Building Multiple Weak Segmentors for Strong Mass Segmentation in Mammogram

Yu Zhang, Noriko Tomuro, Jacob Furst, Daniela Stan Raicu
School of Computing, College of Computing and Digital Media
DePaul University, Chicago, IL 60604, USA
{jzhang2, tomuro, jfurst, draicu}@cs.depaul.edu

ABSTRACT

This paper proposes to build multiple segmentations for identifying mass contours for a suspicious mass in a mammogram. In this study, by using various parameter settings of the image enhancement functions, we perform multiple segmentations for each suspicious mass (region of interest (ROI)), and multiple mass contours are generated. Each of such segmentations is called a "weak segmentor", since there is no single image enhancement which produces the optimal segmentation for all mass images. Then for each image, we select the contour which has the highest overlapping ratio as the final segmentation (i.e., the "strong segmentor"). The results show that the overall success rate (81.22%) of the strong segmentor was higher than that of any single weak segmentor. This indicates that using multiple weak segmentors is an effective method to generate a strong mass segmentation for mammograms.

Keywords: Mammogram, Image Enhancement, Mass Segmentation

1. INTRODUCTION

Breast cancer is the second leading cause of cancer related deaths for women in the U.S. after lung cancer. In 2010, it was estimated that 207,090 new cases of breast cancer would be diagnosed among women in the United States. There were an estimated 40,230 breast cancer deaths (39,840 women, 390 men) in 2010 [1].

Breast cancer is treatable when it is discovered early, so early detection is the best protection. At the present, the most effective method for the early detection of breast cancer is mammogram screening. However, the problem with mammogram screening is that the error rate is high. A study showed that, among all breast biopsies recommended by radiologists after findings of suspected abnormal tissues in mammogram screening, 65-80% of the biopsies resulted in a benign diagnosis [2]. Another study results showed that among the women who had mammogram screenings and were recommended to have a biopsy for further confirmation, only 25% of the cases were found to have breast cancer [3]. Those studies indicate that some breast biopsies can be avoided if radiologists can more accurately diagnose those abnormalities in mammograms.

Many Computer-Aided Diagnosis (CADx) systems have been developed as a second opinion to assist radiologists in their diagnosis [4]. Previous studies have shown that CADx systems can assist radiologists as a second opinion to analyze a suspected abnormality in a mammogram, and improve the diagnosis accuracy [5]. A CADx system has the advantages to extract a variety of shape and texture features, identify the most distinguished features by feature selection, and detect slight changes which may not be noticeable by human eyes.

Mass and microcalcification are the two most common types of abnormalities associated with breast cancer in mammograms [6]. The research presented in this paper is part of an ongoing project whose aim is to develop a CADx system for classifying suspicious masses in mammograms as malignant or benign. Our system processes images in five stages: 1) extraction of suspicious mass regions, 2) mass segmentation, 3) feature extraction, 4) feature selection, and 5) classification. In this paper, we focus on the second stage (mass segmentation).

Most mammogram images have low intensity contrasts; therefore, image enhancement is usually applied before mass segmentation. However, not only do mammogram have varied intensity contrast ranges, patients also have different breast density levels. With those variability factors, it is impossible to apply the same image enhancement, and produce the optimal mass segmentation for all images.

In this research, we propose to perform multiple segmentations for each ROI image to adapt the varied intensity contrast ranges of mammograms. Each of such segmentations is called a "weak segmentor", since there is no one segmentation which produces the optimal results for all images. At the end, using the weak segmentors, we build a strong segmentor to generate the final mass segmentation result.

Figure 1 displays the framework of the proposed multiple segmentation approach. By applying different image enhancements to a mass ROI image, several enhanced images are generated, and ROI energy images are built. Then, using an edge-based segmentation method, one contour is detected from each energy image. Among those detected contours, the one from the "strong segmentor" is used as the final mass contour. In the next stage of the proposed CADx system, mass shape features are extracted from the segmented contours for classification.

This paper is organized as follows. In Section 2, we review related works of mass segmentation. In Section 3, we present the data and methodology. In Section 4, the preliminary results are presented and the image enhancement for mass segmentation is discussed. In Section 5, the conclusion and future work are discussed.

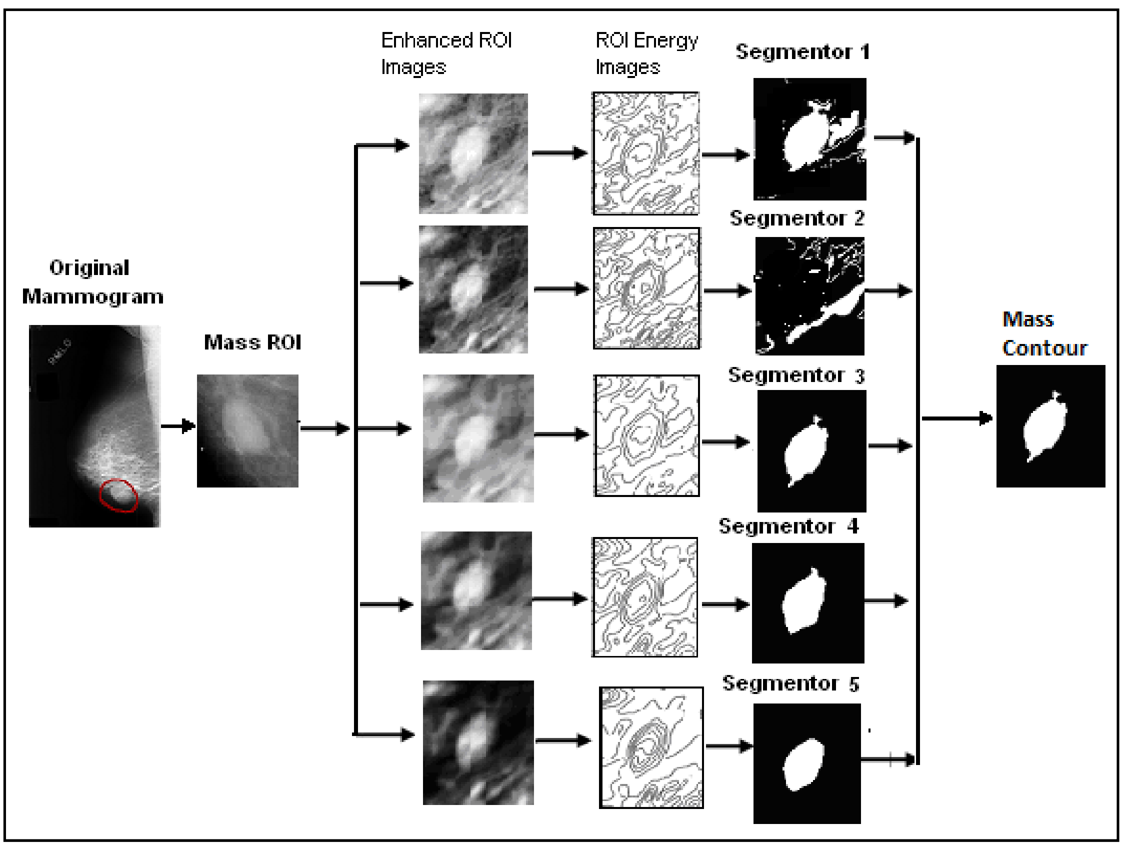


Figure 1. Framework

2. MASS SEGMENTATION

Masses are thickenings of breast tissue which appear as lesions in mammograms. For radiologists, the shape and margin (spiculation level) of masses are the two most important criteria in distinguishing malignant from benign masses. A mass with poorly defined shape is more likely to be malignant than a well-circumscribed mass; and a mass with ill-defined margins or spiculated lesions is much more likely to be malignant than a mass with smoothed margins [6].

In a CADx system for a suspicious mass, segmentation separates a mass region from its background and captures the shape and boundary of the suspicious mass. After segmentation, the contour of a mass is identified; and the shape features and spiculation level can be computed for classifying the mass as benign or malignant. Previous studies have shown that it is critical for a CADx system to extract accurate shape and margin information for suspicious masses; and that improving the mass segmentation can significantly improve the accuracy of mass diagnosis [7, 8].

Many mass segmentation methods for mammogram images have been developed. There are two basic approaches: 1) region-based segmentation methods and 2) edge-based segmentation methods. In region-based methods, mass regions are iteratively grown by comparing all neighboring pixels and including the pixels with similarity to the respective regions. The similarity can be measured with different types of properties, such as pixel intensity or computed texture features. In edge-based methods, segmentation is based on edge detection. Usually image enhancement is applied to ROI images to enhance relevant edges prior to the edge detection stage [9].

Jiang et al. [10] applied a gamma correction and a Gaussian filter to mass ROI images to improve contrast and remove image noise. Then, using the principle of maximum entropy, optimal thresholds were selected to obtain initial segmented mass regions. Mencattini et al. [8] modified a region-growing mass segmentation procedure in their Computer Aided Detection (CAD) system. Their segmentation method adjusted mass image contrast by applying a non-linear operator, and applied a region growing segmentation, where pixel intensity was used for similarity measurement. Song et al. [11] developed an edge-base segmentation method using the plane fitting and dynamic programming techniques to find the "optimal" contour of a mass. Yuan et al. [12] developed a method, where a radial gradient index (RGI)-based segmentation was applied to yield an initial mass contour. Kupinski et al. [13] developed lesion segmentation in mammogram images using a RGI and a probabilistic algorithm. Petrick et al. [14] developed a region-based mass segmentation algorithm. In their system, the suspicious areas were adjusted using adaptive enhancement method for variability of the image contrast ranges and patients' breast density levels.

3. DATA AND METHODOLOGY

3.1 Data Description

In this work, all mass ROI images were extracted from the Digital Database for Screening Mammography (DDSM) from the University of South Florida [15]. DDSM is the largest publicly available resource for the mammogram analysis research community. In DDSM images, suspicious regions (ROIs; including masses and microcalcifications) are marked by experienced radiologists, and BI-RADS information is annotated for each abnormal region [16]. However, in DDSM, most mass ROIs are marked for the mass location, and do not trace the detailed outline of the mass.

In DDSM, mammogram images are digitized by different scanners with different resolutions. In this research, for data consistency purposes, all mass ROI images are collected from the same type of scanner and resolution. We chose the scanner type LUMSYSYS because the largest number of cases are digitized by this type in DDSM. In our experiment, we first extracted all mass ROIs from the mammogram images digitized by LUMSYSYS. Then, we removed the instances with extreme digitization artifacts (e.g. incorrectly ordered scan lines) and of extremely large size (over 2000 x 2000 pixels). We also removed instances with mixed BI-RADS descriptors and those masses which displayed only a portion of a mass. After removing those instances, a total of 543 mass ROI images were left for this study, where 272 instances were benign and 271 instances were malignant.

Figure 2 and 3 show the distribution of the BI-RADS shape and margin features respectively.

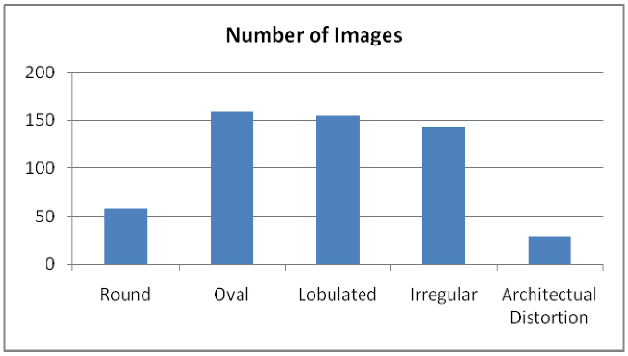


Figure 2. Mass BI-RADS shape distribution

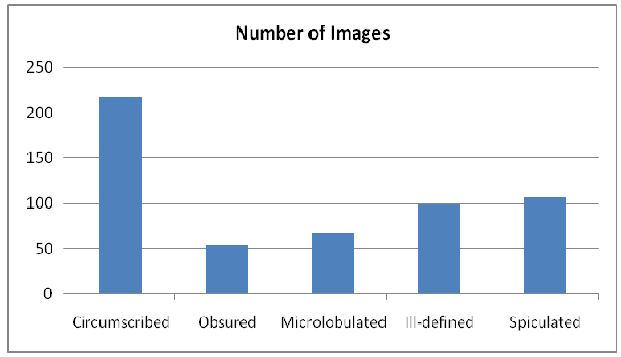


Figure 3. Mass BI-RADS margin distribution

3.2 Methodology of Building Multiple Mass Segmentors

In this study, we propose a novel approach in which each ROI image is processed by multiple weak segmentors. In our experiment, for each suspicious mass, a rectangle image was extracted as a ROI, which includes the suspicious mass and its surroundings. Then we applied the following four steps to build multiple weak segmentors and generate a mass contour from each ROI image.

Step1: Image enhancement

For each mass ROI, we first applied Histogram Equalization (HE) to increase and normalize the contrast range between 0 and 255; then for each normalized image, we applied several gamma corrections (with different γ values) to adjust the image intensities. Then, a Gaussian filter was applied to the contrast-adjusted images to remove the noise. At the end, multiple enhanced images were generated. In Table 1, column (a) displays an original mass ROI image and its five enhanced images obtained after gamma corrections (γ = 0.5, 1, 2, 5 and 7.5) and Gaussian filtering (σ = 5); and column (b) displays the histograms of those enhanced images.

Step 2: Construct a texture image – pixel-based energy image

Energy is a commonly used texture feature, which measures the heterogeneity of an image. In this step, from each enhanced image, a texture image was constructed using the energy value of each pixel, which was computed from a gray-level co-occurrence matrix [17]. In our experiment, for each pixel in a ROI, we first computed a co-occurrence matrix with angle = 0 and distance = 1 using a neighborhood size of 7x7 pixels [18]. Then, we obtained an energy value for each pixel by computing the number of occurrences of the pairs of the same value within the co-occurrence matrix:

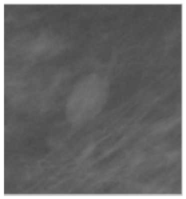
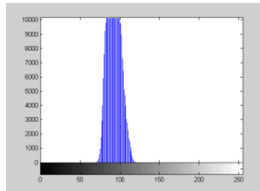
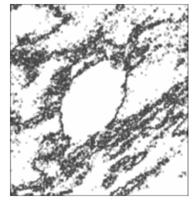
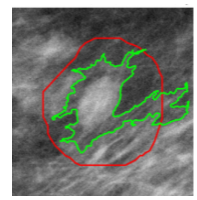
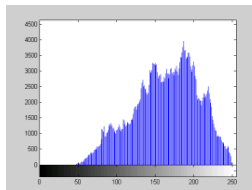
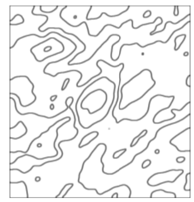
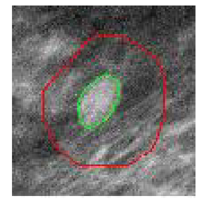
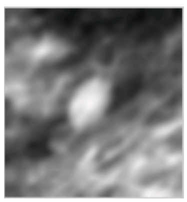
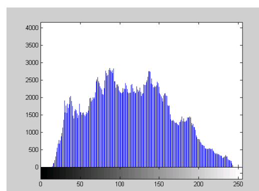
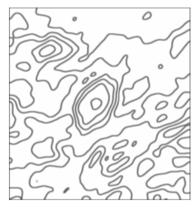
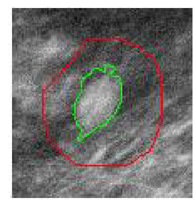
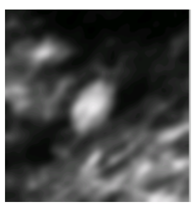
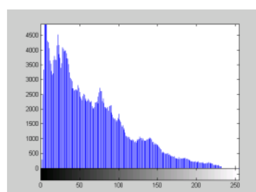
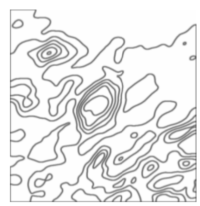
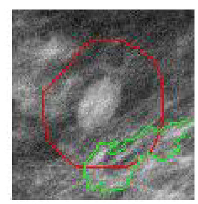
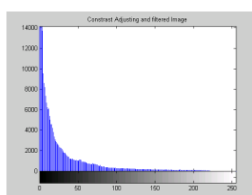
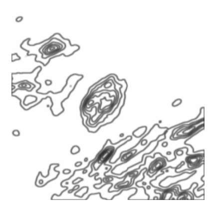
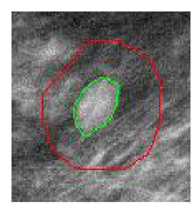
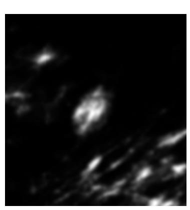
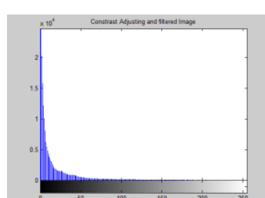
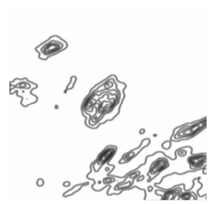
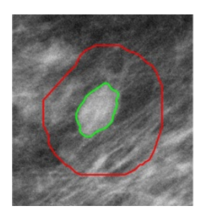
$$Energy = \sum_{i}^{M} \sum_{j}^{N} P_{ij}^{2} \tag{1}$$

where M and N are the size of row and column of the matrix respectively, and P_{ij} is the probability of the pixel pair (i, j) in the matrix. Finally an energy texture image was constructed from the energy value of all pixels in the mass ROI image. Table 1, column (c) displays the energy texture images of enhanced images.

Step 3: Detect the possible mass regions -- weak segmentors

From each texture image, using our edge-based segmentation method [19], a mass contour will be generated. Table 1, column (d) shows the segmented contours from the original mass ROI and five weak segmentors. We call each of such segmentations a "*weak segmentor*", since there is no one segmentation which produce the optimal result for all images. In each image, the green line is the detected mass contours; the red line is the mass outline marked by the radiologist.

Table 1 Example of Multiple Weak Segmentors with Varied Gamma Correction Values

	Enhanced Images (a)	Image Histograms (b)	Texture Images (c)	Segmentation Results (d)
Original ROI Image				
Weak Segmentor 1: Image Enhancement $\gamma = 0.5$ $\sigma = 5$				
Weak Segmentor 2: Image Enhancement $\gamma = 1$ $\sigma = 5$				
Weak Segmentor 3: Image Enhancement $\gamma = 2$ $\sigma = 5$				
Weak Segmentor 4: Image Enhancement $\gamma = 5$ $\sigma = 5$				
Weak Segmentor 5: Image Enhancement $\gamma = 7.5$ $\sigma = 5$				

Step 4: Evaluate the mass segmentation

At the last step, each weak segmentor was evaluated as successful or unsuccessful based on the *overlapping ratio* -- the proportion of the segmented region over the ROI central area. In our experiment, the ROI central area is defined as a rectangle made of the center half of the width and length of the mass ROI [19]. We considered a segmentation was successful if its overlapping ratio was above a certain threshold. For example, for the mass instance displayed in Table 1, using 25% for the threshold, the segmentors 1, 2, 4 and 5 are evaluated as successful, while the segmentor 3 is evaluated as unsuccessful. Then among the successful segmentors, the one with the highest overlapping ratio is selected as the "strong segmentor" (the segmentor 2 in the example in Table 1); and its output contour is used as the final segmented mass contour.

4. PRELIMINARY RESULTS AND DISCUSSION

4.1 Image Enhancement

Most mammogram images have low intensity contrasts. In the experiment, for each ROI, after applying HE to increase and normalize the contrast range, we applied five Gamma corrections (with $\gamma = 0.5$, 1, 2, 5 and 7.5) to adjust the image contrast.

Mammogram images have different noise levels, and the noise is also enhanced by HE and gamma corrections. A Gaussian filter was applied to the contrast-adjusted images to remove the image noise. In this study, to search for the optimal filtering, we tested four Gaussian functions (with $\sigma = 1$, 2, 5 and 10 where the filtering size was set as 8*sigma for all cases) to a contrast-adjusted image, and generated noise-removed images. The results showed that, a Gaussian filter with a very high sigma value (such as $\sigma = 10$) removed too much detail to reveal the mass margin information. But when the original ROI images had higher noise, a smaller sigma value (such as $\sigma = 1$ or 2) was not strong enough to remove most noise. Our results showed that a Gaussian filter with $\sigma = 5$ achieved better mass segmentation results for most images in the dataset (>80%). In image enhancement stage, using gamma corrections with $\gamma = 0.5$, 1, 2, 5, 7.5, and a Gaussian filter with $\sigma = 5$, we generated five enhanced images from each mass ROI for segmentation.

4.2 Successful Segmentation Rate of Individual Weak Segmentors

In our experiment, we first performed the edge-based segmentation with original ROI images. Using a threshold of 25% overlapping ratio, only 47.69% of the images in the dataset were successfully segmented without any image enhancement.

Then, we performed the edge-based segmentation with the enhanced ROI images, and five weak segmentors were built to detect mass contours. Using the same threshold of 25% overlapping ratio, the contours detected by each weak segmentor were evaluated. Table 2 lists the individual success rates of the five weak segmentors. The results show that for all five segmentors, their individual success rates were much higher than that of the original image (47.69%). The results indicated that the image enhancement can greatly improve the edge-based segmentation results. And weak segmentors with different image enhancement parameter values had different segmentation performance.

Table 2 Segmentation Results by Each Weak Segmentor

	Segmentor 1	Segmentor 2	Segmentor 3	Segmentor 4	Segmentor 5	Original Image
Image Enhancement	$\gamma = 0.5$ $\sigma = 5$	$\gamma = 1$ $\sigma = 5$	$\gamma = 2$ $\sigma = 5$	$\gamma = 5$ $\sigma = 5$	$\gamma = 7.5$ $\sigma = 5$	None
Successful Segmentation Rate	60.40%	66.30%	72.59%	76.61%	74.95%	47.69%

4.3 Overall Successful Segmentation Rate of Strong Segmentors

Then, we investigated how much the use of multiple weak segmentors overall helped improve successful segmentation. We defined a ROI image as successfully segmented if one of the overlapping ratios from the weak segmentors was above the threshold (25%). And for those images which yielded more than one segmented contour, the one with the highest overlapping ratio was selected as the final segmentation (i.e., the strong segmentor).

Table 3, the first column shows the overall success rates of using five weak segmentors. By using all five weak segmentors, 82.32% of the images in the dataset were successfully segmented by at least one weak segmentor. The overall success rate was higher than that of any five individual weak segmentors we tested (the best success rate was 76.61% achieved by segmentor 4). This result indicates that using multiple weak segmentors is an effective method to generate a strong mass segmentation for mammograms.

We further investigated which segmentors made more contribution to successful segmentation than others. Among the five weak segmentors, we used segmentor 2 (with $\gamma = 1$) as the baseline segmentor, which is a linear contrast enhancement. Starting from all five segmentors, we iteratively removed one segmentor at a time, which had the lowest success rate, until the overall success rate significantly dropped. Table 3 lists the overall success rates of using different weak segmentors. At the end, using three weak segmentors (γ =1, 2 and 5), the strong segmentor achieved 81.22% overall success rate. Comparing to the success rate of using five segmentors, the drop in the success rate (82.32% down to 81.22%) was not statistically significant (p-value> 0.05). Also, the 81.22% success rate is still higher than the rate achieved by the best individual segmentor. This means segmentors 2, 3, 4 were the most effective segmentors for our dataset, and we could achieve a high overall success rate with a fewer number of segmentors.

Table 3 Overall Successful Segmentation Rates by Strong Segmentor

Weak Segmentor	Segmentors: 1, 2, 3, 4, 5	Segmentors: 2, 3, 4, 5	Segmentors: 2, 3, 4	Segmentors: 2, 3	Segmentors: 2, 4
Image Enhancement	γ = 0.5, 1, 2, 5, 7.5 σ = 5	γ = 1, 2, 5, 7.5 σ = 5	γ = 1, 2, 5 σ = 5	γ =1, 2 σ = 5	γ = 1, 5 σ = 5
Overall Success Segmentation Rate	82.32%	81.22%	81.22%	75.51%	79.37%

5. CONCLUSIONS AND FUTURE WORK

Previous studies in mammograms have shown that image enhancement greatly affects the quality of segmentation. Because of various variability factors including the image contrast ranges and patients' breast density levels, it is difficult to select an/one optimal image enhancement which can fit all images for mass segmentation.

In this research, we investigated a multiple segmentation approach, which built a set of weak segmentors for a given ROI by using various image enhancements. The results show that using three weak segmentors (γ =1, 2 and 5), the strong segmentor achieved 81.22% overall success rate, which is higher than the rate achieved by the best individual segmentor (76.61%). This result indicates that using multiple weak segmentors is an effective method to generate a strong mass segmentation for mammograms.

In future work, we will investigate other segmentation methods such as region-based segmentation as an alternative method for those mass ROI images which could not be segmented by any of the weak segmentors.

After mass segmentation, the shape and spiculation features will be extracted from the segmented mass contours. We will feed the extracted shape features from each segmentor for classification. Currently, we use success segmentation rates to evaluate the weak segmentors. In future, we may use the classification accuracy from each segmentor to evaluate and select the stronger segmentors. By this approach, we expect to improve the overall classification accuracy of the proposed CADx system.

References

[1] National Cancer Institute, "American Cancer Society Cancer Facts & Figures 2010" (http://www.cancer.org).

[2] Polakowski, W.E., Cournoyer, D.A., Rogers, S.K., DeSimio, M.P., Ruck, D.W., Hoffmeister, J.W., Raines, R.A., " Computer-Aided Breast Cancer Detection and Diagnosis of Masses Using Difference of Gaussians and Derivative-Based Feature Saliency", IEEE Trans. Med. Imaging 16(6): 811-819, (1997).

[3] Ries, LAG, Harkins, D., Krapcho, M., et al., "SEER Cancer Statistics Review, 1975-2003", National Cancer Institute (2006).

[4] Mu, T., Nandi, A. and Rangayyan, R., "Classification of Breast Masses Using Selected Shape, Edge-sharpness, and Texture Features with Linear and Kernel-based Classifiers", Journal of Digital Imaging, Volume 21, Number 2, 153-169 (2008).

[5] Cheng, H. D., Shi, X. J., Min, R., Hu, L. M., Cai, X. P, et al., "Approaches for Automated Detection and Classification of Masses in Mammograms", Pattern Recognition (2006).

[6] Winchester, D. J., Winchester, D. P., Hudis C. A. and Norton, L., [Breast Cancer(Second Edition)] , Springer (2007).

[7] Domínguez1, A. R. and Nandi, A. K., "Toward Breast Cancer Diagnosis Based on Automated Segmentation of Masses in Mammograms", Pattern Recognition, Volume 42 (2009).

[8] Mencattini, A., Rabottino, G., Salmeri, M., Lojacono, R. and Colini, E., "Breast Mass Segmentation in Mammographic Image by an Effective Region Growing Algorithm", Advanced Concepts for Intelligent Vision Systems Conference (2008).

[9] Marlagelada, O., "Automatic Mass segmentation in mammographic images" (Doctoral Dissertation), Universitat de Girona (2007).

[10] Jiang, L., Song, E., Xu, X., Ma, G. and Zhang, B., "Automated Detection of Breast Mass Spiculation Levels and Evaluation of Scheme Performance", Acad Radiol (2008).

[11] Song, E., Jiang, L., Jin, R., Zhang, L., Yuan, Y. and Li, Q., "Breast Mass Segmentation in Mammography Using Plane Fitting and Dynamic Programming", Academic radiology 16(7), 826-35(2009).

[12] Yuan, Y., Giger, M. L. Li, H., Suzuki, K. and Sennett, C., "A Dual-stage Method for Lesion Segmentation on Digital Mammograms ", Med. Phys. Volume 34, Issue 11, 4180-4193(2007). Kupinski, M.A. and Giger, M.L., "Automated Seeded Lesion Segmentation on Digital Mammograms", IEEE Transaction on Medical Imaging, vol.12 (1998).

[13] Kupinski, M.A. and Giger, M.L., "Automated Seeded Lesion Segmentation on Digital Mammograms", IEEE Transaction on Medical Imaging, vol.12 (1998).

[14] Petrick, N., Chan, H.P., Sahiner, B., Helvie, M.A., "Combined Adaptive Enhancement and Region-growing Segmentation of Breast Masses on Digitized Mammograms", Med. Phys. 26, 1642 (1999)

[15] DDSM, The Digital Database for Screening Mammography, http://marathon.csee.usf.edu/Mammography/Database.html

[16] Heath, M., Bowyer, K., Kopans, D., Moore R. and Kegelmeyer, W. P., "The Digital Database for Screening Mammography", Proceedings of the Fifth International Workshop on Digital Mammography, Medical Physics Publishing, 212-218 (2001).

[17] Haralick, R. M., "Statistical and Structural Approaches to Texture", Proceedings of the IEEE, vol. 67, pp.786-804 (1979).

[18] Susomboon, R., Raicu, D.S. and Furst, J.D., "Pixel-Based Texture Classification of Tissues in Computed Tomography", DePaul CTI Research Symposium (2006).

[19] Zhang,Y., Tomuro,N., Raicu,D.S., Furst,J.D., "Image Enhancement and Edge-based Mass Segmentation in Mammogram", SPIE Medical Imaging Conference (2010).