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Abstract

The goal of this proposed project is to develop an automated technique to assist radiologists in estimating mammographic breast density. The computerized image analysis tool can provide a consistent and reproducible estimation of percent dense area on routine clinical mammograms, thereby contributing to the understanding of the relationship of mammographic density to breast cancer risk, detection, and prognosis, and the prevention and treatment of breast cancer.

During this project year, we have improved our automated mammographic density segmentation program, referred to as Mammographic Density ESTimator (MDEST), for both digital mammograms (DMs) and digitized film mammograms (DFMs). The performance of the re-trained MDEST system was evaluated and compared with manually segmented mammographic density by experienced radiologists. The improved system was found to provide higher correlation and lower RMS error than the previous system in 10 of the 12 comparisons. The results indicate that the MDEST system is useful for mammographic density estimation for both DMs and DFMs. To further improve the estimation of percent dense area, we have designed new techniques and refined the existing methods for automatically tracking the breast boundary and the pectoral muscle edge on MLO view mammograms. These new methods improve the segmentation of breast boundary and pectoral muscle edge on noisy images over the previous methods. We will continue to improve the accuracy of the segmentation program and complete the development next year.

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(4) Introduction

Previous studies have found that there is a strong correlation between mammographic breast density and the risk of breast cancer. Mammographic breast density has been used by researchers in many studies to estimate breast cancer risk of epidemiological factors, monitor the effects of preventive treatments such as tamoxifen or dietary interventions, monitor the breast cancer risk of hormone replacement therapy, and investigate factors affecting mammographic sensitivity and cancer prognosis. However, most studies used Breast Imaging Reporting and Data System (BI-RADS) density rating as a measure of mammographic breast density, which contributes large inter- and intraobserver variations and may reduce the sensitivity of the analysis.

The goal of this proposed project is to develop a fully automated technique to assist radiologists in estimating mammographic breast density. We hypothesize that the computerized technique can accurately and efficiently segment the dense area on digitized or digital mammograms, thereby eliminating inter- and intra-observer variations. The dense area as a percentage of total breast area thus estimated will be more consistent and reproducible than radiologists' subjective BI-RADS rating. To accomplish this goal, we will (1) collect a large database of mammograms, including digitized film mammograms and digital mammograms, for training and testing the dense area segmentation program; (2) evaluate the correlation between the radiologists' breast density classification based on BI-RADS lexicon and the percent breast dense area; (3) study the correlation of percent breast dense area between different views of the same breast and between the same view of the two breasts; and (4) investigate the correlation between the percent breast dense area estimated from mammograms and the volumetric dense breast tissue estimated from a data set of magnetic resonance (MR) breast images. These comparisons will provide important information regarding the consistency of the BI-RADS rating with the measured percent breast dense area, the appropriate measure of % dense area from different mammographic views, and the usefulness of using the percent breast dense area on mammograms as an indicator of volumetric breast tissue density.

It is expected that this project will produce a fully automated and effective tool for analysis of mammographic breast density, which can be applied to routinely acquired mammograms without special calibrations. This will facilitate studies of various factors associated with breast cancer risk and mammographic sensitivity, and monitoring the effects of interventional or preventive strategies. The image analysis tool will therefore contribute to the understanding of the relationship of density to breast cancer risk, detection, prognosis, and to the prevention and treatment of breast cancer.

(5) Body

The current year (7/1/04-6/30/05) is the first no-cost-time-extension year of the project. We requested and obtained approval for a second-year no-cost time extension. Therefore, this is an annual progress report instead of the final report. We will describe in the following details of the studies that we performed this year.

In the current project year, we continued to improve the automated segmentation system for both the DMs and the DFMs. We have also improved the pectoral muscle segmentation method, further improving the dense area estimation for mediolateral oblique (MLO) view mammograms. These studies are described in the following.

(A) Collection of a Database of Full Field Digital Mammograms (DMs) and Digitized Mammograms (DFM)

In this project year, we continued to enlarge the data set of full field direct digital mammograms acquired from a GE Senographe 2000D system. With IRB approval, a data set of over 250 patients with over 500 pairs of digital mammogram (DM) and over 300 patients with over 600 digitized screen-film mammogram (DFM) have been collected to date. The data set was used in studies for development of a breast density analysis tool for digital mammograms and compare with that for DFMs.

A subset of 101 pairs of DM and 101 pairs of DFM mammograms from the same 99 patients was manually segmented using interactive thresholding by five Mammography Quality Standards Act (MQSA) radiologists as discussed in last year's report. Both the DMs and the DFMs were acquired with automated exposure techniques that selected the appropriate target, filter, and kVp. Each pair contained the craniocaudal (CC) view and the mediolateral oblique (MLO) view. The "gold standard" of percent dense area for each mammogram was obtained by averaging the manually segmented percent dense areas of four of the radiologists. The results of one of the radiologists who perceived the DMs as denser than the DFMs were not included because that appeared to be an outlier. The gold standard was used for evaluation of the segmentation performance of the automated system.

(B) Automated Segmentation of Dense Areas on Full Field Digital Mammograms

In last year's report, we presented the performance of the Mammographic Density ESTimator (MDEST) on DMs. The MDEST is an automated breast density segmentation system that we developed originally for segmentation of DFMs. The system was first applied to the DMs without re-training. The study was conducted to identify areas in the MDEST system that need improvement in order to be adapted to DMs. In this project year, we have modified the system to improve its performance on DMs, as detailed below.

(a) Data Set

The set of 101 pairs of DM from 99 patients was used in this study. The DM images were acquired at a pixel size of 100 μm x 100 μm . To avoid the dependence on GE's proprietary image processing methods, raw images were used as input to the MDEST system. The raw images were

logarithmic-transformed, convolved with a 16x16 box filter and downsampled to a 800 μm x 800 μm image before density segmentation processing.

(b) Methods

The improved system includes the same three major stages in the MDEST system: breast region segmentation, image enhancement, and gray level thresholding based on histogram analysis. First, the breast region is segmented from the surrounding background by automated gray level thresholding. For MLO view images, since our current pectoral muscle trimming program is not 100% accurate, the pectoral muscle was manually trimmed in this study in order to separate the errors due to breast density segmentation from those due to pectoral muscle trimming. Second, a Laplacian pyramid multi-resolution preprocessing method [1] is used for image enhancement. At the third stage, rule-based classification is used to classify the breast image into one of four classes (fatty, mixed, dense, very dense) according to the characteristic features of its gray level histogram [2]. In this study, we improved the third stage of density segmentation by incorporating an Expectation-Maximization (EM) algorithm to extract gray level features from the histogram (described below). A rule-based classifier is then trained to estimate a gray level threshold for segmenting the dense area from the breast region adaptively. The breast density is estimated as the percentage of the segmented dense area relative to the breast area. To evaluate the performance of MDEST for DMs, the computer segmentation results were compared to those by manual segmentation by MQSA radiologists.

The EM algorithm is used to extract features from the gray level histogram. We assume that there are three classes of Gaussian distributed gray levels in the image histogram: the dense area, the fatty tissues and the dark breast periphery. The iterative EM algorithm is used to estimate three Gaussians to fit the gray level histogram. The features of the EM-estimated Gaussian distributions include the size of the peaks, the ratio of the height and width of the peak, the mean and the standard deviation of the Gaussians, the distance between the peaks, and the percent overlap of the peaks. A rule-based classifier is designed to merge the peaks based on their features. For example, for a very fatty breast, two peaks representing the background and fatty tissue can be merged. The remaining peak that has a large height/width ratio and a small standard deviation will depict the small dense area in the breast region. For a mixed dense breast, the three Gaussians representing the background, fatty tissue and dense area have height/width ratios that are within a median range. There are less overlap and larger separation between these peaks so that no Gaussians will be merged. After the peaks are merged and reclassified into one of the four classes, a gray level threshold is determined adaptively to segment the dense area from breast region.

(c) Results

The performances of the MDEST system for DMs before and after the incorporation of the EM estimation and re-training are compared in Table 1. The correlation between the computer-estimated percent dense area and the radiologists' manual segmentation improved from 0.85 and 0.87 to 0.94 and 0.92, respectively, for CC and MLO views. The root-mean-square (RMS) errors improved from 7.3% and 5.7% to 4.2 and 4.4%, respectively, for CC and MLO views. The scatter plots of the percent dense area between the computer segmentation before retraining and the radiologists' segmentation are shown in Fig. 1(a)-(c) for the CC view, the MLO view, and the average of the two views, respectively. Similar comparisons after re-training are shown in Fig. 2 (a)-(c).

Table 1. The correlation and RMS error between computer segmentation and the average of four radiologists' manual segmentation in DMs.

FFDM	Performance	CC view	MLO view	Average of CC and MLO view
Without EM	Correlation	0.85	0.87	0.90
	RMS	7.3%	5.7%	5.5%
Re-trained with EM	Correlation	0.94	0.92	0.96
	RMS	4.2%	4.4%	3.6%

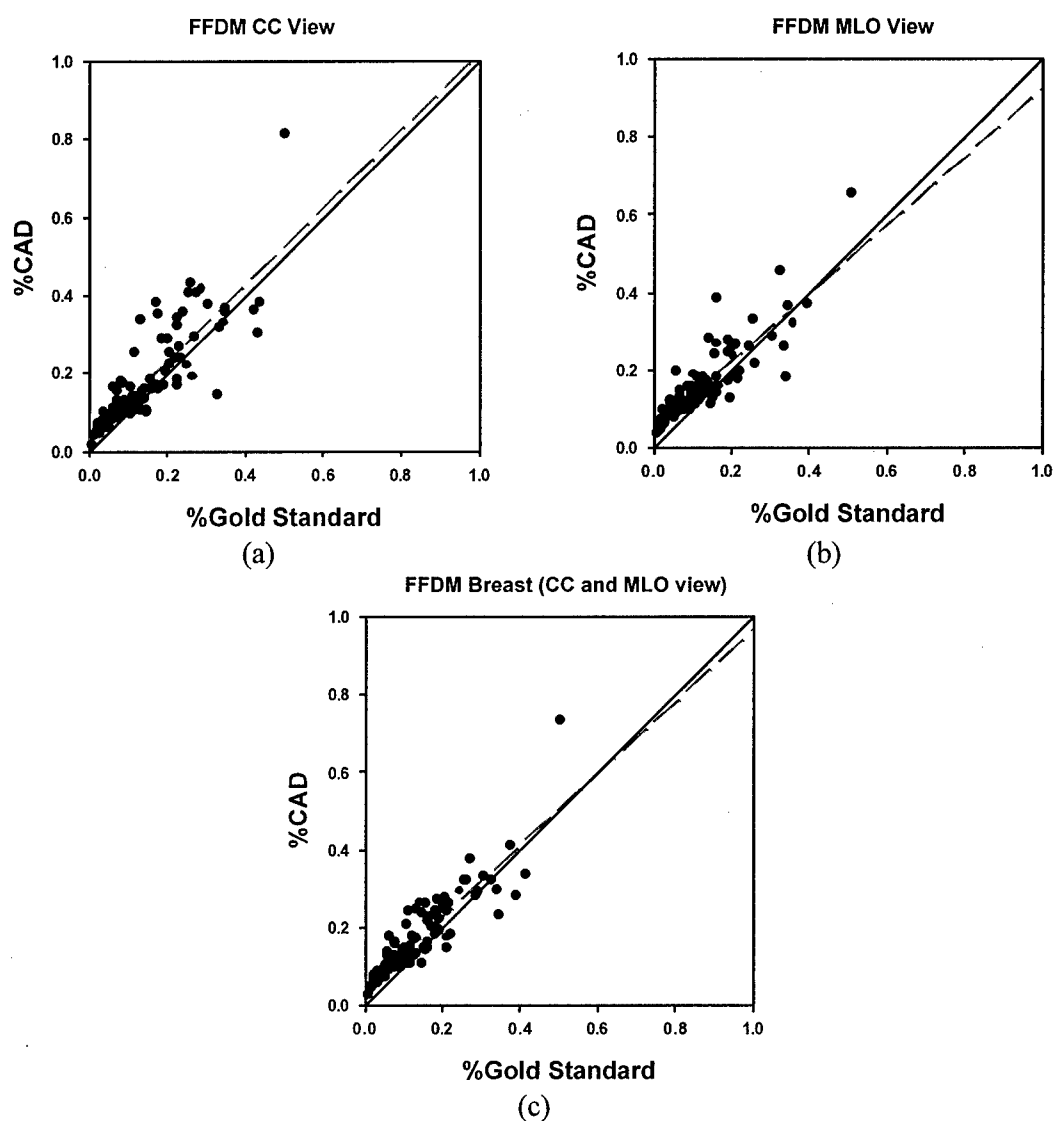


Fig. 1. Comparison of the percent dense area obtained from the MDEST system (%CAD) without EM estimation and that from the average of four MQSA radiologists (%Gold Standard) for DMs: (a) CC view, (b) MLO view, and (c) average of the CC and MLO

views.

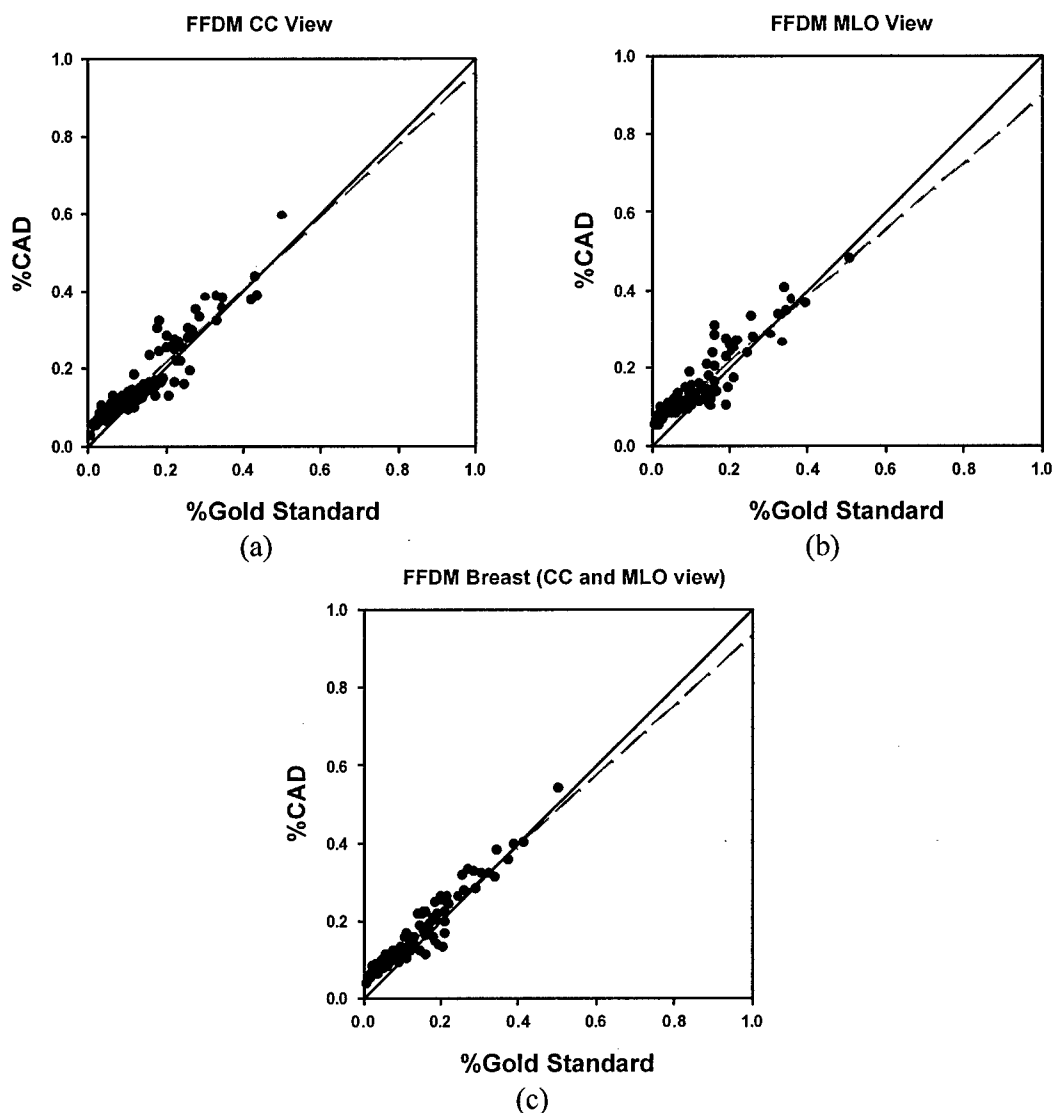


Fig. 2. Comparison of the percent dense area obtained from the MDEST system (%CAD) with EM estimation and that from the average of four MQSA radiologists (%Gold Standard) for DMs: (a) CC view, (b) MLO view, and (c) average of the CC and MLO views.

(C) Automated Segmentation of Dense Areas on Digitized Film Mammograms

The MDEST system for DFMs was also improved by incorporating the EM algorithm and retraining. The performances before and after the modification are compared, as detailed below.

(a) Data Set

In this study, the set of 101 pairs of DFMs from the same 99 patients as those for the DMs used in the study above was used. The DFMs were digitized with the LUMISYS 85 laser film scanner

at a pixel size of 50 μm x 50 μm and 4096 gray levels. The digitized mammogram was convolved with a 16x16 box filter and downsampled to a 800 μm x 800 μm image for the density segmentation processing.

(b) Methods

The MDEST system for DFMs was basically the same as that described in Section (B). It also contains three stages: breast region segmentation, image enhancement, and gray level thresholding based on histogram analysis. There are two main differences: one in the breast region segmentation stage and the other in the image enhancement stage. For breast region segmentation, automated breast boundary tracking was performed to separate the breast region from the surrounding background. For image enhancement, an adaptive dynamic range compression technique was used to enhance the DFM images [2]. A similar EM algorithm as that described above is also used in the improved MDEST system for DFMs. The EM algorithm extracts gray level features from the histogram. These features are used in the rule-based classification of the breast histogram into one of the four classes in the subsequent step. The system was re-trained and its performance was compared to that of the previous version.

(c) Results

The performances of the MDEST system for DFMs before and after the incorporation of the EM estimation and re-training are compared in Table 2. The correlations between the computer-estimated percent dense area and the radiologists' manual segmentation were 0.89 and 0.76, respectively, for CC and MLO views before and 0.88 and 0.86, respectively, after re-training. The correlation for CC view was slightly lower but that for MLO view improved substantially with the EM algorithm. The RMS errors changed from 6.8% and 9.1% to 7.1 and 7.2%, respectively, for CC and MLO views. Again, the RMS error for the CC view decreased slightly but that for the MLO view improved substantially. The scatter plots of the percent dense area between the computer segmentation before retraining and the radiologists' segmentation are shown in Fig. 3(a)-(c) for the CC view, the MLO view, and the average of the two views, respectively. Similar comparisons after re-training are shown in Fig. 4(a)-(c).

Table 2. The correlation and RMS error between computer segmentation and the average of four radiologists' manual segmentation in DFMs.

FFDM	Performance	CC view	MLO view	Average of CC and MLO view
Without EM	Correlation	0.89	0.76	0.90
	RMS	6.8%	9.1%	6.4%
Re-trained with EM	Correlation	0.88	0.86	0.92
	RMS	7.1%	7.2%	5.7%

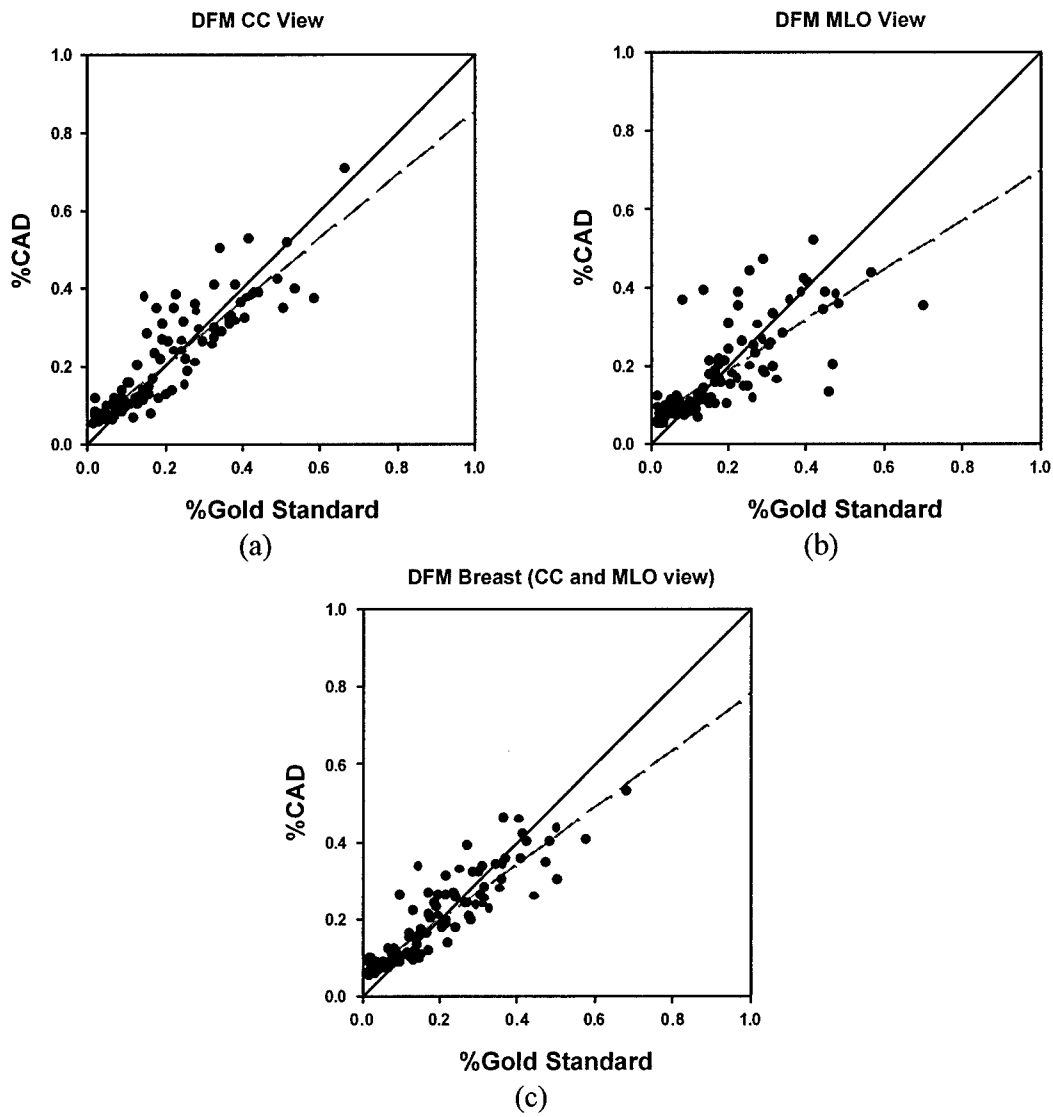


Fig. 3. Comparison of the percent dense area obtained from the MDEST system (%CAD) without EM estimation and that from the average of four MQSA radiologists (%Gold Standard) for DFMs: (a) CC view, (b) MLO view, and (c) average of the CC and MLO views.

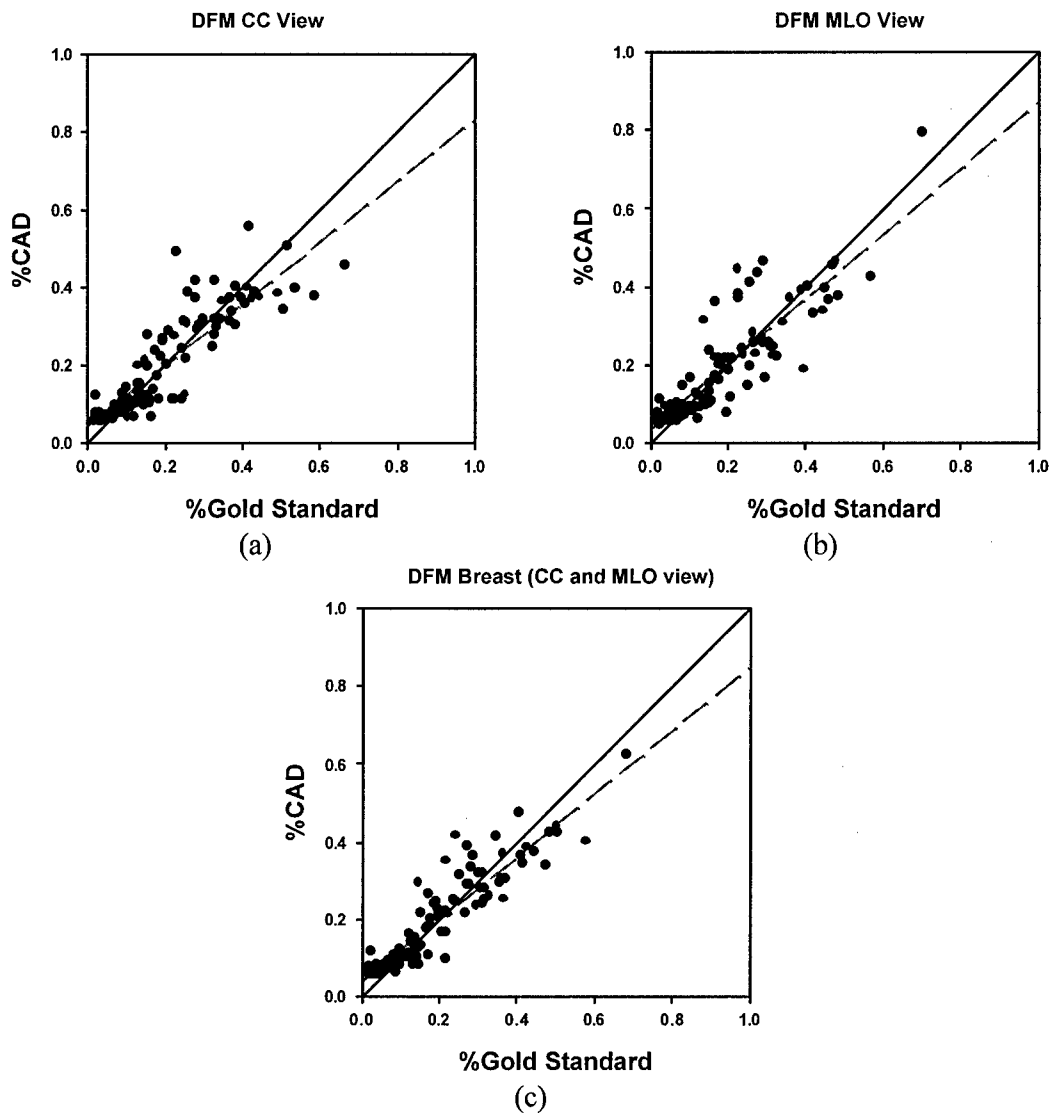


Fig. 4. Comparison of the percent dense area obtained from the MDEST system (%CAD) with EM estimation and that from the average of four MQSA radiologists (%Gold Standard) for DFMs: (a) CC view, (b) MLO view, and (c) average of the CC and MLO views.

(D) Breast Segmentation: Breast Boundary Detection and Pectoral Muscle Trimming

(a) Breast boundary detection

Methods

We have developed a breast boundary tracking method previously for segmentation of the breast area from the background for DFMs. The method sometimes fails when the image is noisy. A new breast boundary tracking method is being developed to improve the segmentation. A Sobel edge detection method is first applied to the image to extract vertical (V) and horizontal (H) edges. We

defined the edge gradient direction along the breast boundary as positive in the direction from the outside to the inside of the breast region.

A set of edge thresholds ranging from 10 to 200 is applied to the Sobel filtered images. For each Sobel filtered image in a given direction, the set of thresholds creates a set of corresponding contours along the breast boundary. Each contour is used to segment the breast into a binary image. The set of binary images from the contours is then summed up to generate a new image, which is referred to as the contour image. By applying the same set of thresholds to the Sobel-filtered images in three edge directions – the positive horizontal edges, the positive vertical edges, and the negative vertical edges – three contour images are generated. The three contour images are summed to generate a complete contour image. Morphological “closing” and “opening” operations are then used to remove the noise from the summed contour image and extract the initial breast boundary. Finally, an active contour method is used to further refine the breast boundary points based on the initial detected breast boundary.

Results

Examples of the three contour images and the summed contour image are shown in Fig. 5. Fig. 6 shows the initial boundary and the final boundary refined by active contour. The overall accuracy of the breast boundary detection method will be evaluated with a large data set in the coming year.

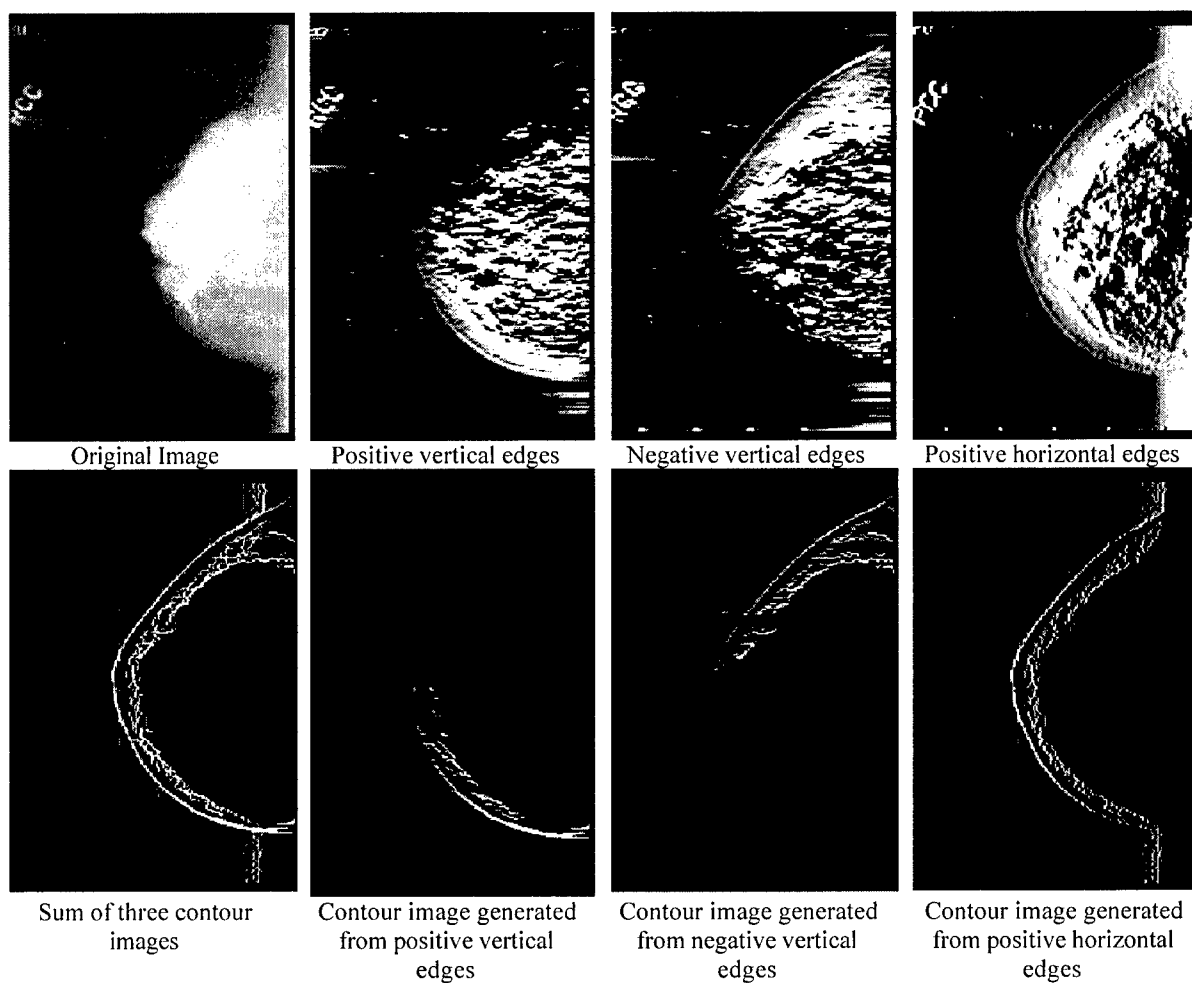


Fig. 5. Examples of Sobel edges and contour images.

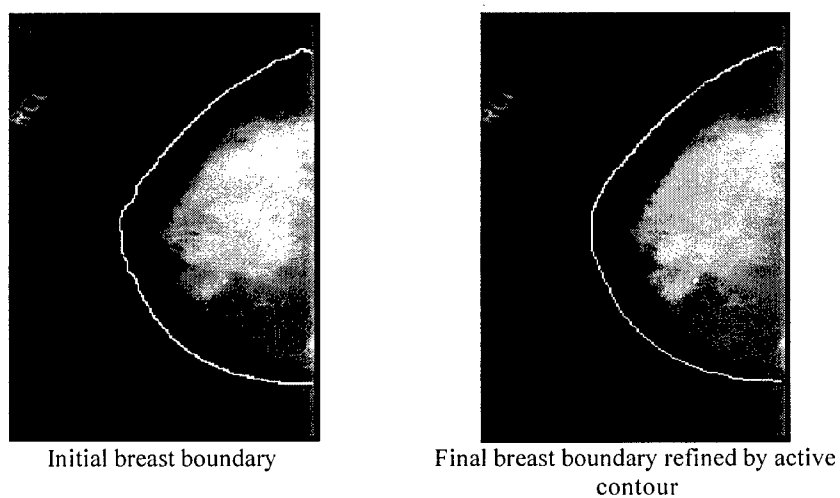


Fig. 6 Example of the initial breast boundary and active contour refined boundary

(b) Pectoral muscle trimming

Methods

To extract the breast area in the MLO view, it is important to trim the pectoral muscle accurately. The pectoral muscle boundary is often very noisy and overlaps with glandular tissue, especially near the tail region. We have developed a pectoral muscle trimming method previously but its accuracy is only about 70%. In this project year, we continue to improve the pectoral muscle trimming by designing a new method, as described below.

The interference due to overlapping of the glandular tissue with the pectoral muscle region is first reduced by smoothing the mammogram using an edge preserving anisotropic diffusion filter [3]. Since less glandular tissue appears at the upper part of the pectoral muscle, the pectoral boundary in this region usually remains sharp after smoothing and can be detected robustly by searching for the maximum horizontal gradients on the diffused image. The extrapolation of the detected upper pectoral boundary provides a coarse global direction of the pectoral boundary.

To refine the entire pectoral boundary, a gradient-based directional (GD) filter was first employed to enhance the linear texture structures on the mammogram. The orientation of the digitized image can be automatically determined by the curvature of the breast boundary. For example, if the image is positioned such that the chest wall is on the right side, it can be assumed that the pectoral boundary is at a direction approximately from the top-left to the bottom-right with less than 45 degree deviation. Therefore, in our study, the kernel of the GD filter is designed as a step function with 45 degree orientation. After the pectoral edge is enhanced by the GD filter, a gradient-based texture analysis [4] is used to compute an orientation image which represents the dominant texture orientation at each pixel. The orientation image is smoothed using an edge preserving mean shift algorithm [5] that iteratively shifts each pixel to the average of the pixels in its neighborhood. The texture patterns with dominant texture orientations directing from the top-left to the bottom-right, which are more likely to be the pectoral edges, are enhanced by applying a second GD filter to the smoothed orientation image. Candidate edges of the pectoral muscle are detected on the enhanced orientation image using a ridge-tracking algorithm. The ridges are tracked by searching for the local maximum along the coarse global direction estimated, as described above, by the upper pectoral boundary on the anisotropic diffused image. With the guidance of the estimated global direction of the pectoral boundary and the anatomical constraints, an edge flow propagation algorithm is then used to extract the boundary points of the pectoral muscle by pruning the edges that are less likely to lie on the pectoral boundary. A second order curve fitting is finally used to generate the pectoral muscle boundary.

Results

In this study, 118 MLO-view mammograms from 103 patients were randomly selected from the database collected for the project. An experienced MQSA-radiologist used a graphical user interface to manually draw the pectoral muscle boundary on each MLO-view mammogram, which was then used as the gold standard for the evaluation of the performance of our pectoral muscle detection program.

For each MLO view mammogram, the accuracy of pectoral boundary detection was evaluated by two performance metrics: the percentage of overlap, defined as the ratio of the overlap area between

the computer detected pectoral muscle area and the gold standard relative to the gold standard, and the RMS distance obtained by calculating the shortest distance point by point between the computer-identified pectoral boundary and the manually marked pectoral boundary. For the data set of 118 MLO view mammograms, 99.2% (117/118) of the pectoral muscles could be identified, the average of the percent overlap area is 94.8% with a standard deviation of 20.9%, the average of the RMS distance is 4.3 mm with a standard deviation of 5.9 mm.

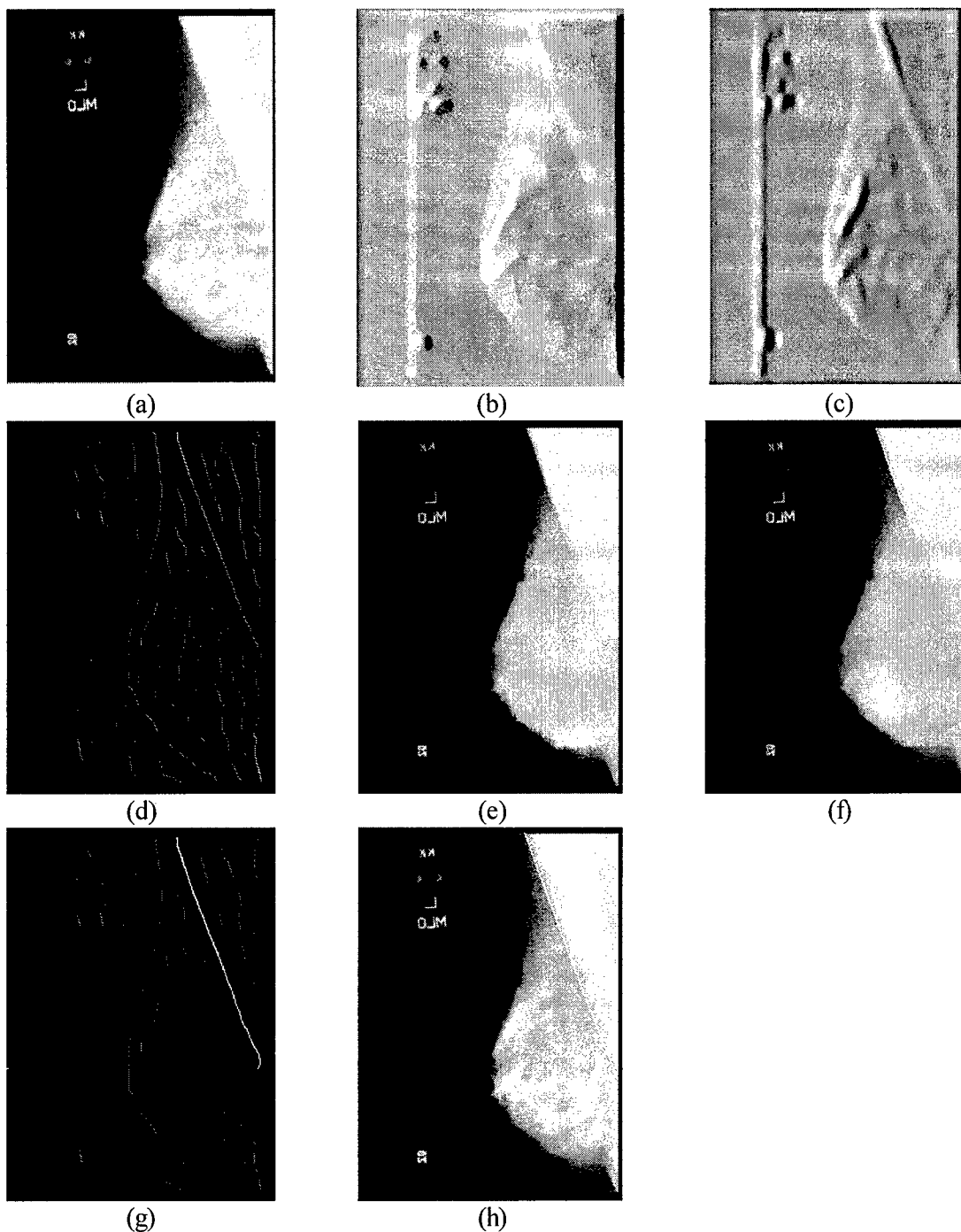


Fig. 7. Example of boundary enhancement and segmentation of pectoral muscle. (a) original image; (b) texture orientation image after first GD filter and texture-flow analysis; (c) ridge image enhanced by the 2nd GD filter; (d) tracked ridges; (e) smoothed image using anisotropic diffusion filter; (f) initial pectoral edges detected from the smoothed image in (e) for the estimation of the coarse direction of the pectoral boundary; (g) propagated pectoral edges on the ridge image (c) with the guidance of the coarse direction estimated from the smoothed image shown in (f); (h) the final identified pectoral boundary after 2nd order curve fitting.

(6) Key Research Accomplishments

- Continue to collect the data sets of digitized film mammograms and digital mammograms for development of the automated density segmentation program (Task 1).
- Improve the mammographic density segmentation program for digitized film mammograms (DFMs) (Task 2).
- Compare automated density segmentation results on DFMs with MQSA radiologists' manual segmentation and evaluate the performance of the automated program (Task 2).
- Improve the mammographic density segmentation program for digital mammograms (DMs) (Task 4).
- Compare automated density segmentation results on DMs with MQSA radiologists' manual segmentation and evaluate the performance of the automated program (Task 4).
- Develop an improved method for breast boundary detection, thus improving the accuracy of breast area estimation for calculation of percent dense area (Task 2 and Task 4).
- Develop an improved method for pectoral muscle trimming, thus improving the accuracy of breast area estimation for calculation of percent dense area (Task 2 and Task 4)

(7) Reportable Outcomes

As a result of the support by the USAMRMC BCRP grant, we have conducted studies to investigate the correlation between the computer-segmented mammographic density on DMs with radiologists' manual segmentation, and the correlation between the computer-segmented mammographic density on DFMs with radiologists' manual segmentation. We have developed a new pectoral muscle trimming method for improvement of the accuracy of breast area estimation on MLO view mammograms. The results of these investigations have been presented or submitted for presentation in this project year. A manuscript on the pectoral muscle trimming method is being prepared for publication.

Conference Presentation:

1. Zhou C, Hadjiiski LM, Paramagul C, Sahiner B, Chan HP, Wei J. Computerized pectoral muscle identification on MLO-view mammograms for CAD applications. Poster presentation at the SPIE International Symposium on Medical Imaging, San Diego, CA, February 12-17, 2005.
2. Zhou C, Chan HP, Helvie MA, Wei J, Ge J, Hadjiiski LM, Sahiner B, Computerized mammographic breast density estimation on full field digital mammogram and digitized film mammogram. Submitted for presentation at the 91th Scientific Assembly and Annual Meeting of the Radiological Society of North America, Chicago, IL. November 27-December 2, 2005.

(8) Conclusions

During this project year, we have improved our automated mammographic density segmentation program, referred to as Mammographic Density ESTimator (MDEST), for both DMs and DFMs. The improvement was achieved by incorporating an EM algorithm to extract the gray level features from the image histogram and retraining. The performance of the re-trained MDEST system for both DMs and DFMs was evaluated and compared with manually segmented mammographic density by experienced radiologists. The improved system was found to provide higher correlation and lower RMS error than the previous system in 10 of the 12 comparisons. The two exceptions were the correlation and the RMS error of the CC view DFMs, of which the correlation decreased and the RMS error increased slightly with the modifications. The results indicate that the automated MDEST system is useful for estimation of mammographic density for both DMs and DFMs. We will continue to improve the accuracy of the segmentation program in the coming year.

To further improve the estimation of percent dense area, we have designed new techniques and refined the existing methods for automatically tracking the breast boundary and the pectoral muscle edge on MLO view mammograms. The new methods improve the segmentation of breast boundary and pectoral muscle edge on noisy images over the previous methods. We will complete the development next year.

When the MDEST system is completed, we expect that it can provide a consistent and reproducible estimation of percent dense area on routine clinical mammograms. The automated image analysis tool may improve the sensitivity of quantifying mammographic density changes, thereby contributing to the understanding of the relationship of mammographic density to breast cancer risk, detection, and prognosis, and the prevention and treatment of breast cancer.

(9) References

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2. Zhou C, Chan HP, Petrick N, Helvie MA, Goodsitt MM, Sahiner B and Hadjiiski LM, "Computerized image analysis: Estimation of breast density on mammograms," Medical Physics 28, 1056-1069 (2001).
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4. Rao AR and B.G.Schunck, "Computing oriented texture fields," CVGIP: Graphical models image processing 53, 157-185 (1991).
5. Comaniciu D and Meer P, "Mean shift: A robust approach toward feature space analysis," IEEE Trans on Pattern analysis and machine intelligence 24, 603-619 (2003).

(10) Appendix

Copies of the following publications are enclosed with this report:

Conference Presentation:

Zhou C, Hadjiiski LM, Paramagul C, Sahiner B, Chan HP, Wei J. Computerized pectoral muscle identification on MLO-view mammograms for CAD applications. Poster presentation at the SPIE International Symposium on Medical Imaging, San Diego, CA, February 12-17, 2005.

Zhou C, Chan HP, Helvie MA, Wei J, Ge J, Hadjiiski LM, Sahiner B, Computerized mammographic breast density estimation on full field digital mammogram and digitized film mammogram. Submitted for presentation at the 91th Scientific Assembly and Annual Meeting of the Radiological Society of North America, Chicago, IL. November 27-December 2, 2005.



University of Michigan
Medical School

Computerized Pectoral Muscle Identification on MLO-view Mammograms for CAD Applications

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ABSTRACT

Automatic identification of the pectoral muscle on MLO or lateral view is an essential step for computerized analysis of mammograms. It can reduce the bias of mammographic density estimation, will enable region-specific processing in lesion detection programs, and also may be used as a reference in image registration algorithms. We are developing a computerized method for the identification of pectoral muscle on mammograms.

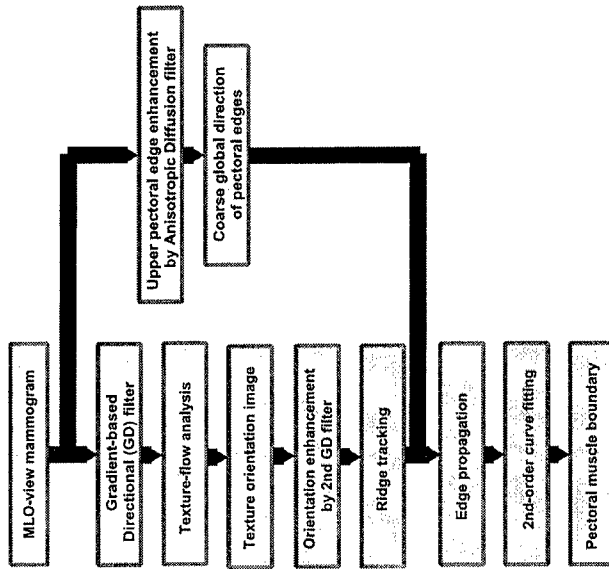
The upper portion of the pectoral edges was first detected to estimate the direction of the pectoral muscle boundary. A gradient-based directional (GD) filter was used to enhance the linear texture structures, and then a gradient-based texture analysis is designed to extract a texture orientation image that represented the dominant texture orientation at each pixel. The texture orientation image was enhanced by a second GD filter. An edge flow propagation method was developed to extract edges around the pectoral boundary using geometric features and anatomic constraints. The pectoral boundary was finally generated by a second-order curve fitting.

MATERIALS

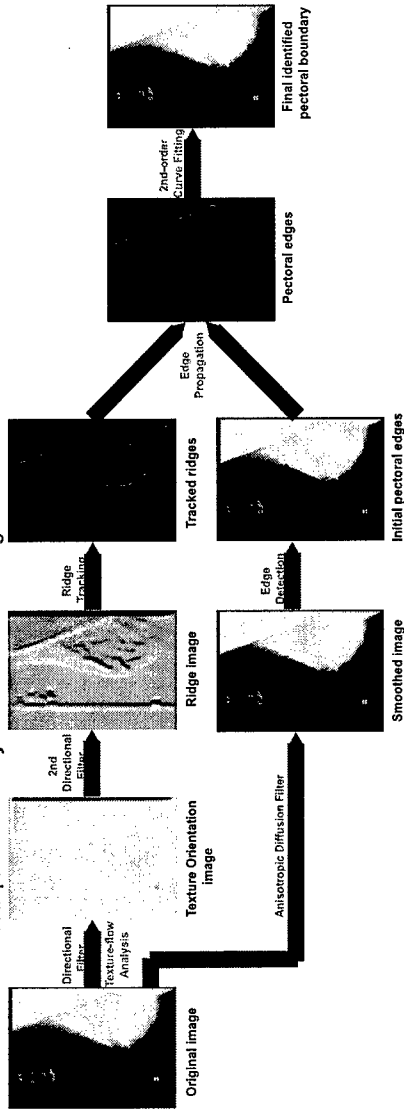
118 MLO view mammograms from 103 patients were randomly selected for the evaluation of the algorithm in this study. The mammograms were digitized with 0.05 mm/pixel resolution and reduced to a resolution of 0.8 mm/pixel for pectoral muscle detection.

An experienced MQSA-radiologist used a graphical user interface to manually draw the pectoral muscle boundary on each mammogram, which was then used to define the pectoral muscle region and used as the gold standard for the evaluation of computer performance.

METHODS



Example of Boundary Enhancement and Segmentation of Pectoral Muscle

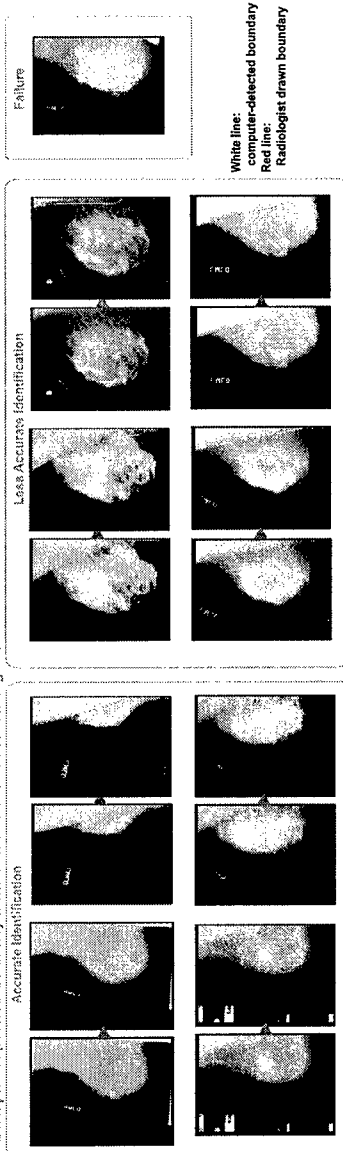


RESULTS

For each MLO view mammogram, the accuracy of pectoral boundary detection was evaluated by two performance metrics: the percentage of computer detected pectoral muscle area overlapped with the gold standard, and the root-mean-square (RMS) distance between the computer-identified pectoral boundary and the manually marked pectoral boundary.

For 118 MLO view mammograms, 99.15% (117/118) of the pectoral muscles could be identified. The average of the percent overlap area is 94.8% with a standard deviation of 20.9%, the average of the RMS distance is 4.31 mm with a standard deviation of 5.94 mm.

Examples of pectoral boundary identification on difficult mammograms



CONCLUSION

The newly developed gradient-based directional filter and the dominant texture orientation image estimation method can enhance the pectoral boundary regions. The edge flow propagation method can accurately extract pectoral edges to generate the pectoral boundary. Automatic pectoral muscle identification will provide the foundation for many image analysis tasks in CAD applications.

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Title: Computerized mammographic breast density estimation on full field digital mammogram and digitized film mammogram

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PURPOSE:

We have previously developed an automatic mammographic density estimator (MDEST) on digitized film mammograms (DFM). In this study, we modified MDEST to estimate breast density on full field digital mammograms (FFDM) and further improved the performance of the MDEST on DFM.

METHOD & MATERIALS:

The breast region is first extracted by breast boundary detection. The pectoral muscle is trimmed if it is an MLO view. An adaptive dynamic range reduction technique is used to reduce the gray level range in the low frequency background. The breast image is classified into one of four classes ranging from fatty to very dense based on the characteristics of their gray level histograms. For each class, an Expectation-Maximization (EM) algorithm is developed to extract gray level features and a rule-based classifier is trained to segment the dense regions from the fatty background. The parameters of the new rule-based method are trained separately for FFDMs and DFMs. The breast density is estimated as the percentage of the segmented dense area relative to the breast area. Two-view FFDMs and the corresponding DFMs from 99 patients with 202 images in each set were used as the test set. The computerized segmentation on the two sets of mammograms is compared to the "gold standard", which is obtained from interactive thresholding segmentation averaged over 4 MQSA radiologists for each mammogram.

RESULT:

For FFDM, the correlation between the computer estimated percent dense area and the gold standard was 0.94 for CC view, 0.92 for MLO view, and 0.96 for each breast with the percent dense area estimated as the average of two views. The corresponding root-mean-square (RMS) error was 4.2%, 4.4%, and 3.5%, respectively. For DFM, the corresponding correlations were 0.88, 0.86 and 0.92 with RMS error of 7.0%, 7.1% and 5.7%, respectively.

CONCLUSION

The results demonstrate the feasibility of estimating breast density automatically on FFDMs and DFMs using the same MDEST system by only incorporating a new EM estimation step. The adaptability of the new EM method improved the robustness of our breast density estimation technique for mammograms acquired with different imaging systems.