Development of Anatomically Realistic Numerical Breast Phantoms With Accurate Dielectric Properties for Modeling Microwave Interactions With the Human Breast

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Abstract—Computational electromagnetics models of microwave interactions with the human breast serve as an invaluable tool for exploring the feasibility of new technologies and improving design concepts related to microwave breast cancer detection and treatment. In this paper, we report the development of a collection of anatomically realistic 3-D numerical breast phantoms of varying shape, size, and radiographic density which can readily be used in finite-difference time-domain computational electromagnetics models. The phantoms are derived from T1-weighted MRIs of prone patients. Each MRI is transformed into a uniform grid of dielectric properties using several steps. First, the structure of each phantom is identified by applying image processing techniques to the MRI. Next, the voxel intensities of the MRI are converted to frequency-dependent and tissue-dependent dielectric properties of normal breast tissues via a piecewise-linear map. The dielectric properties of normal breast tissue are taken from the recently completed large-scale experimental study of normal breast tissue dielectric properties conducted by the Universities of Wisconsin and Calgary. The comprehensive collection of numerical phantoms is made available to the scientific community through an online repository.

Index Terms—Biomedical applications of electromagnetic radiation, biomedical electromagnetic imaging, breast cancer detection, breast cancer treatment, finite-difference time-domain (FDTD) methods, microwave hyperthermia, microwave imaging.

I. INTRODUCTION

MANY candidate microwave techniques for breast cancer detection and treatment applications have been pro-

posed in recent years. The growing interest in microwave breast imaging is evidenced by the increasing number of publications on the topic. In the 1990s, there were approximately a dozen journal papers related to microwave breast imaging (see, for example, [1]–[4]), whereas between 2000 and the present, nearly 100 journal papers have appeared (see, for example, [5] and references therein) with over a quarter of those published last year. The body of work on microwave breast cancer detection is quite diverse, and includes narrow-band and wideband inverse scattering or tomographic techniques [6]–[10]; ultrawideband radar and other time-domain techniques, such as time reversal [11]–[15]; microwave-induced thermoacoustic tomography [16], [17]; microwave radiometry [18]–[20]; and microwave holography [21]. There is also continuing interest in research and development of microwave therapeutic techniques for the breast, such as microwave-induced hyperthermia and microwave ablation. Numerous technological advancements for treatment and temperature monitoring techniques have been reported recently (see, for example, [22]–[28]).

Research on both diagnostic and therapeutic microwave techniques benefits from anatomically realistic numerical breast phantoms that model structural complexities, tissue heterogeneity, and dispersive dielectric properties. One well-accepted tool used in the investigation of these microwave techniques is the finite-difference time-domain (FDTD) [29] computational electromagnetics model of the breast (referred to here as a numerical breast phantom). To date, most numerical breast phantoms have been limited to anatomically realistic 2-D phantoms [7], [13] or relatively simple 3-D phantoms [13], [30]. In all of these cases, as well as the few examples of anatomically realistic 3-D phantoms [14], [31], the accuracy of the assumed dielectric properties of the various tissues in the breast has been limited by gaps and discrepancies in previously published small-scale experimental dielectric spectroscopy studies. None of these previous phantoms is consistent with the comprehensive findings on normal breast tissue dielectric properties reported recently in the large-scale Wisconsin–Calgary dielectric characterization study [32], [33]. FDTD models of other parts of the human body—namely those that are comprised of well-delineated tissue types, each with spatially invariant dielectric properties—are derived from MRIs with relative ease and are arguably commonplace these days. In contrast, the accurate derivation of numerical breast phantoms from MRIs is nontrivial, and in fact, quite...
an involved process due to the complex network of glandular, adipose, and fibroconnective tissue in the breast and the significant heterogeneity of dielectric properties of normal breast tissue, as revealed by the Wisconsin–Calgary study.

In this paper, we report for the first time the development of a collection of anatomically and dielectrically realistic 3-D numerical breast phantoms of varying shape, size, and radiographic density. The structural heterogeneity of the breast is derived from 3-D MRIs of patients with normal breast tissue (no malignancy or other abnormality) while the frequency-dependent and tissue-dependent dielectric properties are derived from the Wisconsin–Calgary study. The primary novel contribution is the introduction of a physiologically realistic method for mapping breast MRI voxel intensity to accurate dielectric properties of normal breast tissue. Our mapping is based on a two-component Gaussian mixture model (GMM) [34] and is motivated by the fact that normal breast tissue is composed of two tissue types that are distinctly different in terms of both physiology and dielectric properties. The numerical breast phantoms presented in this paper are not intended to exactly mimic any specific patient’s breast, but rather to serve as representative models of the human breast for use in computational studies. The phantoms will support further development of novel diagnostic and therapeutic microwave techniques for breast cancer detection and treatment, and provide a common ground for comparison among methods.

The rest of the paper is organized as follows. Section II is divided into two parts. Section II-A describes in detail the image processing steps used to construct anatomical models from MRIs. Section II-B discusses the mapping between the voxel intensity of the anatomical models and the dielectric properties of normal breast tissue. Examples of 3-D anatomically realistic numerical breast phantoms are illustrated in Section III and are followed by concluding remarks in Section IV.

II. METHOD FOR DEVELOPING A NUMERICAL BREAST PHANTOM

The goal is to create a collection of realistic numerical breast phantoms where the breast tissue is modeled as a uniform grid of spatially dependent dielectric properties. We seek to capture in a representative sense both the structural heterogeneity of normal tissue and the dispersive dielectric properties of normal breast tissue. Structural realism is achieved in the proposed phantoms through the use of 3-D breast MRIs while dielectric properties realism is achieved through the use of data from the Wisconsin–Calgary study [32], [33]. The key steps are described next.

A. MRI Processing and Structural Development

The numerical phantoms are derived from T1-weighted MRIs of prone patients. The anonymous breast MRI datasets are obtained from the University of Wisconsin Hospital and Clinics. Each breast MRI is assigned a classification based on the standard tissue composition descriptors used by radiologists to classify X-ray mammograms. The American College of Radiology (ACR) defines four categories of breast composition according to the radiographic density of the breast: (I) almost entirely fat; (II) scattered fibroglandular; (III) heterogeneously dense; and (IV) extremely dense [35]. A series of sagittal slices comprises each 3-D MRI. The spacing between slices is typically 1.5 mm, but varies from patient to patient. Each sagittal slice contains 256 × 256 pixels. The field-of-view for a sagittal slice varies from patient to patient depending on breast size, but for a typical field-of-view of 16 cm × 16 cm, the MRI voxel size is 0.625 cm × 0.625 cm × 1.5 cm. Several image processing steps are applied to the original MRIs to remove image artifacts and to automate the structural development of the numerical phantoms.

The first step in the structural development of the phantoms is to reduce the dominant artifact in the breast MRI. Nonuniformity of the magnetic fields leads to slowly varying intensity gradients in the image, particularly in the tissue region near the coils. This image artifact is illustrated in Fig. 1(a) for a coronal slice through the 3-D image. A homomorphic filter [36] is applied to the MRI to mitigate these effects by filtering out the low-frequency spatial variations in the image. Fig. 1(b) shows the same coronal slice after homomorphic filtering.

Next, the MRI is linearly interpolated to achieve a 3-D grid of 0.5-mm cubic voxels while preserving the physical dimensions of all structures in the MRI. The grid cell size of 0.5 cm × 0.5 cm × 0.5 cm is chosen to satisfy the grid resolution requirements for FDTD computational electromagnetics modeling in the microwave frequency range. For example, at 10 GHz, this grid cell size corresponds to a sampling density of approximately 10 points per wavelength in those grid cells containing the densest tissue properties (which, for the phantoms discussed in this paper, correspond to glandular/fibroconnective tissue, with peak values of $\epsilon_r = 52.64$, $\sigma = 14.97$ S/m, $\lambda = 4$ mm).

The breast volume is then segmented from the background by applying an edge finding algorithm to each coronal slice of the interpolated 3-D image. Each coronal slice is treated as a 2-D matrix where the matrix elements are the MRI voxel intensities. We traverse each line in the matrix (either a row or column) in four directions: left to right, right to left, top to bottom, and bottom to top. For each direction of traversal, we create a logical mask—an matrix containing 1’s and 0’s. For example, while traversing each row of the coronal slice, shown in Fig. 1(b) from left to right, each matrix element in the logical mask is set to zero until a voxel intensity in the coronal slice
is found to exceed a specified threshold; the threshold value is usually chosen to be the voxel intensity close to that of the skin or the subcutaneous fat layer near the skin contour. The remaining matrix entries along that row are set to one. The resulting logical mask is shown in Fig. 2(a). An analogous procedure is used to create the other three logical masks shown in Figs. 2(b)–(d). The four masks are combined using element-by-element matrix multiplication to produce a coronal composite mask that is used to segment the breast interior from the background. The coronal composite mask of the coronal slice, shown in Fig. 1(b), is shown as the shaded area in Fig. 2(e).

The segmentation works particularly well on coronal slices where there is a well-defined contrast between the MRI voxel intensity of the tissue and the background region. However, imperfections still arise in the coronal composite masks. For example, the coronal composite mask in Fig. 2(e) does not have a smooth edge. Such roughness, which is nonphysical and may lead to unrealistic scattering, is eliminated by fitting each coronal composite mask with an ellipse to ensure smooth contours on the 3-D phantom. An example of a best-fit ellipse for a coronal composite mask is plotted in Fig. 2(e) as a dashed-dotted line. The ellipse is fit to boundary points of the previously identified coronal composite mask using a penalized least-squares criterion to select the coordinates of the center of the ellipse and the major and minor axes that minimize the penalized error. The penalty function is chosen to give preference to ellipses whose contours fall on or inside the segmented tissue region and to discourage those extending beyond the segmented tissue region and into the background region. The selected ellipses, one from each coronal slice, are stacked to form a smooth 3-D breast surface, as illustrated in Fig. 3(a). The breast interior is now defined by the volume enclosed by the smooth breast surface.

The skin is usually not imaged with high fidelity and is mostly eliminated during segmentation. Hence, a 1.5-mm-thick skin layer is artificially introduced into the model by performing image erosion [37] on the previously obtained smooth breast surface. The thickness of the skin layer is chosen to be the average value of breast skin thickness reported in [38]. Finally, the breast interior region comprises all voxels contained within the 3-D breast surface after image erosion is performed. The skin region comprises all the voxels contained between the surfaces before and after erosion. A 1.5-cm-thick subcutaneous fat layer and a 0.5-cm-thick muscle chest wall are introduced at the base of the breast to complete the structural development of the model. The chosen thickness of the subcutaneous fat layer represents the average thickness from 35 MRI datasets; this parameter can be easily adjusted to account for more or less fat on the chest wall. Fig. 3(b) and (c) shows coronal and sagittal slices of the resulting 3-D anatomical model.

**B. Dielectric Properties Mapping**

The voxel intensities within the 3-D anatomical model are transformed into dielectric properties via a piecewise-linear map. An example of a piecewise-linear mapping between MRI voxel intensity and dielectric properties is illustrated in Fig. 4. The piecewise-linear map provides the necessary flexibility to account for the facts that 1) the MRI voxel intensities of fatty and fibroconnective/glandular tissue tend to exhibit bimodal distributions and 2) while the dielectric properties of normal breast tissue in the microwave regime span a wide and continuous range of values, they too are clustered based on tissue type.

Our mapping between MRI voxel intensity and dielectric properties consists of seven linear segments, each corresponding to a specific tissue category. We define the seven tissue categories as follows: glandular/fibroconnective-1, glandular/fibroconnective-2, glandular/fibroconnective-3,
represented as 

represents an MRI intensity region corresponding to either 

diuretic/fibroconnective tissue. Each component of the GMM 

tissue while lower voxel intensities correspond to gland-

Higher voxel intensities in the T1-weighted MRI correspond to 

togram of MRI voxel intensities from the breast interior 

heterogeneity reported in [32] and [33]. The corre-

maximum of three categories is needed to account for physiological 

properties data reported in the Wisconsin–Calgary study. A min-

transitional, fatty-1, fatty-2, and fatty-3. Our decision to use 

seven categories was motivated by the format of the dielectric 

properties data reported in the Wisconsin–Calgary study. A mini-

of three linear segments, instead of three, provides greater flexibility in capturing the 

heterogeneity in the breast. The use of seven linear segments, 

instead of three, provides greater flexibility in capturing the 

dielectric properties in- 

Fig. 4. Representative piecewise-linear map illustrating the linear mapping 

between seven intervals along the MRI voxel intensity axis ($I_g$, $I_f$, $I_{trans}$, 

$I_{f1}$, $I_{f2}$, $I_{g3}$, $I_{g1}$) and seven intervals along the dielectric properties axis ($P_g$, 

$P_f$, $P_{trans}$, $P_{f1}$, $P_{f2}$, $P_{g3}$). The MRI in this example is of a patient with 

extremely dense breast tissue. 

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$P_f$, $P_{trans}$, $P_{f1}$, $P_{f2}$, $P_{g3}$). The MRI in this example is of a patient with 

extremely dense breast tissue. 

togams and their two-component GMM are shown in Figs. 5(a) 

and 6(a) for patients with extremely dense breast tissue and al-

most entirely fat breast tissue, respectively. Figs. 5(b) and 6(b) 

each show the two individual Gaussian components of the GMM 

and their mean ($\mu$) and standard deviation ($\sigma$). 

With the exception of breast compositions that are almost 

entirely fat, we have found the two Gaussians to be well 

separated, as illustrated in Fig. 5. When the breast is almost 

entirely fat, there are very few voxels with low intensities (gland-

ular/fibroconnective tissue voxels) and the two Gaussian com-

ponents are both fit to the dominant peak in the fatty tissue 

region, as illustrated in Fig. 6. 

The eight piecewise-linear mapping parameters are defined 

distribution parameters of the GMM. We define the 

minimum, intermediate, mean, and maximum voxel intensi-

ties as $m_g$, $m_{sg}$, $\mu_g$, and $M_g$, respectively, for glandular/ 

fibroconnective tissue and $m_f$, $m_{sf}$, $\mu_f$, and $M_f$, re-

spectively, for fatty tissue. The eight piecewise-linear mapping 

parameters are indicated along the MRI voxel intensity axis 

in Figs. 5(b) and 6(b) for patients with extremely dense breast 

tissue and almost entirely fat breast tissue, respectively. We 

summarize the relationship between the piecewise-linear map-

ning parameters and the GMM distribution parameters (shown 

in Figs. 5(b) and 6(b)) below. 

For the case where the two Gaussians are well separated, as 

in the extremely dense case of Fig. 5, the upper bound of the 

glandular/fibroconnective region ($M_{g}$) is defined as an intensity 

value that is one standard deviation above the mean $\mu_g$, while 

the lower bound of the same region ($m_g$) is the lowest voxel 

intensity value in the image. Conversely, the lower bound of the 

fatty region ($m_f$) is defined as an intensity that is one standard 

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deviation below \( \mu_2 \), while the upper bound of the region \( (M_f) \) is defined as the highest voxel intensity value in the image. For both the glandular/fibroconnective and fatty regions, the mean \( (\mu_g \) or \( \mu_f \)) is calculated as the expected value of the voxel intensity using the GMM for that region. We define the intermediate voxel intensity as an intensity that is one standard deviation below \( \mu_2 \) for the fatty region \( (m_{ef}) \) and as an intensity that is one standard deviation below \( \mu_1 \) for the glandular/fibroconnective region \( (m_{eg}) \).

For the case where the two Gaussians are not well separated, as in the almost entirely fat case of Fig. 6, the upper bound of the glandular/fibroconnective region \( (M_g) \) is separated from the fatty region by a user-defined positive scalar, \( \delta \). The intermediate voxel intensity for the glandular/fibroconnective region \( (m_{eg}) \) is defined as an intensity that is \( M_g - \mu_g \) below the mean voxel intensity of the glandular/fibroconnective region \( (\mu_g) \). The other piecewise-linear mapping parameters \( (m_g, \mu_g, M_g, M_f, and \mu_f) \) are defined as in the preceding case. Hence, the eight piecewise-linear mapping parameters are selected as follows. Let \( X \) be the set of voxel intensities in the breast interior; then

\[
m_g = \inf(x : x \in X)
\]

\[
M_g = \begin{cases} 
\mu_1 + \sigma_1, & \text{if } (\mu_2 - \sigma_2) - (\mu_1 - \sigma_1) > \delta \\
\mu_2 - \sigma_2 - \delta, & \text{otherwise}
\end{cases}
\]

\[
\mu_g = \int_{x < m_g} x g(x; \alpha_1, \alpha_2, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2) \, dx
\]

\[
m_{eg} = \begin{cases} 
\mu_1 - \sigma_1, & \text{if } (\mu_2 - \sigma_2) - (\mu_1 - \sigma_1) > \delta \\
2\mu_g - M_g, & \text{otherwise}
\end{cases}
\]

\[
m_f = \mu_2 - \sigma_2
\]

For the case where the two Gaussians are not well separated, as in the almost entirely fat case of Fig. 6, the upper bound of the glandular/fibroconnective region \( (M_g) \) is separated from the fatty region by a user-defined positive scalar, \( \delta \). The intermediate voxel intensity for the glandular/fibroconnective region \( (m_{eg}) \) is defined as an intensity that is \( M_g - \mu_g \) below the mean voxel intensity of the glandular/fibroconnective region \( (\mu_g) \). The other piecewise-linear mapping parameters \( (m_g, \mu_g, M_g, M_f, and \mu_f) \) are defined as in the preceding case. Hence, the eight piecewise-linear mapping parameters are selected as follows. Let \( X \) be the set of voxel intensities in the breast interior; then

\[
m_g = \inf(x : x \in X)
\]

\[
M_g = \begin{cases} 
\mu_1 + \sigma_1, & \text{if } (\mu_2 - \sigma_2) - (\mu_1 - \sigma_1) > \delta \\
\mu_2 - \sigma_2 - \delta, & \text{otherwise}
\end{cases}
\]

\[
\mu_g = \int_{x < m_g} x g(x; \alpha_1, \alpha_2, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2) \, dx
\]

\[
m_{eg} = \begin{cases} 
\mu_1 - \sigma_1, & \text{if } (\mu_2 - \sigma_2) - (\mu_1 - \sigma_1) > \delta \\
2\mu_g - M_g, & \text{otherwise}
\end{cases}
\]

\[
m_f = \mu_2 - \sigma_2
\]

\[
M_f = \sup(x : x \in X)
\]

\[
\mu_f = \int_{x > m_f} x g(x; \alpha_1, \alpha_2, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2) \, dx
\]

\[
m_{ef} = \mu_2 + \sigma_2
\]

The eight piecewise-linear mapping parameters are used to specify the voxel intensity intervals corresponding to the seven tissue categories as \( I_g = (m_g, M_g) \), \( I_f = (m_f, \mu_f) \), \( I_{g3} = (\mu_g, M_g) \), \( I_{f3} = (M_f, m_f) \), \( I_{g1} = (m_f, \mu_f) \), \( I_{f2} = (\mu_f, m_f) \), and \( I_{f3} = (m_{ef}, M_f) \).

2) Dielectric Properties Assignment: Each of the seven MRI voxel intensity intervals is linearly mapped to an appropriate range of normal breast tissue dielectric properties. The seven ranges of dielectric properties are defined by the eight wideband dielectric properties curves shown in Fig. 7. An example of the eight bounding dielectric constant values evaluated at 6 GHz is illustrated in the graph in Fig. 4, wherein the bounding values are labeled as maximum, glandular-high, glandular-median, glandular-low, fat-high, fat-median, fat-low, and minimum. The curves in Fig. 7 are derived from the 0.5–20 GHz results reported in [32] and [33] as follows:

a) The maximum and minimum curves (dotted) are the upper and lower bounds, respectively, of the frequency-dependent dielectric properties data presented in [32]. The lower dotted curve corresponds to the dielectric properties of lipids measured in our laboratory, while the upper dotted curve corresponds to the frequency-by-frequency maximum dielectric properties (envelope) of all the curves shown in Fig. 8 of [32].

b) The solid curves are the median dielectric properties curves associated with the adipose-defined tissue groups 1 and 3 reported in [32] and [33]. We refer to these two curves as “glandular-median” and “fat-median” curves.

c) The two pairs of dashed curves are the 25th and 75th percentile dielectric properties curves for tissue groups 1 and 3 reported in [32] and [33]. We refer to these curves as “glandular-low” (25th percentile, group 1), “glandular-high” (75th percentile, group 1), “fat-low” (25th percentile, group 3), and “fat-high” (75th percentile, group 3).

The eight wideband dielectric properties curves are used to specify the dielectric properties intervals as \( P_{f3} = \text{minimum, fat-low} \), \( P_{f2} = \text{fat-low, fat-median} \), \( P_{f1} = \text{fat-median, fat-high} \), \( P_{trans} = \text{fat-high, glandular-low} \), \( P_{g3} = \text{glandular-low, glandular-median} \), \( P_{g2} = \text{glandular-median, glandular-high} \), and \( P_{g1} = \text{glandular-high, maximum} \).

Single-pole Cole–Cole parameters for the eight curves in Fig. 7 are summarized in Table I. While these Cole–Cole models provide a compact, general representation of the dispersive dielectric properties of breast tissue, they are not easily incorporated into wideband FDTD simulations. The Cole–Cole models can be replaced by other dispersion models suitable for use in FDTD computations. For example, a simple Debye model has been shown to accurately capture the frequency dependence of these properties in the microwave frequency range [40]. As dictated by the piecewise-linear map, the dielectric properties values themselves (in the case of a single-frequency simulation)
Fig. 7. (a) Wideband dielectric constant and (b) effective conductivity curves that define the bounds on seven ranges of dielectric properties. The range labels \( (P_{g1}, P_{g2}, P_{g3}, P_{trans}, P_{f1}, P_{f2}, \text{ and } P_{f3}) \) correspond to seven tissue categories. The two dotted curves represent the maximum and minimum tissue properties. The two solid curves represent the median properties of predominantly glandular/fibroconnective tissue and predominantly fatty tissue. The two pairs of dashed curves represent the 25th and 75th percentile properties for predominantly glandular/fibroconnective tissue and predominantly fatty tissue. The Cole–Cole parameters for these eight curves are given in Table I.

or the appropriate dispersion model parameters (in the case of a wideband simulation) for a specific voxel in the breast interior are computed as a weighted average of the upper and lower bound dielectric properties curves for the tissue category into which the MRI voxel intensity falls. In summary, the voxel intensities within the glandular/fibroconnective region, \( I_{g1}, I_{g2}, \text{ and } I_{g3} \), are mapped to dielectric properties \( P_{g1}, P_{g2}, \text{ and } P_{g3} \); voxel intensities within the fatty region, \( I_{f1}, I_{f2}, \text{ and } I_{f3} \), are mapped to dielectric properties \( P_{f1}, P_{f2}, \text{ and } P_{f3} \); and voxel intensities within the transitional region, \( I_{\text{trans}} \), are mapped to dielectric properties \( P_{\text{trans}} \).

### III. EXAMPLES

We provide examples of four anatomically realistic numerical breast phantoms with realistic wideband dielectric properties of normal breast tissue. Each phantom is derived from a representative MRI from each of the four ACR classifications. Since there exists no standard procedure for classifying MR images into the four categories, for the purpose of our research, we adopt a procedure to classify a numerical phantom according to its relative tissue composition based on the parameters of the GMM. We classify a phantom into one of the four categories based on the probability of a voxel being assigned to fatty tissue \( \Pr(x > m_f) = \int_{x > m_f} g(x; \alpha_1, \alpha_2, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2) \, dx \). Phantoms with a relatively large proportion of fatty tissue (smaller proportion

<table>
<thead>
<tr>
<th>( \epsilon_\infty )</th>
<th>( \Delta \epsilon )</th>
<th>( \tau ) (ps)</th>
<th>( \alpha )</th>
<th>( \sigma_s ) (S/m)</th>
</tr>
</thead>
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<tr>
<td>maximum</td>
<td>1.000</td>
<td>66.31</td>
<td>7.585</td>
<td>0.063</td>
</tr>
<tr>
<td>glandular-high</td>
<td>6.151</td>
<td>48.26</td>
<td>10.26</td>
<td>0.049</td>
</tr>
<tr>
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<td>41.48</td>
<td>10.66</td>
<td>0.047</td>
</tr>
<tr>
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<td>26.60</td>
<td>10.90</td>
<td>0.003</td>
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<tr>
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<td>4.031</td>
<td>3.654</td>
<td>14.12</td>
<td>0.055</td>
</tr>
<tr>
<td>fat-median</td>
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<td>1.708</td>
<td>14.65</td>
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</tr>
<tr>
<td>fat-low</td>
<td>2.908</td>
<td>1.200</td>
<td>16.88</td>
<td>0.069</td>
</tr>
<tr>
<td>minimum</td>
<td>2.293</td>
<td>0.141</td>
<td>16.40</td>
<td>0.251</td>
</tr>
</tbody>
</table>

Fig. 8. Sagittal cross sections showing MRI voxel intensity for patients with (a) almost entirely fat breast tissue (ACR I), (b) scattered fibroglandular breast tissue (ACR II), with the corresponding cross sections of the 3-D numerical breast phantoms showing the dielectric constant at 6 GHz. The two phantoms in (c) and (d) (shown in color) were derived from (a) and (b), respectively, using the GMM-based piecewise-linear mapping scheme proposed in this paper. The two phantoms in (e) and (f) (shown in color) were derived from (a) and (b) using a uniform mapping scheme.
of glandular/fibroconnective and transitional tissues) are assigned to ACR categories I or II, while phantoms with a smaller proportion of fatty tissue (larger proportion of glandular/fibroconnective and transitional tissues) are assigned to ACR categories III or IV. We use the following rules to classify a phantom into a tissue composition category $C$:

$$
C = \begin{cases}
  I, & \Pr(x > m_f) > 0.95 \\
  II, & 0.9 < \Pr(x > m_f) \leq 0.95 \\
  III, & 0.8 < \Pr(x > m_f) \leq 0.9 \\
  IV, & \Pr(x > m_f) \leq 0.8.
\end{cases}
$$

The four examples are illustrated in Figs. 8 and 9. Figs. 8(a) and (b) and 9(a) and (b) show sagittal cross sections of MRIs classified as ACR I, II, III, and IV, respectively. Figs. 8(c) and (d) and 9(c) and (d) show the corresponding cross sections of the phantoms derived using the GMM-based piecewise-linear mapping scheme proposed in this paper. The dielectric constant at 6 GHz is displayed in all phantom images. To illustrate the importance of the piecewise-linear map, we include in Fig. 8 two phantoms derived with an alternative mapping scheme applied to the latest dielectric properties data—namely the uniform mapping approach between MRI voxel intensity and dielectric properties. Recently reported dielectric properties of normal breast tissue reported in [33]. The result is a set of phantoms that captures the heterogeneity and range of microwave dielectric properties expected in women. We have also introduced a breast composition classification scheme based on the tissue composition of each phantom. An online repository containing a comprehensive collection of anatomically realistic numerical breast phantoms as well as detailed instructions is accessible through our research group Web site: http://uwcem.ece.wisc.edu/.
contributions in the early-stage development of the numerical breast phantoms.

REFERENCES


Earl Zastraw (S’03) received the B.S. and M.S. degrees in electrical engineering in 2003 and 2005, respectively, from the University of Wisconsin, Madison, where she is currently working toward the Ph.D. degree in electrical engineering.

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