.

Masking estimates the breast boundary. Mask is generated by BCV (Between Class Variance) thresholding

and dilated to ensure no missing of breast region. Mask is applied to remove the background noise. Enhancement of masked image is done to improve the contrast by adaptive histogram equalization. Masking causes zero intensity to back ground pixels. This causes hard edges along the border of enhanced image. Blending of image is done to dissolve the hard edges which if present will be misinterpreted. Gaussian–Laplacian pyramid based image blending is used to blend the masked image with the original image only along the outer breast boundary. Cropping of image is done to avoid the thick hard edge and limit further processing to the desired area to reduce computation. The results of the above steps of pre-processing are given below in Fig. 2.

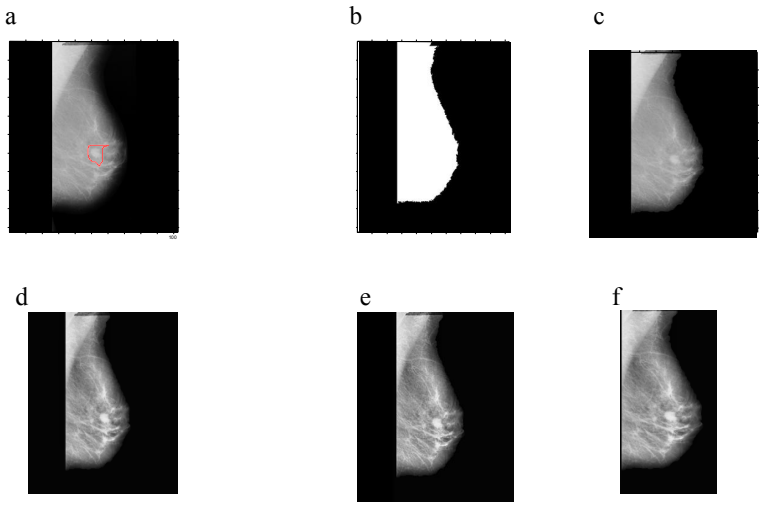

Fig. 2. Pre-processing results

(a) original image with suspicious region marked; (b) mask; (c) masked image; (d) enhanced image; (e) blended image; (f) cropped image.

3.2. Saliency based segmentation

After pre-processing, the region of interest (region where mass is expected) is to be segmented. It is difficult to differentiate between pectoral muscles and mass due to the varied density of breast parenchyma for an automatic algorithm. The visual saliency based ROI segmentation in mammograms does not require the location of pectoral muscles at any time of processing to detect the ROI. Visual saliency models the ability of humans to perceive salient features in an image. In computer vision, visual saliency models are bottom-up techniques which emphasize on particular image regions such as regions with different characteristics[3]. Graph based visual saliency (GBVS) computes saliency of a region with respect to its local neighbourhood using the directional contrast. The directional contrast of mass with respect to the local neighbourhood helps in identifying such masses along with the masses present in fatty region. Saliency map generated in 3 steps: feature map, activation map and normalization of activation map[4]. Feature maps are computed from contrast values along four different orientations of 2D Gabor filters (0^0, 45^0, 90^0, and 135^0) since the contrast of mass containing regions is significantly different from the remaining breast parenchyma. Ergodic Markov chains are modelled on a fully connected directed graph obtained from feature maps. The equilibrium distribution of Ergodic Markov chains are used to compute activation maps[5]. The equilibrium distribution will cause edges of salient regions to have higher weights. The weight of the link from node (i,j) to node (p,q) is a measure of their dissimilarity and closeness. For each link between node (i,j) and node (p,q) weight assigned as[2]

$$W\big((i,j),(p,q)\big) = D.F(i-p, j-q) \tag{1}$$

where

$$F(a,b) = \exp\left(-\frac{a^2+b^2}{2\delta^2}\right) \quad (2)$$

F is the distance measure or connectivity.
D defines the dissimilarity measure of $M(i,j)$ and $M(p,q)$.

$$D = \left|log\left(\frac{M(i,j)}{M(p,q)}\right)\right| \quad (3)$$

where $M(i,j)$ represents a node in the feature map and δ set to 0.15 times the image width[1].

Normalization of activation map is performed to avoid uniform saliency maps resulting from lack of accumulation of weights in salient regions[6].

3.3. ROI by thresholding of saliency map

Since GBVS algorithm extracts salient regions in a more generic manner, along with mass, the segmented regions contain some normal tissues as well. A threshold equal to half of the maximum value in saliency map is used to obtain the ROI. For different threshold values degree of segmentation varies. Hence optimum threshold is chosen. As threshold varies the accuracy also varies and it is measured as the number of True Positives. The thresholded saliency is given below.

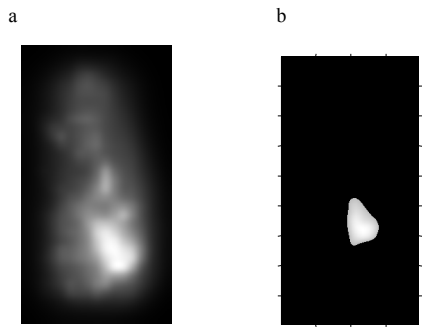

Fig. 3. ROI from saliency by thresholding (a) saliency map; (b) thresholded saliency.

3.4. ROI extraction by processing of saliency map

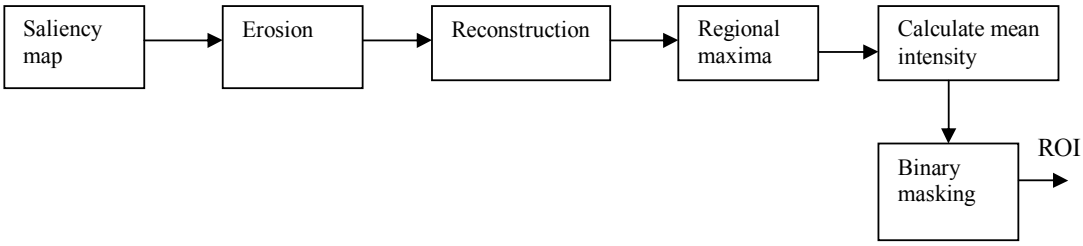

Fig. 4. ROI extraction by processing of saliency map.

To improve the result of thresholding, the saliency map was subjected to erosion using a suitable structuring element

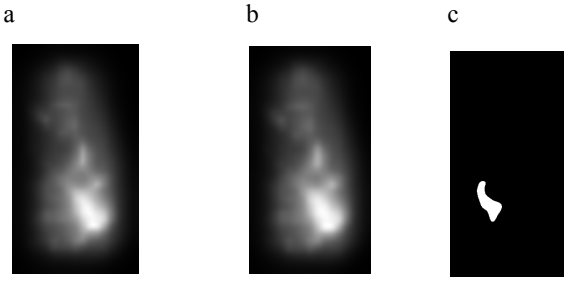

Fig. 5. (a) eroded saliency; (b) reconstructed saliency; (c) ROI isolated by mask.

as first step to remove the small scale details in the image and it tunes the ROI further. The eroded saliency map is reconstructed and the regional maxima on saliency map are obtained. Pixels below a threshold are discarded from the map and the binary mask is constructed by considering pixels having mean intensity greater than threshold. The final binary mask gives the isolated ROI from the saliency map.

3.5. *Extraction of ROI by morphological & watershed transform method*

The contribution of this work is an improved method to extract the suspicious ROI for mass detection compared to the above two methods. The method includes pre-processing the image for enhancement and cropping and finding the edges by filtering. The gradient magnitude of image is obtained which is used to get watershed transform of morphologically reconstructed image with regional maxima[7]. The object boundaries are obtained to give the extracted ROI. The various steps involved are shown in Fig. 6.

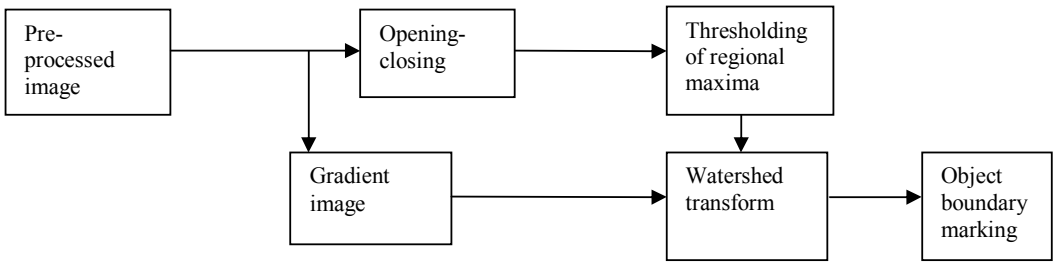

Fig. 6. Morphological & watershed method.

The results of the above processing are given below in Fig. 7.

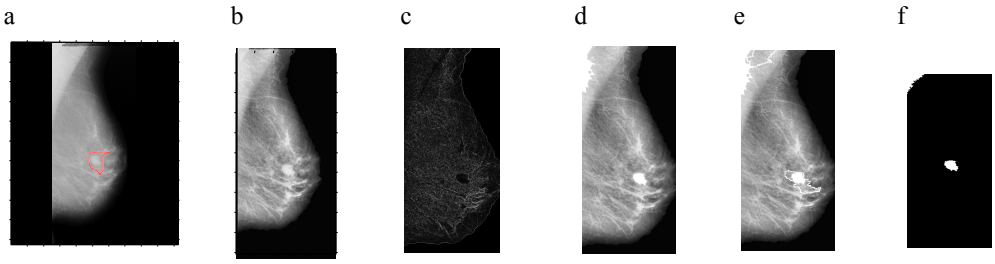

Fig. 7. (a) original; (b) pre-processed & cropped; (c) gradient magnitude; (d) regional maxima; (e) object boundaries; (f) ROI extracted.

4. Comparison of Results

4.1. Database

Database used were samples from MIAS database of mammograms. 25 positive samples for masses and 25 negative samples were studied with the above methods.

4.2. Quantitative analysis

A quantitative analysis of the results of segmentation by the proposed method along with existing saliency thresholding and saliency morphological methods are done by estimating the total area of the extracted region. It is observed that the area of ROI extracted by watershed transform (proposed) method has the closest approximation to the actual area compared to the other two methods.

Table 1. Quantitative analysis.

Sample	Area of ROI Extracted			
	Original	Thresholding of saliency	Regional maxima of saliency	Watershed method
1	7068	2.0512e+004	8.6826 e+003	5.6616e+003
2	2941	1.3354e+004	4.6771 e+003	2.4584e+003
3	3856	1.0925e+004	5.2259 e+003	4.2606e+003

4.3. Comparison by similarity measure

Comparison of ROI results obtained with ground truth (original) is done using Dice Similarity Co-efficient. Dice co-efficient measures agreement between 2 sets A and B by the ratio of size of overlapping area of the 2 sets to the total size of 2 sets[8].

$$D(A,B) = 2\,|A \text{ and } B|/(|A| + |B|) \tag{4}$$

It is also given by

$$dice\ co-eff\ = 2 * \frac{(overlap\ \ area\ of\ segmentation\ and\ \ ground\ truth)}{(total\ area\ of\ segmentation\ and\ ground\ truth)} \tag{5}$$

Table 2 .Comparison by Dice co-efficient.

Sample	Dice similarity coefficient		
	Thresholding of saliency	Regional maxima of saliency	Watershed method
1	0.5125	0.8896	0.8975
2	0.3609	0.7721	0.9105
3	0.5218	0.8492	0.9501

A value of 0 indicates no overlap or common area between ground truth and segmentation; a value of 1 indicates cent percent common area. Higher numbers indicate better agreement and indicate that the results match the standard better than results that produce lower Dice coefficients. It is found from the above table that the dice similarity co-efficient is the highest for ROI obtained by watershed method. This means that the overlapping region matches the ground truth to the maximum extent in this case.

4.4. Performance analysis by ROC curves

Performance rating of a classifier is done by estimating the accurate or desired output obtained with reference to the original samples. The correct detections out of the total actual original targets are called True Positive Rate (TPR) and the detections of the classifier which were found as targets out of the total non-targets are called False Positive Rate (FPR).

Receiver Operating Characteristics (ROC) curve is obtained by TPR vs FPR and the area under the curve regarded as an indication of the classifying power of the detector. This is the performance metric used to measure how well a classifier predicts target locations on a given image. It predicts the responsivity and sensitivity of the method or system studied.

A perfect classifier with no overlap in the positive and negative classes has an ROC curve passing through the upper left corner. Thus the proximity of ROC curve to the upper left corner indicates higher accuracy of the classifier[9].

ROC curves are obtained for the above methods for comparison.

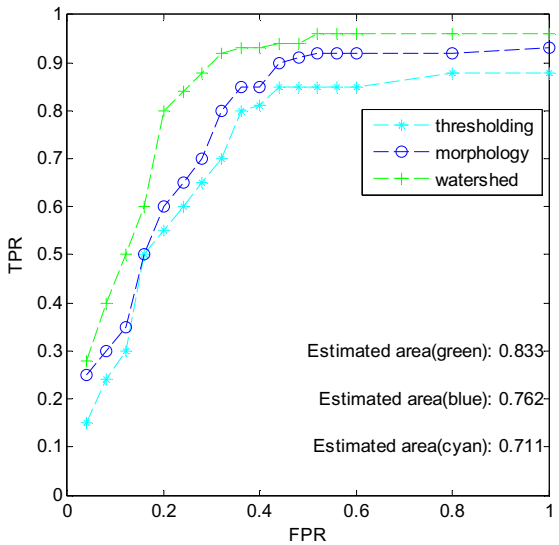

Fig. 8. ROC curves for the three methods.

5. Observation and Conclusion

As seen from graph, ROC for the first two methods lie in the upper half of the area while the watershed transform method gives better accuracy since ROC curve approaches upper left corner. Area Under Curve (AUC) for the three methods are shown in graph. The watershed method gives maximum AUC as seen.

Table 3. Comparison of methods by ROC curves.

Method	Thresholding of saliency	Regional maxima of saliency	Watershed method
AUC	0.711	0.762	0.833

The region of interest (ROI) extracted is expected to contain the actual mass region, the detection of which involves identification of features of mass region such as texture features, shape features etc. Eventhough the saliency thresholding avoids removal of pectoral muscle for ROI segmentation, the accuracy varies with threshold chosen. Likewise, the accuracy of morphological detection of ROI after saliency depends on the structuring element chosen. However the ROI obtained through watershed method approximates the ground truth as evident from the above comparative studies. The accuracy of ROI segmentation thus determines the effectiveness of mass detection for diagnosis of malignant or benign cases.

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