MIXTURE MODELING FOR DIGITAL MAMMOGRAM DISPLAY AND ANALYSIS[1]

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Abstract: We have devised a mammogram modeling system which greatly simplifies the development of, and can improve the accuracy and consistency of, computer-aided display and analysis algorithms for digital mammography. Our system segments the five major components of a mammogram: background, uncompressed-fat, fat, dense, and muscle. Differences in the amount and distribution of these components account for much of the variation between mammograms. Via segmentation, the corresponding variations are isolated; automated algorithms can consider the components independently or adapt their parameters based on component-specific statistics.

In this paper, we present our system and demonstrate its versatility. Our system is able to segment a wide variety of digital mammograms because of its combined use of geometric (i.e., gradient magnitude ridge traversal) and statistical (i.e., Gaussian mixture modeling) techniques. Using images from Fischer, General Electric, and Trex digital mammography units, we define and evaluate automated, component-based algorithms for (1) "general" intensity windowing, i.e., displaying a digital mammogram such that it resembles a screen-film mammogram for breast cancer screening; (2) component-specific intensity windowing for breast lesion characterization; and (3) breast density estimation for breast cancer risk assessment.

1. Introduction

Digital mammography has the potential to outperform screen-film mammography for the detection and characterization of breast lesions. Digital mammography:

- records a broad, finely-sampled range of x-ray energies. It captures the subtle density differences associated with lesions embedded in dense breast tissue.
- decouples the record and display processes. These processes can be optimized independently. Multiple visualizations can be generated from a single acquisition.
- integrates computers into the record-display sequence. This facilitates the use of computer-aided display and analysis algorithms.

Until these potentials are sufficiently exploited, however, they can interfere with mammographic interpretations. Most notably, automated intensity windowing (IW) becomes not only feasible but actually critical. The human visual system cannot simultaneously appreciate the 2^{16} energy levels recorded by some digital mammography units. Displaying an unwindowed digital mammogram produces an image with poor apparent contrast (Figures 1 and 2). IW maps a recorded range to an appropriate display

[1] Appears in *Digital Mammography*, N. Karssemeijer, et al. Editors, Computational Imaging and Vision Series, Vol. 13, Kluwer Academic Publishers, Dordrecht, 1998 pp. 305-312

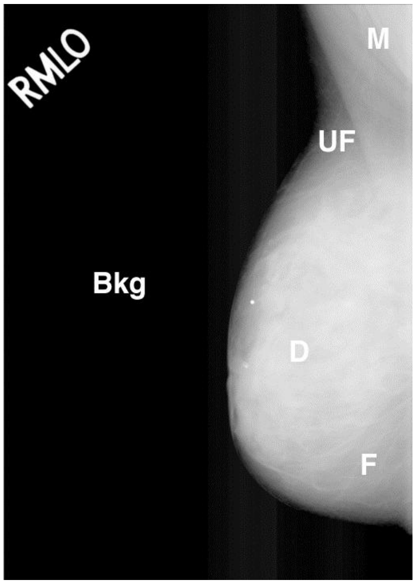

Figure 1. A digital, medial-lateral oblique mammogram without IW; low apparent contrast; components labeled.

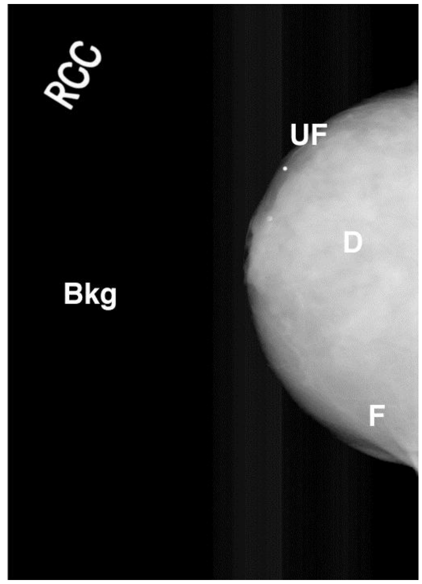

Figure 2. A digital, cranial-caudal mammogram of the same breast as in Figure 1.

range (~ 2^{10} levels of gray). IW parameters can be chosen so as to make a displayed digital mammogram resemble a screen-film mammogram, called "general" IW. Component-specific IW can be used to accentuate lesions which may otherwise be obscured. The development and performance of automated methods such as IW are, however, confounded by the highly varied appearance of mammograms.

Our mammogram modeling system greatly simplifies the development of, and can improve the accuracy and consistency of, computer-assisted display and analysis algorithms for digital mammography. The premise of our system is that much of the variation between mammograms is due to differences in the amount and distribution of five components[2]: background, uncompressed-fat, fat, dense, and muscle. By delineating and labeling ("segmenting") those components in each mammogram being processed (Figures 1 and 2), that portion of mammogram variability is eliminated; automated algorithms can consider the components independently, the statistical characteristics of those components can be normalized across mammograms, and thereby more accurate and consistent information can be provided to radiologists.

Our system is able to consistently segment digital mammograms because of its combined use of geometric and statistical analysis techniques. Our system is insensitive to patient anatomy, image noise, select image preprocessing algorithms (e.g., edge enhancement), and even acquisition parameters such as resolution and digital detector response function. We use a gradient magnitude ridge traversal algorithm to define the breast's edge and extract the pectoral-muscle component. Erosion and dilation of the breast's edge are used in defining the background and uncompressed-fat components. Mixture modeling is used to statistically differentiate fat from dense component pixels.

In this paper we describe our mammogram modeling system; define methods which use our system for general IW, component-specific IW, and breast density estimation;

[2] Mammographic components are formed by projection and are not comprised of a single tissue type.

and discuss the application of those methods to images from Fischer, GE, and Trex digital mammography units.

2. Methods

This section provides an overview of our breast and pectoral-muscle edge identification algorithms. It then provides details concerning the role of those edges and Gaussian mixture modeling in mammogram component segmentation.

2.1. BREAST EDGE IDENTIFICATION

Our system uses the breast edge in defining the background and uncompressed-fat components. In general, methods based on absolute intensity (e.g., thresholding) cannot be used to distinguish breast from background. The selection of an appropriate threshold is made difficult, and often impossible, by highly variable uncompressed-fat intensities and background noise. In some digital mammograms, the background noise is structured, abuts the uncompressed fat, and appears brighter than the uncompressed fat.

Our method avoids intensity related difficulties since it is based on large-scale gradient-magnitude ridge traversal (i.e., image geometry). It is not affected by absolute intensity values, small-scale image noise, or image data which is not local to the breast's edge. Additionally, it provides a sub-voxel estimate of the edge's location. Our method consists of two steps: (a) finding an initial point on the breast's edge and (b) traversing the gradient magnitude ridge that defines the breast's edge.

(a) An initial breast edge point is defined by the point of maximum gradient magnitude along a line passing horizontally through the center of a breast. Given a mammographic image I, its gradient magnitude image $I_{|\nabla|}$ at scale σ = 60 mm is defined by convolving it with Gaussian derivative kernels $G_\sigma dx$ and $G_\sigma dy$.

$$I_{|\nabla|} = \left[(I \otimes G_\sigma dx)^2 + (I \otimes G_\sigma dy)^2 \right]^{1/2} \qquad (1)$$

We define the center of a breast as the center-of-mass (x_{COM}, y_{COM}) of the pixels in the image. An initial breast edge point (x_0, y_0) is therefore defined by

$$x_0 = \mathrm{argmax}_x \left[I_{|\nabla|} (x, y_{COM}) \right] \text{ and } y_0 = y_{COM} \qquad (2)$$

(b) To extract the extent of the breast’s edge, a ridge traversal algorithm is applied to the gradient magnitude image starting at the initial breast edge point. The minimum eigen-valued eigen-vector of the Hessian at a point on a ridge approximates the ridge's tangent direction. The maximum eigen-valued eigen-vector approximates the ridge's normal direction. At a ridge point, by stepping 0.1 pixel units in the tangent direction and then finding the local maximum normal to that point, a subsequent ridge point is found. This process is repeated until a point near the image boundary is reached, the tangent direction changes rapidly, or the spatial location of the next ridge point is far from the previous ridge point. [1]

2.2. PECTORAL MUSCLE EDGE IDENTIFICATION

Pectoral muscle appears within most medial lateral oblique images and can interfere with many automated analysis algorithms. For example, since the pectoral-muscle component appears at approximately the same intensity as the dense component, intensity-based methods cannot be used to differentiate it from the dense component, and therefore the pectoral-muscle component can bias breast density estimates.

To consistently and accurately extract the pectoral muscle, we find the prominent line within the upper portion of a breast. We assume that the pectoral edge is well approximated by a straight line and that it intercepts the top of the image before crossing the breast's edge. We apply our gradient magnitude ridge traversal algorithm (a) at a small scale and (b) at multiple initial points and then resolve the resulting multiple edge definitions via (c) a voting scheme. This method parallels that of Karssemeijer [4].

(a) Because of the sharpness of the pectoral edge, we extract the gradient magnitude ridges at a scale of 1.5 mm. Using a small scale increases the effect of image noise on the traversal algorithm and further necessitates the use of multiple initial points and a voting scheme to determine the prominent edge.

(b) Because of the striations inherent in the mammographic appearance of muscle, the determination of an appropriate initial point can be difficult. We therefore consider potential edges at regular horizontal intervals at the top of the image. Within the breast, at each horizontal interval, we extract the edge nearest the breast’s edge and the edge at the largest gradient magnitude. As a result, multiple edges are extracted and the same edge may be extracted multiple times.

(c) To determine the prominent edge, we determine the most common tangent direction and top-of-image intercept among all of the edge points extracted. That slope / intercept pair defines the line of the pectoral muscle's edge.

2.3. COMPONENT MODELING

Building from the extracted breast and pectoral muscle edges, our system forms geometric and statistical representations of the mammographic components. Geometric models are used to represent the non-breast (i.e., the background and muscle) components. Statistical models are used to define the breast (i.e., the uncompressed-fat, fat, and dense) components.

2.3.1. *Geometric Models: Representing Background and Muscle Components*

Geometric models are formed by dilating the extracted breast and pectoral-muscle edges. We acknowledge that our system’s edge identification, erosion, and dilation processes do not exactly define the spatial bounds of the components. We have, however, found these large-scale constructs to be sufficient for the tasks in this paper. If a small-scale representation is desired (e.g., in order to localize the breast’s nipple), a coarse-to-fine snake algorithm can be employed to refine the representations.

Background: The background component is defined as the portion of the image outside of a dilation of the extracted breast edge. Dilation is necessary since the breast edge is defined at a large scale and therefore is partially contained within the breast. We perform dilation using a circular operator with a radius equal to the scale at which the edge was identified, i.e., 60 mm.

Muscle: The representation of the pectoral-muscle component is formed by dilating the pectoral-muscle line using a radius of 1.5 mm, the scale used in defining that line.

2.3.2. *Statistical Models: Representing Uncompressed-Fat, Fat, and Dense Components*

Our system forms statistical models of the breast components using (a) pixel intensities, (b) the concept of distribution sampling, and (c) Gaussian mixture models.

(a) The implementation presented in this paper considers intensity and not local texture when determining a pixel’s mammographic component. Future implementations will consider both so as to better distinguish the fat and dense components.

(b) We rely on distribution sampling to overcome the ambiguity of mammographic components. Since breast components are formed via projection, their exact delineation cannot be achieved. However, by identifying a large number of pixels from the breast components (i.e., by sufficiently sampling their pixel intensity distribution) a statistical model can be formed.

(c) Statistical models are formed via Gaussian mixture modeling. In Gaussian mixture modeling, multiple Gaussians are weighted and linearly combined to represent a non-Gaussian distribution. The parameters of the mixture are iteratively determined via expectation-maximization which maximizes the log-likelihood of the data representing the distribution. [3]

Uncompressed-fat: A statistical model of the uncompressed-fat component is formed by modeling the pixel intensities in the area about the breast edge. Such a region is defined by an erosion and a dilation of the breast's edge. The distribution of intensities in that region is, however, highly skewed because in that region breast thickness is a function of distance from the edge. Such a skewed distribution can be well represented by multiple Gaussians in a mixture model. For the tasks in this paper, we have found it sufficient to approximate the distribution with a single Gaussian.

Fat and Dense: The fat and dense component models are formed simultaneously. Eroding the breast edge and dilating the pectoral-muscle line produces a section of image containing only fat and dense component pixels. We apply Gaussian mixture modeling using two Gaussians to represent the intensities in that image section. The correct labels (fat/dense) for the Gaussians can, however, be ambiguous. We found that if a dense component is less than ~1/10th the size of the fat component, the Gaussian mixture model often uses both Gaussians to represent just the fat component. To automatically identify such "fatty" breasts, we use a breast's medial-lateral oblique image. If the mean pectoral-muscle intensity is more than two standard deviations above both Gaussians in the fat/dense mixture, we conclude that the fat/dense mixture models for all images of that breast actually only represent the fat component.

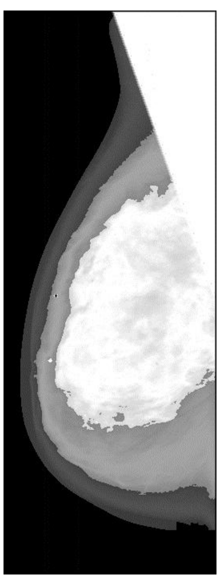

Figure 3. Segmentation of Figure 1

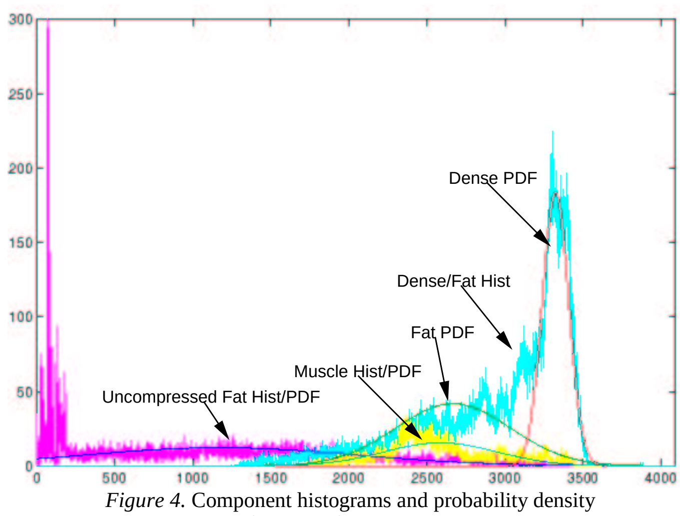

Figure 4. Component histograms and probability density functions from Figure 1

2.3.3. *Viewing Segmentations*

To visualize the segmentations, every pixel in an image can be gray-level coded to reflect the component to which it has been assigned. For example, Figure 3 is the segmentation of Figure 1. The image has been automatically cropped based on the extent of the breast's edge. White represents the pectoral-muscle component, shades of light gray indicate dense component pixels, shades of medium-gray indicate fat, uncompressed fat is colored dark gray, and the background is black. The subtle shadings of the breast components reflect each pixel's estimated probability of belonging to its assigned component; lighter shades indicate higher membership probabilities.

Alternatively, the histogram from each component can be generated and the probability density functions (PDFs) of the Gaussians in a mixture model can be overlaid. Figure 4 contains the histograms from the uncompressed-fat, combined fat/dense, and pectoral-muscle components of Figure 1. The probability density functions for the uncompressed-fat, fat, dense, and muscle Gaussians are overlaid.

3. Display and Analysis of Mammograms via Components

We have devised a number of display and analysis algorithms based on our mammogram segmentation system. In this paper we present three: (1) general IW for breast cancer screening, (2) component-specific IW for breast lesion characterization, and (3) breast density estimation for breast cancer risk assessment.

3.1. INTENSITY WINDOWING: LESION DETECTION AND DIAGNOSIS

IW parameters are easily defined using mammogram component information. Our algorithm utilizes a sigmoidal mapping function. A sigmoidal function has a central linear section and curves at its extremes. Our sigmoidal function is parameterized by six variables; for each of the low and high curves there are intercepts (i_L and i_H), curve starting points (a_L and a_H), and rates of curvature (b_L and b_H). Figure 5 illustrates the change in the shape of the sigmoid for different a_L and b_L values. For automated IW, we define intercept parameters in terms of the means (e.g., μ_D) and standard deviations (e.g., σ_D) of the mammographic components' intensities. Appropriate values for the curve parameters (i.e., a**.** and b**.**) were chosen via a small preference study; those values are fixed based on the mammography unit's manufacturer.

We realize that IW is not a complete solution to improving breast cancer detection or characterization. For example, edge enhancement is useful in emphasizing spiculated

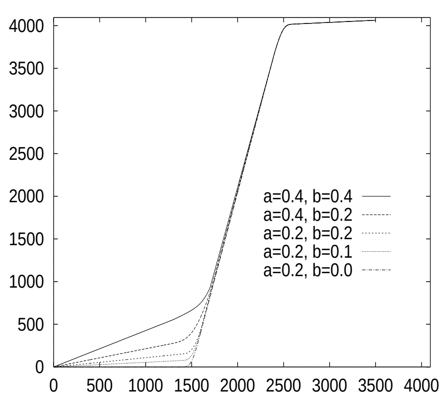

Figure 5. Various sigmoidal curve parameterizations

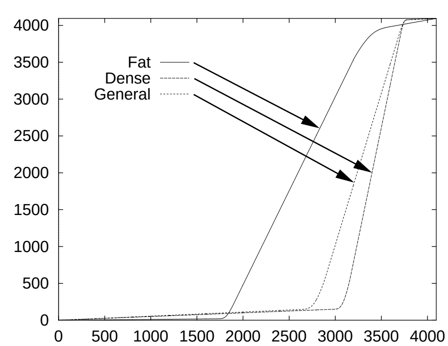

Figure 6. IW functions for Figure 1

masses and architectural distortions. IW, however, is a necessary part of the solution.

General intensity windowing: The goal of general IW for breast cancer screening is the emphasis of detail within the dense and fat components. By default, we define $i_L = \mu_F$ and $i_H = \mu_D + 4\sigma_D$. For fatty breasts (Section 2.3.2: fat and dense), we define $i_L = \mu_F - 2\sigma_F$ and $i_H = \mu_F + 4\sigma_F$. Figure 7 is a general IW of Figure 1. Figure 6 contains the corresponding sigmoidal function.

Component-specific intensity windowing: Suspecting a lesion, the radiologist using a softcopy display can call upon alternative visualizations of a digital mammogram for lesion characterization. Component-specific IW utilizes all of the display contrast to emphasize the information in a single component. Via preference studies, we have defined intercept functions **i.** for each component. Figure 8 is a dense-component-specific IW of Figure 2.

3.2 BREAST DENSITY ESTIMATION: BREAST CANCER RISK ASSESSMENT

Breast density has been associated with breast cancer risk. Much research has focused on the development of semi-automated and fully automated methods for quantifying breast density using mammographic images. [2]

Given a segmented mammogram, breast density estimation reduces to pixel counting. A breast's density is the ratio of the number of dense-component pixels to the number of uncompressed-fat, fat, and dense-component pixels.

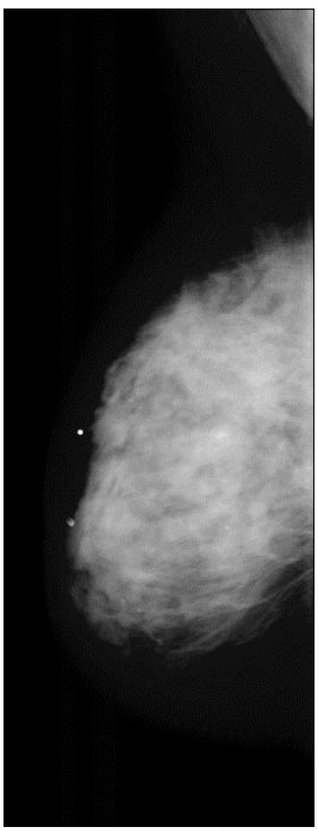

Figure 7. General IW of Figure 1

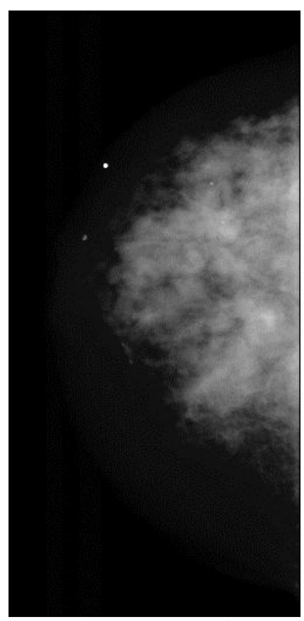

Figure 8. Dense-component-specific IW of Figure 2

4. Results

We have evaluated our segmentation, IW, and density estimation algorithms using images from three digital mammography unit manufacturers: Fischer, GE, and Trex. We have evaluated approximately 30 images from our Fischer unit and 10 two-view, single breast, image pairs from each of the other manufacturers (70 images total). The images were judged by expert mammographers to be "clinically interesting." Most contained subtle masses, calcifications, and/or architectural distortions.

- For every image, the geometry models were generated successfully. The breast edge and pectoral-muscle line were consistently well approximated.
- For most (~95%) of the images, the statistical models were generated successfully. The separation of fat and dense-component pixels was not achieved in some cases (most were from a single manufacturer). Those cases will probably be handled by using additional Gaussians in the mixture and considering image texture.
- For every image with a successful statistical model,
  - the heuristic for identifying "fatty" breasts was accurate. Fatty breasts comprised approximately 20% of the test cases.
  - appropriate general IWs were automatically specified. In a preliminary analysis they were judged to be nearly as good as hand IWs. We are in the process of conducting a preference study involving eight radiologists.
  - appropriate dense-component-specific IWs were specified. We are conducting observer studies to quantify how they influence the conspicuity of lesions.
  - breast density estimates are quite good. To quantify their accuracy, we are comparing those estimates with semi-automated estimates generated by experts.

5. Conclusion

Our mammogram modeling system is able to segment a wide variety of mammograms. Using those segmentations, it is simple to define mammogram display and analysis algorithms. Preliminary results, using 70 images from digital mammography units from different manufacturers, indicate that those algorithms perform well. Quantitative evaluations using a large number of images are underway. Future research is focusing on the application of our system to the development of an algorithm for distinguishing benign from malignant pathologies.

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6. References

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