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Abstract. Accurate and automatic segmentation of the pectoralis muscle is essential in many breast image processing procedures, for example, in the computation of volumetric breast density from digital mammograms. Its segmentation is a difficult task due to the heterogeneity of the region, neighborhood complexities, and shape variability. The segmentation is achieved by pixel classification through a Markov random field (MRF) image model. Using the image intensity feature as observable data and local spatial information as *a priori*, the posterior distribution is estimated in a stochastic process. With a variable potential component in the energy function, by the maximum *a posteriori* (MAP) estimate of the labeling image, given the image intensity feature which is assumed to follow a Gaussian distribution, we achieved convergence properties in an appropriate sense by Metropolis sampling the posterior distribution of the selected energy function. By proposing an adjustable spatial constraint, the MRF-MAP model is able to embody the shape requirement and provide the required flexibility for the model parameter fitting process. We demonstrate that accurate and robust segmentation can be achieved for the curving-triangle-shaped pectoralis muscle in the medio-lateral-oblique (MLO) view, and the semielliptic-shaped muscle in cranio-caudal (CC) view digital mammograms. The applicable mammograms can be either “For Processing” or “For Presentation” image formats. The algorithm was developed using 56 MLO-view and 79 CC-view FFDM “For Processing” images, and quantitatively evaluated against a random selection of 122 MLO-view and 173 CC-view FFDM images of both presentation intent types. © 2014 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: [10.1117/1.JMI.1.3.034503](https://doi.org/10.1117/1.JMI.1.3.034503)]

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1 Introduction

Accurate and automatic segmentation of the pectoralis muscle is an essential component in many image processing procedures for breast imaging, for example, in the computation of volumetric breast density (VBD) from digital mammograms. For a single image, or a small set of images, manual segmentation of the pectoralis muscle is not overly taxing. However, for very large datasets, manual segmentation becomes labor intensive and susceptible to error due to readers' subjectivity and reader fatigue. A fully computerized quantitative breast density estimation tool is highly desirable to facilitate large-scale breast density studies.

A mammogram is a representation of the transmission of x-rays as they travel along paths through the breast, being attenuated by various types of tissues. The main tissues encountered are skin, fibroglandular tissue, adipose tissue, and pectoralis muscle. In the projection image, areas representing paths through pectoralis muscle have similar intensity to those areas corresponding to fibroglandular tissue, but the radiologist can easily visually determine the pectoralis by its shape and location. The shape and location of the pectoralis are dependent on the standard view used. In the cranio-caudal (CC) view, when the image of the pectoralis is seen, it appears as a semi-ellipse oriented along the chest wall edge of the breast image.

The size and the curvature of the pectoralis boundary vary significantly from person to person, and the position along the chest wall is highly dependent on patient positioning and physical habitus. Finally, < 50% of CC-view images demonstrate a pectoralis muscle shadow. In medio-lateral-oblique (MLO) view mammograms, the pectoralis muscle occupies a larger area toward the upper part of the image, roughly appearing as a curving-right triangle. The overlap of the image signals from this muscle tissue with those from the existing fibroglandular tissue and sometimes lymph nodes creates a region with much heterogeneity. Some pectoralis regions are very dense and have high contrast with the neighboring tissue, which easily distinguishes them from the breast parenchyma. However, frequently, the pectoralis muscle is thinner, and has lower contrast with the surrounding adipose and dense tissue, resulting in weak boundaries. Further, the muscle may appear to be attached to fibroglandular tissue when its density is similar to that of the adjacent breast parenchyma. The segmentation task is to delineate the pectoralis muscle from the surrounding adipose tissue and fibroglandular tissue, and to remove its image from the region of the breast used for further computation. This is typically a difficult task due to the heterogeneity of the region, the neighborhood complexities, and the shape variability.

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Much attention has been devoted to pectoralis muscle segmentation in the past decade for the MLO-view, with very few approaches for CC-view images. To date, an integrated segmentation approach for both CC- and MLO-view mammograms has not been proposed. For example, the approaches described by others¹⁻¹¹ were presented for MLO-view mammograms only. Most of them use the assumption that the pectoralis muscle appears as a triangular area located in the upper corner (left or right) of the image with a near-straight line boundary in an angle of 45 deg to 90 deg. Unfortunately, this assumption is not always valid. An early technique used a Hough transform¹ which provides a good tool for linear boundary detection and can be followed by a Gabor filter² to enhance the edge. Iterative cliff detection³ was also employed to refine the boundary. Several other approaches, such as graph theory,⁴ nonlinear diffusion,⁵ and wavelet decomposition,⁶ have also been presented to detect the “true” boundary accurately. More recently a texture-based method¹⁰ was proposed to enhance the weak pectoralis boundaries, thus leading to robust and accurate segmentation. By using a dynamic programming optimization technique based on Markov random field (MRF)¹¹ better segmentation results than those with the Hough transform have been reported. The method described in Zheng et al.¹¹ utilizes certain assumptions regarding the geometric arrangement of different tissues. Although this works well for MLO view images, the enforced tissue layout constraint is not suitable for CC-view images. As well, the results showed that the *ad hoc* parameters work for the “For Presentation” image format; however, it is not known whether they would also apply in the “For Processing” format. A common problem with many techniques is that they impose a model which is not applicable for all appearances of the pectoralis muscle.

We have previously developed an intensity-based region growing method¹² which segments the pectoralis region in CC-view mammograms. *Ad hoc* parameters were used in the stopping criteria, which mainly determine the segmentation performance. The limitations of the method relate to noise sensitivity. Overlapping fibroglandular tissue tends to result in an erroneous growing path which could cause oversegmentation or undersegmentation and even false negative results. MLO-view mammograms have a larger and more heterogeneous pectoralis region since the large triangle of muscle overlaps fibroglandular tissue and even lymph nodes. The motivation for this work is to develop an algorithm which gives robust and accurate segmentation of the pectoralis muscle on both CC and MLO views.

In this work, the segmentation is achieved by pixel classification through an MRF-based image model.¹³ Based on the observable image intensity and the incorporated spatial information through the neighboring sites as *a priori*, the posterior distribution can be estimated in a stochastic process. This sequence evolves by local changes in a pixel-labeling field. With an adjustable spatial constraint encoded as a variable potential energy component in the energy function, by the maximum *a posteriori* (MAP) estimate of the labeling image given the observable intensity which is assumed to follow Gaussian distribution, we achieved convergence properties in an appropriate sense by Metropolis sampling¹⁴ the posterior distribution of the selected energy function. By exploiting the variable spatial constraint, this MRF-MAP based image segmentation model can provide flexibility in model parameter fitting. We demonstrate that accurate and robust segmentation can be achieved for the

curving-triangle-shaped pectoralis muscle in MLO-view, as well as the semiellipse-shaped muscle shadows in CC-view mammograms.

2 Posterior Probability Distribution

Our purpose is to segment the pectoralis muscle from the remainder of the mammogram. In the preprocessing step, Otsu thresholding¹⁵ was applied to separate the image into objects (breast and any markers) and air background. Next, the breast segmentation was achieved by extracting the largest connected component from the object class. Any small objects such as view markers outside of the breast area were removed. This “clean background” image is used hereafter in our segmentation model.

The image intensity field will be represented by an MRF¹⁶ Y , on image lattice sites $I = \{1, 2, \dots, N\}$, while the lowercase, y , will be a realized intensity field, i.e., a particular mammogram. The basic MRF concepts are summarized in Appendix A.

A labeling field, X , which is an unobservable MRF, will be constructed on the same sites, I . In this application, X , could be a map of tissue types (e.g., pectoralis, mixed breast tissue). An image, y , is represented as

$$y = \{y_i, i \in I, y_i \in D\},$$

where D represents the set of gray-scale values of the image. The labeling image, x , is expressed as

$$x = \{x_i, i \in I, x_i \in L\},$$

where L represents the set of labels to be classified.

Let Ω be the configuration space of the random field X , i.e., the set of all possible configurations of X

$$\Omega = \{x = (x_1, x_2, \dots, x_N) | x_i \in L, i \in I\}.$$

For example, for an image with the number of sites, N , and allowable labels, M , the number of possible labeling images is M^N which is the dimension of the configuration space. Each of the possible labeling images is called a configuration of the labeling field.

After introducing an image labeling field which is an unobservable MRF, the segmentation problem becomes an optimization problem. In the optimization process, we use the posterior probability value to label pixels to different classes (dense, non-dense). For example, for the class, “dense,” the posterior probability is the probability that a pixel labeled as belonging to the dense class is actually a member of that class. It is calculated based on the conditional probability distribution and the spatial prior probability. The conditional probability distribution is obtained from the image intensity feature. It is calculated from the intensity of that pixel relative to the intensity distribution of the dense class. Also, a similar description applies for “nondense” labeled pixels. The spatial prior probability is governed by the local context, i.e., whether the neighbors of that pixel belong to the dense or nondense class. A neighborhood system (Fig. 1) is used to describe the spatial relationship of neighboring pixels. The basic idea of introducing a neighborhood system is to take the local spatial property of the image into account such that the classification of each pixel depends on its intensity feature and its neighbors’ classifications as well.

The top row shows the lattice points of a gray-scale image. In most mammograms, the lattice points correspond to square

pixels. Some representative neighborhood configurations are shown below, arranged in clique types (c), as described in Sec. 4.3. The first row in S depicts the first-order neighborhood configurations that correspond to the lattice point itself and the vertical and horizontally adjacent lattice points (five possibilities). Some of the neighborhoods in the second-order clique types are shown in the last row, which consists of the diagonal adjacent points and combinations of the first-order neighborhood lattice points. Higher-order configurations are not shown.

For each site i in I , let S_i represent the set of neighbors of site i . Let $S = \{S_i, i \in I\}$ be a neighborhood system on I . The neighborhood system can be defined in different dimensions. Figure 1 shows a set of pixel pairs that represent the first-order and second-order neighborhood configurations. Further details of the neighborhood configuration are shown in Appendix A for up to the order of $n = 8$. The details of definition on the neighborhood system S in our model are in Sec. 4.3.

Under the predefined neighborhood system S , the probability of the joint event $P(y, x)$ can be expressed as

$$P(y, x|X_S) = P(y|x)P(x|X_S), \quad (1)$$

where $P(y|x)$ stands for the probability distribution of the intensity feature given the segmented result $X = x$ and $P(x|X_S)$ stands for the prior probability of x from the configuration space Ω of the random field X under the defined neighborhood system $\{I, S\}$.

Based on the joint probability [Eq. (1)], we seek a labeling image x^* on sites I , which is an estimation of the true labeling image $x^\wedge$, according to the MAP criterion

$$x^* = \arg \max_{x \in \Omega} \{P(y|x)P(x|X_S)\}. \quad (2)$$

In summary, the optimization consists of determining a labeling image, x^* , from the set of all possible segmentations (the configuration space, Ω) that yields the highest posterior probability. The conditional probability can be represented as

$$P(y|x) = \prod_{i \in I} p(y_i|x_i). \quad (3)$$

For site i , and label x_i , the probability of an intensity y_i is $p(y_i|x_i)$. Here, we will make the simplifying assumption that each label $\ell \in L$ has a Gaussian distribution of pixel intensities (gray levels), where the distributions have a mean μ_ℓ and standard deviation σ_ℓ

$$p(y_i|\ell) = \frac{1}{\sqrt{2\pi}\sigma_\ell} e^{-\frac{(y_i - \mu_\ell)^2}{2\sigma_\ell^2}}. \quad (4)$$

The joint probability over the entire image of pixels taking the intensity values y_i , given that their class label is x_i under the labeling status at a particular iteration is simply the product of the conditional probabilities, $p(y_i|x_i)$, over all pixels

$$\begin{aligned} P(y|x) &= \prod_{i \in I} p(y_i|x_i) \\ &= \prod_{i \in I} \left[\frac{1}{\sqrt{2\pi}} e^{-\frac{(y_i - \mu_{x_i})^2}{2\sigma_{x_i}^2}} \ln \sigma_{x_i} \right] \\ &= \frac{1}{Z'} e^{-U(y|x)}, \end{aligned} \quad (5)$$

where Z' is a normalizing constant and

$$U(y|x) = \sum_{i \in I} \left[\frac{(y_i - \mu_{x_i})^2}{2\sigma_{x_i}^2} + \ln \sigma_{x_i} \right], \quad (6)$$

which can be interpreted as an “energy” of the class intensity feature. The optimization is then a matter of minimizing the energy.

The second factor in Eq. (2) can be re-expressed in terms of energy as follows. According to the Hammersley–Clifford theorem,⁵ the probability density of the MRF, x , can be given by the Gibbs distribution. A Gibbs distribution, relative to its neighborhood system, $\{I, S\}$, is a probability measure of x on Ω with the following representation:

$$P(x|X_S) = \frac{1}{Z} e^{-\frac{U(x)}{kT}}, \quad (7)$$

where Z is the normalizing constant, k is the Boltzmann constant, and T is the absolute temperature, which in our case, will be a constant hereafter (for simplicity we used $kT = 1$). The spatial energy function $U(x)$ will be discussed in detail later in Sec. 4.3.

The posterior probability distribution can now be rewritten as

$$P(y|x)P(x|X_S) = e^{-U(x,y)}, \quad (8)$$

where the posterior energy is

$$U(x, y) = U(y|x) + \beta U(x) + \text{const}. \quad (9)$$

The MAP estimation is accomplished by minimizing the posterior energy function [Eq. (10)] over Ω

$$\begin{aligned} x^* &= \arg \max_{x \in \Omega} \{P(y|x)P(x|X_S)\} \\ &= \arg \min_{x \in \Omega} \{U(y|x) + \beta U(x)\}, \end{aligned} \quad (10)$$

where β is a weighting factor for the spatial potential energy component $U(x)$ and the constant term in Eq. (9) can be ignored.

3 Metropolis Sampler

The MAP estimation is computationally formidable as the dimension of the configuration space is huge. The direct search of the true labeling image $x^\wedge$ in the configuration space is highly impractical even for a small image with a size $N = 64$, to be labeled to two classes ($M = 2$). The number of possible labeling images will be M^N . Each possible labeling image corresponds to a potential segmentation. It is theoretically possible but impractical to calculate the posterior probabilities for all 2^{64} labeling images to find the maximum among them. In the case of a typical mammogram, the possibilities would exceed $2^{2,000,000}$. Iterative improvement methods are usually used to get an optimal solution for the MAP estimation.

Two sampling methods are generally used to implement the MAP criterion: the Gibbs sampler¹³ and the Metropolis sampler¹⁴ to avoid a possible local minimum trap. Deterministic, iterative algorithms¹⁷ generate a sequence of labeling images that monotonically decrease the posterior energy. In contrast, the Metropolis sampler permits changes that increase the posterior energy as well. These are made based on the transition

probabilities. The posterior energy of an MRF follows the Gibbs (Boltzmann) distribution due to the Gibbs distribution and MRF equivalence. The approach of sampling from the energy distribution based on the transition probabilities is the same as sampling under thermal equilibrium in statistical physics. Pixel intensities and the labels are viewed as states of atoms or molecules in a lattice-like physical system.¹⁸ This effort is being made to achieve ergodicity in the huge configuration space through the limited number of realizations produced in the limited number of iterations.

Briefly, the sampling algorithm in Metropolis et al.¹⁴ is as follows. Given the state of the system at “time” t , say $x(t)$, one randomly chooses another configuration η and computes the energy change $\Delta\epsilon = \epsilon(\eta) - \epsilon[x(t)]$ and the quantity

$$q = \frac{P(\eta)}{P[x(t)]} = e^{-\Delta\epsilon/kT}. \quad (11)$$

If $q > 1$, the algorithm updates to the new configuration, whereas if $q \leq 1$, the decision to choose the new configuration is made with probability q . The change in energy is the difference between $U(x, y)$ in the new and the current configurations. When the difference in energy is negative, the new configuration with the lower energy is always selected. If the energy increases, then the new configuration is selected if a uniform random number ($0 \leq \xi \leq 1$) is less than q . This allows for random changes that move away from a possible local minimum trapping.

4 Segmentation by the MRF-MAP Model

Our task is to segment the pectoralis muscle from the surrounding adipose tissue and fibroglandular tissue. The observable intensity image is regarded as a realized MRF. A neighborhood system $\mathcal{S}$ is defined on the image sites I . An image labeling field will be estimated iteratively in the MAP optimization process. The posterior probability represents the probability that a given pixel belongs to one class. Equation (2) can be used to estimate the highest probability of the constructed label image based on the observed intensity value and the image model by the MAP criterion. Due to the Gibbs distribution and MRF equivalence, the posterior probability is reformed in the posterior energy function. Therefore, the MAP estimation problem is converted to an energy minimization problem.

During each iteration, every pixel is visited in order and reclassified driven by energy minimization. Using the Metropolis sampler, which allows for unreduced energy change by transition probabilities, we extract samples from the configuration space based on the distribution in order to avoid traps to local minimum.

By defining a gradually reduced potential energy component in the energy function, samples from the posterior distribution are forced toward the minimal energy configurations as the iteration number t increases. During the initial iterations, the potential energy component plays a major role in the total energy function; the strong spatial constraint sharply decreases the contribution of feature energy. By this mechanism of gradually relaxed spatial constraint, the labeling process is developed in a properly controlled manner to ensure the accurate parameter fitting and the isolation of the target region.

Finally, by shape validation, we can get pectoralis muscle segmentation from the minimal energy configurations.

4.1 Feature Parameters

The segmentation performance clearly depends on choices made at the modeling stage, in our case the specific energy functional form, and feature parameters. The image intensity is used as the only image feature in this work. We have assumed that the intensity distribution of each class is a Gaussian function. The class features will be represented by the parameters (μ, σ) after the analytic form is determined. Parameters could be estimated from training data in the case of supervised segmentations. A more efficient way is to carry out segmentation and parameter estimation simultaneously as the status of the MRF changes. A practical MRF-based model should be able to learn the parameters under an unsupervised environment, and should be tolerant to the feature variations. Our mammography images have demonstrated high variations in terms of intraclass intensity range and interclass contrast. We need a way to achieve consistent segmentations for highly varied features in the overall results.

A common way to get a focused region on the target is to draw an enlarged mask which covers not only the target but also sufficient background from an image. In general, the initial localization is a difficult problem. In our case, although it is known that the target is always along the chest wall edge, its size and the size of the surrounding tissue varies largely due to differences in physical habitus. An enlarged mask covering the target with adequate background cannot be guaranteed. Therefore, we have taken a different approach and do not use an enlarged mask area. Instead, we employ Otsu thresholding to discriminate between denser and less dense tissue (mixed fibroglandular and adipose) in the uniformly compressed region of the breast. The less dense areas are used as a surrogate for background. From the remaining dense tissue, a region proximal to the chest wall is then used as a candidate for the pectoralis in subsequent processing steps.

The expectation-maximization (EM)¹⁹ algorithm has been used in parameter estimation to find MAP solutions for image segmentation.²⁰ Our algorithm is similar to the EM algorithm with an E-step and M-step in the iteration process. However, in order to avoid biased parameters from fibroglandular tissue, the conditional expectation is not calculated in our E-step. The parameter is estimated cautiously as [Eq. (12)] and [Eq. (13)]. In our spatial constraint controlled labeling process, the target region is enlarged gradually from the small initial configuration, and the parameters are updated accordingly based on the current labeling image. As the segmented region iteratively approaches the true target region, the parameters gradually approximate the real feature.

The intensity energy term $U(y|x)$ is obtained from Eq. (6) where the mean μ and the standard deviation σ of image gray-scale values for each type ℓ at iteration $t + 1$ are updated as follows:

$$\mu_{\ell}^{(t+1)} = \frac{1}{N_{\ell}} \sum_{i \in I, x_i = \ell} y_i^t, \quad (12)$$

$$(\sigma_{\ell}^{(t+1)})^2 = \frac{1}{N_{\ell}} \sum_{i \in I, x_i = \ell} (y_i^t - \mu_{\ell}^t)^2. \quad (13)$$

4.2 Initial Configuration

The initial values for the feature parameters are extracted from the initial configuration. Since the target pectoralis muscle appears similar to dense tissue in intensity, the initial configuration is taken from the uniformly compressed area of the breast and the dense region (if it exists) adjacent to the chest wall. In order to avoid errors from the uneven field, the breast peripheral region which usually has lower intensities is excluded rather than using a peripheral equalization to pseudoflatten the breast image. This can be done by eroding a certain width along the breast edge such that the breast shape is kept in the core area image.

Now, we can find the initial target and background from the core area image by Otsu thresholding method again. The basic idea of Otsu thresholding is to find a threshold which maximizes the interclass variances and minimizes the intraclass variances at the same time. The Otsu threshold separates the image into two classes. We use $\ell = 1$ to denote the dense class, and $\ell = 0$ for nondense background. Finally, we select a narrow vertical rectangular region from the dense class object which touches the chest wall edge as the initial pectoralis configuration while keeping the background unchanged. The location and height of the initial pectoralis configuration depend on the selected dense class object; the width was set to six pixels to make the initial configuration small enough so that it is highly likely to contain pectoralis muscle. The mean and standard deviation, μ and σ , for each type, ℓ , can then be used as the initial parameters for further estimation.

4.3 Clique Potential Energy

At this point, the feature energy has an initial estimate based on Gaussian distributions for the two labels (nondense and dense). The remaining piece of the puzzle is to impose the spatial potential energy component, $U(x)$. This energy term can be calculated from the distances between nearby points. However, pixels that are far from the point are unlikely to contribute to probability of the i 'th pixel to be given a certain label. Instead, a small number of primitive neighborhoods will be considered. One kind of primitive neighborhood is a clique, c which is a subset of S_i for which every pair of sites are adjacent neighbors. A clique set C is a set of clique types, $C = \{c | c \in S\}$. A partial set of C for the first-order and second-order neighborhood systems is displayed in Fig. 1 and further examples are shown in Appendix A (Fig. 6).

Fig. 1 Pixel neighborhood configuration examples.

From Fig. 1, we can see that the number of clique types increases rapidly with the order of the neighborhood system. In our model, only first-order cliques and the two diagonal pair cliques of the second-order were actually employed, which is the common implementation in MRF-based image restoration and segmentation modeling techniques.^{13,20,21} Nonetheless, it is expected that more complex images will necessitate more complex clique types. Our experiments suggest that the additional complexity might be accommodated in another way, i.e., by introducing a variable weighting factor for potential energy while maintaining modest neighborhood sizes.

The potential of a pair clique for a labeling image, in our case a binary image, is defined as follows:

$$V_c(x_{ij}) = \tau(x_i - x_j), \quad j \in c \quad \text{and} \quad d_{ij}^2 \leq 2, \quad i \neq j, \quad (14)$$

where $\tau(x_i - x_j) = 0$, if $x_i = x_j$, $\tau(x_i - x_j) = 1$ otherwise, and d_{ij} denotes the Euclidean distance between sites i and j

$$V_{C_i}(x_i) = \sum_{c \in C_i} V_c(x_{ij}). \quad (15)$$

The potential energy in [Eq. (5)] can be rewritten as

$$U(x) = \sum_{i \in I} V_{C_i}(x_i) = \sum_{i \in I} \left[\sum_{\substack{c \in C_i \\ j \in c}} V_c(x_{ij}) \right]. \quad (16)$$

In other words, the spatial potential energy for the i 'th pixel is the sum of the number of adjacent pixels whose labels are different from that of the i 'th pixel. This is a value that could range from 0 (no neighbors different) to 8 (all neighbors different). The total spatial potential energy is then summed over all pixels. Higher spatial potential energy implies a lower probability that the i 'th pixel is correctly labeled.

4.4 Variable Potential Energy

The Eq. (10) can now be rewritten as

$$U(x, y) = \sum_{i \in I} \left[\frac{(y_i - \mu_{x_i})^2}{2\sigma_{x_i}^2} + \ln \sigma_{x_i} \right] + \beta \sum_{i \in I} \left[\sum_{\substack{c \in C_i \\ j \in c}} V_c(x_{ij}) \right]. \quad (17)$$

The weighting factor β for potential energy used in our experiment is

$$\beta = b * 0.9^t, \quad (18)$$

where t is iteration index, $t = 1, 2, \dots, T$, and the coefficient $b = 4$ has been found empirically to be suitable for both CC- and MLO-view mammograms in both "For Processing" and "For Presentation" formats.

There is a feature modeling component and a variable spatial constraint component in Eq. (17). The feature modeling component gives pixels with high intensity values greater probability to be classified into the "dense" class. The intensity feature alone does not contain sufficient information to differentiate the target pectoralis from fibroglandular tissue. The shape requirement,

embodied as a spatial constraint, is another deciding factor in the segmentation. In [Eq. (18)], we see $\beta > 1$ in the initial rounds of iterations. So the initial strong neighborhood constraints reduce the feature modeling component's contribution to the total energy $U(x, y)$, which prevents the target region from encroaching into the neighboring fibroglandular region too rapidly. A variable weighting factor for the feature modeling component in energy function has been used by Deng and Clausi²¹ where the prevailing feature modeling component initially dominates the feature data fitting process in their simulated annealing scheme. We have intentionally avoided the dominating effect of the feature modeling component in the parameter fitting process.

The posterior energy in the form of [Eq. (17)] is calculated from the image, based on the current labeling condition and parameter values. The samples from the posterior distribution are forced toward the minimal energy configurations as the iteration number t increases, i.e., convergence is achieved based on the property of the total energy, $U(x, y)$.

It is important to note, even with spatial constraint, not only the target but also fibroglandular tissue is classified as "dense class." In order to separate the target region from the entire dense class, we need to extract a connected piece which is rooted at the initial pectoralis configuration. All the other scattered dense pieces (not target-connected) will be discarded.

The gradual relaxations of the neighborhood constraint during the iterations will construct a gradually enlarged target region as the algorithm learns the global feature parameters which could be easily confused with fibroglandular tissue feature. The adoption of a variable weighting factor on such a simple pairwise clique potential results in a practically and mathematically coherent MRF-based segmentation model. Even if the pectoralis region is not piecewise constant, we have obtained consistent segmentation results for images with high intraclass intensity variability. The initial step of the method applies contextual constraints based on neighboring pixels, but does not impose a morphological constraint. In this way, the algorithm provides flexibility of segmenting targets of potentially arbitrary shapes. In the final step, morphological conditions are applied.

4.5 Shape Descriptor

Ultimately, the region selected by the MRF-MAP based segmentation is likely to be the pectoralis region. Here, we examine how closely the region corresponds to primitive shape descriptors. As depicted on a mammogram, the pectoralis muscle is a connected piece along the chest wall edge of the breast, either in the shape of an upside down curving-triangle or a semiellipse. Because normal fibroglandular tissue is frequently attached to the pectoralis region with very similar intensity, a shape descriptor has to be used to make the final judgement from the applicable minimal energy configurations. Another condition, which occurs frequently in CC-view mammograms, is that the produced target corresponds only to normal fibroglandular tissue beside the chest wall edge and the pectoralis is, in fact, not present in the image. If the target area does not demonstrate the expected shape, a condition is imposed to exclude it from being identified as a pectoralis region.

For all images, the orientation is arranged such that the chest wall of the image is aligned to the left-hand side for images of both left and right breasts. The shape of a standard pectoralis region in CC-view mammograms can be described

as a vertically oriented semiellipse, as described in Ge et al.¹² This method is used here again as the final assessment. In MLO-view mammograms, pectoralis muscle demonstrates as a near-right triangle as shown in Figs. 2(f)–2(j). Very often, the lower part is connected with the normal fibroglandular tissue. Even by human visual inspection, it is often not easy to see a line between them. The MRF segmentation model should not be expected to be able to isolate the triangle-shaped pectoralis region from the overall target region in this case. We need to make use of the anatomical shape-based analysis to extract pectoralis from the overall target region.

The task, therefore, becomes identifying the curving "hypotenuse" of the right triangle from the segmented target region. For the simple case as shown in Fig. 2(f), the pectoralis muscle appears as a right triangle. However, this is only a special case. Generally speaking, the region is expected to be a slightly curved line delineating an area that is approximately equal to $1/2 \times \text{base} \times \text{height}$. Segmented regions with areas noticeably different areas ($\sim 6\%$) than this are evaluated in terms of the ratio of sides of the region. Sharp changes in the ratio likely indicate the incorrect inclusion of dense tissue (nonmuscle). To exclude these invalid regions, the upper right edge can be fitted as a straight line, or else, two straight lines with slightly different slopes. For the lower right part, which may be tightly connected with the normal dense tissue, a line is projected from the end of the visible hypotenuse to the end of the lowest left edge. The region on its left side is attributed to the pectoralis region and the remainder on the right is excluded.

Although the shape descriptors used here are very similar to the assumptions implicit in other algorithms they are only imposed on the region if the deviation of the ratio of sides greatly exceeds the expected shapes, otherwise the natural curvature is preserved.

5 Experiments and Results

The segmentation results for five representative images of each type are shown in Fig. 2. These images span the range from easy cases to those that are challenging for an automated segmentation algorithm. In CC-view images [Figs. 2(a)–2(e)], the pectoralis region is relatively small, in the shape of a semiellipse with varying curvature. In the MLO-view, the pectoralis shadow occupies a large region, roughly in the shape of a right triangle. The edge of the pectoralis region is most often not a straight line, as shown in Figs. 2(g)–2(j).

For quantitative performance evaluation, 122 MLO-view and 173 CC-view FFDM "For Processing" images were selected at random from our clinical trial database (all images from one institution). They were all acquired from GE 2000D mammography units at one institution. The CC-view image set is the same as that previously used in testing our region growing algorithm.¹² To serve as a reference set, a trained expert manually segmented pectoralis region for all 295 images. These manual segmentations were used as the ground truth to evaluate the segmentation algorithm. The dice similarity coefficient (DSC),²² a common measure of similarity, was used to evaluate the overlap of the regions selected by the two techniques. For two images with regions defined as binary datasets A and B, DSC is defined as twice the number of pixels occurring in both regions (the intersection) divided by the sum of the number of pixels in each of A and B.

Upon visual inspection, 120 of the images from the MLO-view image set showed pectoralis muscle, while only two

Fig. 2 Segmentation results on representative images [red line outlines the anterior border of the pectoralis muscle. (a)–(e) are cranio-caudal (CC) views and (f)–(j) are medio-lateral-oblique (MLO) views. All images are in “For Processing” type, except for (e), which is “For Presentation.” Examples represent the typical appearance of the pectoralis margin: (a) large and clear, (b) overlapped with dense area, (c) irregular shape, (d) buried in skin fold, (e) in processed image, (f) clear triangle, (g) overlapped with dense tissue, (h) narrow region, (i) uneven muscle region, and (j) convex curve edge. (a) Dice similarity coefficient (DSC) = 0.97, (b) DSC = 0.91, (c) DSC = 0.95, (d) DSC = 0.90, (e) DSC = 0.98, (f) DSC = 0.98, (g) DSC = 0.95, (h) DSC = 0.92, (i) DSC = 0.93, (j) DSC = 0.93.

demonstrated no pectoralis shadow in the image. The algorithm only failed to find a margin on three MLO-view images, an example of which is shown in Fig. 3(a). Compared with the manual segmentation of pectoralis muscle, the mean and standard deviation of the DSC value for the muscle area on the 122 images were 0.87 ± 0.16 , which is similar to the result of 92 MLO-view digital mammograms reported in Zhou et al.¹⁰ The algorithm can be sensitive to the selection of the adipose region. In cases of very extensive breast density as shown in Fig. 3(b), an inappropriate selection of the adipose area impinging on the muscle led to an underestimate of the margin (DSC = 0.68).

In this CC-view image set, only 77 of the 173 showed pectoralis muscle by human visual checking. The mean and standard deviation of the DSC value over these 77 images (the “all-pectoralis” set) were 0.77 ± 0.23 . The algorithm failed to find a margin for five CC-view images [example shown in Fig. 3(c)]. For those 96 images demonstrating no pectoralis muscle, 10 false positive results were produced where a small portion of normal fibroglandular tissue was erroneously identified as pectoralis. The overall mean and standard deviation of the DSC value on all 173 CC-view images were 0.84 ± 0.28 . The improvement compared to the all-pectoralis set is largely due to the high concordance between the algorithm and

Fig. 3 Examples of false or inaccurate segmentation: (a) false negative segmentation on MLO-view image with weak boundary in a heterogeneous density region, (b) inaccurate segmentation on an MLO-view image, (c) false negative on CC-view image with a weak boundary in a heterogeneous density region, and (d) false pectoralis region corresponding to a very small portion of dense tissue. (a) DSC = 0, (b) DSC = 0.68, (c) DSC = 0, (d) DSC = 0.

Fig. 4 Accuracy of segmentation on images with pectoralis muscle on “For Processing” images (blue) and “For Presentation” images (orange). (a) 77 CC-view images DSC distribution. (b) 120 MLO-view images DSC distribution.

human readers when no pectoralis is seen corresponding to a number of automatic $DSC = 1$. Compared with the previous results of the region growing algorithm,¹² the maximum DSC value increased from 0.95 to 0.97. This MRF model-based algorithm was found to be more robust to gray-scale heterogeneity. At the same time, however, the false positive rate on the no-pectoralis type mammograms also increased from 6.3% to 10.4%. In all false positive cases, the pectoralis region was small and the error introduced in a VBD measurement was found to be <0.5 units of VBD (on a scale of 0 to 100). Although the predicted false pectoralis region was small, as shown in Fig. 3(d), for best accuracy, we currently retain the use of the simple region growing method in Ge et al.¹² for CC-view images.

Figure 2(e) is an example of a “For Presentation” image; the others are “For Processing” images. The algorithm was developed for the “For Processing” (raw) image type. Interestingly, it has been found not to be limited to this type of image. This model can also produce similar segmentation results on “For Presentation” images. For evaluation purpose, the corresponding “For Presentation” images were all analyzed in the study for GE Senographe 2000D.

The performance was summarized as DSC distributions in Fig. 4 for CC and MLO view both for “For Processing” and “For Presentation” images. There appeared to be little difference in the distributions for the “For Processing” and “For Presentation” images. Paired t -test was conducted comparing the DSC values in those two image presentation intent types. For CC views, the DSC values “For Processing” ($DSC = 0.77 \pm 0.23$) and “For Presentation” ($DSC = 0.79 \pm 0.20$) were not statistically significant ($p \geq 0.12$). Findings for the MLO views were similar: “For Processing” ($DSC = 0.87 \pm 0.16$) and “For Presentation” ($DSC = 0.88 \pm 0.16$) ($p \geq 0.20$). This suggests that the flexible model parameter fitting process has the ability to self-adjustment on image features, not constrained to pixels’ absolute values.

6 Discussion and Conclusion

An integrated pectoralis muscle segmentation algorithm, which is applicable to both MLO and CC-view digital mammograms in both “For Processing” and “For Presentation” image formats, has been presented. The approach can effectively detect the presence of a pectoralis muscle shadow in images. The accuracy

of segmenting the region approaches that achieved with manual segmentation in terms of shape and size. When applied to our VBD application, it results in a reduction of systematic bias errors due to inadvertent inclusion of the pectoralis muscle. It may also be useful to improve accuracy for other breast cancer CAD systems.

The run time on a modern computer (on an Intel® Core i5-2320 CPU @ 3.0 GHz, 6.00 GB RAM PC) including skin edge detection, background object removal and pectoralis segmentation was measured to be about 20 s per image on a small subset of images. In the future, this algorithm could potentially be optimized for parallel or GPU computing for a marked reduction in execution time.

This MRF-MAP model-based algorithm increased the reliability of segmentation for the cases with heterogeneous pectoralis regions, which is often seen in MLO-view images. It is robust for the cases with weak boundaries (low contrast) between the region and surrounding breast tissue. On CC-view images, it has increased sensitivity to identify a subtle pectoralis region from connected irregular fibroglandular tissue. This improvement is obtained at the cost of increased probability of false pectoralis region detection from normal fibroglandular tissue; however, in most cases, the area of false pectoralis detection is very small. In the future, the MRF approach could be improved by implementing a more sophisticated shape evaluation, potentially reducing the false positive rate.

Selection of the appropriate background is a deciding factor for accurate segmentation. In the initial configuration step of the model, we used the adipose region in the uniformly compressed breast area as the background against which the pectoralis muscle is segmented. The adipose area selected by Otsu thresholding may not be just outside of the pectoralis muscle. This can cause inaccurate or failed segmentation. Also, in the future, it may be worthwhile taking into consideration any variation in the background intensity between the upper and lower parts of the breast.

The images used in the evaluation set were acquired from GE 2000D mammography units. The algorithm has been visually observed working on GE essential images, and a small set of images produced on a Lorad Selenia system. To test the generalizability of the algorithm, a larger set of images, including those from other vendor/model machines should be evaluated.

Fig. 5 Neighborhood configurations for $n = 1, 2, \dots, 8$: (a) $n = 1$, (b) $n = 2$, and (c) $n \leq 8$.

Fig. 6 The clique types of first-order and second-order neighborhood configurations. (a) First-order. (b) Second-order.

A Appendix

A1 Random Field

Let $I = \{1, 2, \dots, N\}$ be a set of image lattice sites and $R = \{r_i, i \in I\}$ is a family of random variables in which each random variable $R_i = r_i \forall i \in I$. Such a family is called a random field.¹⁶

A2 Neighborhood System

Following the approach by Geman and Geman¹³, let $S = \{S_i, i \in I\}$ be a neighborhood system on I where S_i is the set of neighboring site i .

$$i \notin S_i \quad \text{and} \quad i \in S_j \Leftrightarrow j \in S_i$$

Figures 5(a) and 5(b) show the neighborhood configurations for $n = 1, 2$. Figure 5(c) shows the neighborhood configurations up to the order of $n = 8$.

A clique c is a subset of S_i for which every pair of sites are neighbors. A clique set C is a set of clique types, $C = \{c | c \in S\}$ where S represents the neighborhood system. The clique set C for the first-order and second-order neighborhood systems are displayed in Figs. 6(a) and 6(b).

A3 Markov Random Field

A random field X is an MRF with respect to the neighborhood system $S = \{S_i, i \in I\}$ if

$$P(X = x) > 0, \quad \forall x \in \Omega$$

$$P(X_i = x_i | X_j = x_j, j \neq i) = P(X_i = x_i | X_j = x_j, j \in S_i)$$

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