Methodology for generating a 3D computerized breast phantom from empirical data

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The initial process for creating a flexible three-dimensional computer-generated breast phantom based on empirical data is described. Dedicated breast computed-tomography data were processed to suppress noise and scatter artifacts in the reconstructed image set. An automated algorithm was developed to classify the breast into its primary components. A preliminary phantom defined using subdivision surfaces was generated from the segmented data. To demonstrate potential applications of the phantom, simulated mammographic image data were acquired of the phantom using a simplistic compression model and an analytic projection algorithm directly on the surface model. The simulated image was generated using a model for a polyenergetic cone-beam projection of the compressed phantom. The methods used to create the breast phantom generate resulting images that have a high level of tissue structure detail available and appear similar to actual mammograms. Fractal dimension measurements of simulated images of the phantom are comparatively similar to measurements from images of real human subjects. A realistic and geometrically defined breast phantom that can accurately simulate imaging data may have many applications in breast imaging research. © 2009 American Association of Physicists in Medicine. [DOI: [10.1118/1.3140588](https://doi.org/10.1118/1.3140588)]

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I. INTRODUCTION

Early detection of breast cancer has been instrumental in reducing the mortality of the disease.¹ Many new and improved imaging systems and techniques are currently under development for the detection and diagnosis of breast cancer. It is essential for the advancement of breast imaging systems to have a tool that can be used to optimize and evaluate new techniques and to compare methods across different modalities.

Phantoms are often employed to optimize imaging parameters and improve image quality by providing a “known truth” to evaluate new reconstruction algorithms and aid in the development of novel imaging techniques. Physical phantoms used in breast imaging are currently limited in that they cannot adequately represent the variety of breast sizes, shapes, compositions, and parenchymal detail. It would be difficult to generate patient-specific physical phantoms due

to the time consuming production process and the expense of the materials that compose the phantoms. Computerized phantoms, on the other hand, are advantageous in that they can be modified in terms of size and tissue distribution to generate any number of anatomical variations present in a patient population. The anatomy and physiology are user defined so they provide a known truth from which to evaluate imaging devices and techniques without additional material costs and production time other than software processing.

There have been several computerized three-dimensional (3D) breast phantoms created; all were based either on voxelization of real subject data or mathematical models based on geometric primitives.^{2–10} These computerized breast imaging phantoms have used different approaches, each with its own limitations. Mathematical breast phantoms are flexible and can model varying compositions of breasts, but they are too simplistic in their representation of breast tissue, and the resultant images are qualitatively unrealistic. Voxelized

FIG. 1. Surface renderings of the 4D XCAT male (left) and female (right) anatomy.

breast phantoms offer a more realistic approach since they are based on actual imaging data; however, they are modeled after a single breast and do not offer the flexibility needed to represent the variability present in the patient population. In addition, several of the recently introduced voxelized phantoms are based on high-dose breast computed tomography (CT) of mastectomy specimens. These specimens do not adequately represent intact breasts, since they were placed in holders and contain air pockets. There is clearly a need for a realistic and flexible computerized breast phantom.

There are many potential applications in breast imaging research for a phantom with these attributes. Many emerging modalities such as tomosynthesis, dual-energy mammography, elastography, CT, ultrasound, and dynamic contrast-enhanced breast MRI would benefit from having an accurate and validated model of the breast to allow imaging procedures to be optimized under clinically relevant conditions. The effects of acquisition parameters (e.g., number and angular spacing of projections in tomosynthesis), physical processes (e.g., scatter, beam hardening, and heel effect), and sources of variability (e.g., patient anatomy, dose, and positioning) can all be evaluated and studied in tandem or independently using patient-quality simulated data. A realistic computerized phantom would also provide the necessary framework with which to quantitatively compare the effectiveness of different imaging methods in tasks that model clinical practice such as lesion detection. Collaborating or multidisciplinary groups can share the same virtual phantom without having to transport a physical phantom around and impartial comparison can be performed using the same phantom to evaluate claims from competing groups for publication or regulatory approval.

Recent work in phantom development has focused on the creation of more realistic, mathematically based models using techniques from computer graphics. One such phantom is the four-dimensional (4D) extended cardiac-torso (XCAT) phantom (Fig. 1)¹¹ that was developed by Segars *et al.* to provide a realistic, flexible, anatomical, and physiological model of the human body for use in imaging research.^{12–14} Based on patient data and using nonuniform rational b-spline (NURBS) surfaces to define the anatomy, the XCAT phantom combines a voxelized approach with a mathematical one

to offer a phantom with realistic and detailed organs that remain flexible to allow for anatomical variation and organ deformation. The XCAT phantom includes detailed whole body models for the male and female anatomy based on the visible human data from the National Library of Medicine.

When combined with accurate models of the imaging process (e.g., SPECT, PET, MRI, ultrasound, and CT) the 4D XCAT is capable of simulating realistic imaging data close to those of actual patients. The XCAT phantom has gained widespread use in medical imaging research for evaluating and improving instrumentation, data acquisition, and image processing and reconstruction methods.

Despite this success, the XCAT is limited in its applications to breast imaging research. The female anatomy of the XCAT phantom only uses a simple outer surface to model the breast and does not include any detailed structures. In addition, the phantom was created using data from a single patient and does not simulate breast variations among different women.

The goal of the work described in this paper was to create a detailed 3D computer-generated breast phantom based on empirical data obtained from breast CT of human subjects. The breast phantom will be incorporated into the 4D XCAT phantom in order to make it applicable to breast imaging research. To the best of our knowledge, this will be the first breast phantom based on real human data with the ability to simulate a variety of sizes, compositions, and deformations. The work presented here describes the methods we used to create an initial phantom based on high-resolution breast CT data of a single human subject and demonstrates the phantom's ability to simulate multimodality imaging data.

II. METHODS

II.A. Overview

Developing a realistic and useful breast phantom requires many different steps: One must (1) acquire volumetric imaging data, (2) classify the different components of breast tissue as adipose, fibroglandular, or skin, (3) create a flexible model of the breast from the segmented data, and (4) develop realistic methods to simulate compression. Once the phantom is developed, it may be compressed or left uncompressed depending on the modality (x-ray, MR, ultrasound, SPECT, PET) and computer-based simulation methods can be applied to it to generate realistic imaging data.

Any imaging data may be used as the basis for the phantom. For our particular application, we chose dedicated breast CT data due to their high-resolution detail. Depending on the data selected for the phantom, different image processing techniques need to be applied to it so as to facilitate segmentation of the data. Once a data set is segmented, flexible surface models can be created for each breast tissue. We define each structure in the breast using subdivision surfaces.¹⁵ Unlike the NURBS surfaces that define the XCAT phantom, subdivision surfaces have the ability to model complicated branching structures (e.g., the fibroglandular tissue) with a single surface. NURBS surfaces would require defining a surface for each branch, meaning the structure

would be composed of many tiny NURBS surfaces. Subdivision surfaces are, therefore, much better for modeling the complicated structures of the breast. A detailed description of the steps used experimentally to create our phantom is given below.

II.B. Breast CT data acquisition and image processing

As mentioned above, the breast phantom designed in this work is based on CT data which provide a high-resolution detailed anatomy in its natural form. Dedicated breast CT is currently an investigational tool that may eventually have applications in breast cancer screening or diagnostic evaluation. Dedicated breast CT system images reduce anatomical noise from overlapping structures and provide a clear depiction of 3D anatomical detail that will be useful for phantom creation.

There are several groups currently researching dedicated breast CT at the University of California at Davis,^{16–22} Duke University,^{23–31} University of Rochester,^{32–36} University of Massachusetts Medical School,^{37–39} and University of Texas M.D. Anderson Cancer Center.^{40,41} CT image data used in this study were obtained from investigators at the University of California at Davis as part of an IRB approved study using a prototype dedicated breast CT scanner.

The patient lies in the prone position on a scanning table with the pendant breast hanging through an opening in the table without compression. The gantry rotates over 360° in the horizontal plane around the breast and acquires 500 cone-beam projection images in 16.6 s. Each breast is scanned separately and the mean fibroglandular radiation dose delivered to the breast was constrained to be the same as two-view mammography.^{16–22}

The low-dose acquisition of the breast data as well as the cone-beam geometry of the CT system results in image degradation due to scatter radiation and considerable quantum noise. Therefore correction of scatter and noise is a necessary part of this project because the nonuniformity of the background may cause the denser tissue (fibroglandular tissue) values to be lower than the less-dense (adipose tissue) values and vice versa. This presents a problem when the segmentation of breast CT data is performed using value-based techniques in order to create the breast model. Algorithms were implemented to reduce noise and correct for scatter in the breast CT images as described below.

II.B.1. Noise reduction

A denoising algorithm developed by Xia *et al.*^{42,43} was used in order to suppress noise in breast CT projection images prior to reconstruction without loss of spatial resolution. In a breast CT projection image, the noise is larger toward the chest wall, and when the dose is reduced, this phenomenon becomes more pronounced. The method of Xia *et al.* removes noise with a spatially adaptive partial diffusion equation technique that takes into account the nonuniform distribution of noise in the projection images. The projection images were processed with 40 iterations of the denoising

algorithm of Xia *et al.* instead of the recommended 10 iterations based on subjective evaluation of the effect of noise suppression on subsequent segmentation. Tomographic images were reconstructed using a custom written Feldkamp filtered backprojection algorithm^{42,43} and generated 255 768×768 images with an in-plane resolution of 250 μm and slice thickness of 500 μm. The slice thickness was chosen based on having sufficient data for phantom creation. To demonstrate the noise reduction achieved with the denoising algorithm, the projections were processed using different numbers of denoising iterations (0,10,40) before reconstruction. Ten 100×100 regions of interest (ROIs) were chosen across ten slices throughout the reconstructed image volumes and the mean of the standard deviations of these ROIs was measured.

II.B.2. Scatter correction

A postreconstruction scatter correction technique was implemented to correct for background nonuniformity in each axial image.⁴⁴ The cupping artifact due to scatter radiation is modeled as a circularly symmetric additive background signal profile in the reconstructed breast images. The artifact lowers the true tissue signal in a nonuniform way with a greater bias toward the breast center. The correction signal is based on a sampling technique to obtain an estimate of the adipose tissue signal in the axial images. The center of each axial slice was defined and the minimum value of each radius was used to generate an estimate of the adipose tissue signal. Any inconsistencies or trends across the adipose tissue signal were assumed to be from scatter and were manifested in the axial image as a cupping artifact. A second degree polynomial was fitted to each axial slice estimate for the adipose tissue signal. The values for the polynomial function were averaged across all slices and used to simulate the cupping artifact in each slice. The second degree polynomial used for correction was $0.13x^2 - 0.64x + 9858$. The simulated cupping artifact was subtracted from the breast volume in order to correct for scatter.

II.C. Tissue segmentation

After noise and scatter correction, the next step is the automated classification of the CT data into the various breast tissues that will define the appropriate physical characteristics of each pixel during simulated compression and image acquisition. Pixels were categorized as adipose, fibroglandular, or skin.

II.C.1. Breast masking

The first step in segmentation is to define a binary mask for both the breast volume and the skin. The breast mask is used to target the segmentation to the breast volume and not the background. This mask also serves to classify the adipose tissue by default, since the algorithm will assume that everything within the breast volume that is not classified as fibroglandular tissue or skin will be classified as adipose tissue. Several steps are used to define the mask including thresh-

olding, filtering, and morphological operations. The breast volume mask can be defined with a threshold between the background and breast tissue. However, the threshold needs to be tuned to each breast volume since the noise reduction and scatter correction image processing steps may change the values of the data.

The order of binary masking performed is not critical to the overall performance of the phantom. In the experimental method described, the skin mask was defined first since the skin mask requires a nonmasked image to create and masking of the entire breast volume is done directly after the breast mask definition.

II.C.1.a. Breast skin mask definition. To define a mask for the skin, the local standard deviation of each axial slice was determined using the MATLAB `stdfilt` function. The `stdfilt` function requires a structuring element, which was defined as a ball of height and radius of six pixels. The output of `stdfilt` was normalized and thresholded using 0.1 as the cutoff. To define a mask for the skin, the result was morphologically dilated to ensure full skin coverage with the skin mask. The dilation structuring element used was a disk of radius of six pixels. The values used were determined by trial and error for a single example breast.

II.C.1.b. Breast mask definition. The breast volume mask can be defined with a threshold between the background and breast tissue. However, the threshold needs to be tuned to each breast volume since the different image processing steps may change the values of the data. To define a mask for the breast volume, all pixels that were less than 8000 in value were set equal to zero. The remaining breast was morphologically opened using a disk structuring element with a radius of 20 pixels. This ensured that all pixels within the breast volume would be maintained even if some were below 8000 in value. A threshold was found using the MATLAB `graythresh` function and the mask for the breast was defined with this value. The mask was applied to the breast such that all values not defined with the mask were set to zero.

II.C.2. Iterative histogram classification

After the mask was applied to the breast data, all that remained was the breast tissue. A histogram classifier was used to differentiate between adipose and other types of tissues due to differences in their pixel values. Based on a method developed by Packard and Boone,⁴⁵ an initial segmentation of the breast tissues is done by iteratively evaluating the histograms of each axial slice. The histogram for each axial slice of the scatter corrected breast was found. The left and right edges were used to define the center of the histogram. The mean of the left and right sides of the histogram were found and used as the left and right bounds to redefine the center. This process was repeated until there was little to no change in the center value between iterations. The signal containing the center values of each slice was smoothed with a seven-point moving average filter. A second degree polynomial was fitted to the data and the first 60 values were replaced with the moving average filter output. This maintained the larger values near the chest wall and

minimized large swings in the signal. The smoothed signal was used to define the threshold point for each slice such that all values above the smoothed center value were classified as fibroglandular and skin, and all values below were considered to be adipose tissue and are classified as zero. This process left each axial slice of the segmented volume containing an initial segmentation of only fibroglandular and skin tissues.

II.C.3. Breast skin definition and removal

After the initial histogram segmentation, the skin mask was applied. The histogram classifier does not differentiate between skin and fibroglandular tissues; therefore the predefined mask was used for skin definition. All nonadipose tissue specified by the histogram classifier that lies within the skin mask was classified as skin. The segmented skin was saved and removed from the segmented breast and all following steps were performed only on the remaining classified fibroglandular tissue. In addition, single pixel islands that were likely to be residual mis-segmented adipose tissue were removed. All remaining steps were performed on fibroglandular tissue only.

II.C.4. Predefined morphological functions

A binary volume of the fibroglandular tissue was created, and in each axial slice the MATLAB `bwareaopen` function was used to remove any groups of pixels in the slice that contained fewer than five pixels. Then a series of MATLAB `bw-morph` operations was performed to fill in, or bridge, missing pixel connections.

II.C.5. Ellipsoidal connection algorithm

There remained several small groups of less than 50 pixels that visually appeared to be disconnected from nearby groups of pixels. The size was chosen based on the current data set after visually inspecting islands that were known to be connected based on the CT data and disregarding islands that were too large. However, some islands were disjointed sections that appeared as linear objects and appeared to be connected to islands in the current slice and some were circular and appeared to continue through to the next slice. Therefore, it was necessary to differentiate between circular islands and linear islands. In order to define and link the appropriate sections together, the ellipsoidal shape of the islands was evaluated using the MATLAB `regionprops-eccentricity` function. The island was classified as closer to a line and possibly connected in the current plane if it had greater than 85% eccentricity and close to a circle and connected to the next plane if it was less. This differentiation was made assuming that any fibers going between planes would appear rounder than fibers staying within the plane. If an island was found to have greater than 85% eccentricity and an area of less than 50 pixels, then it was considered a candidate for linking to another nearby island. If another group of pixels was within 20 pixels away and along the angular orientation of the candidate island, then the line connecting them was labeled as fibroglandular tissue. This was

done by using MATLAB `imclose` function with a line structuring element of length of 20 pixels at the designated angular orientation.

II.C.6. Targeted region growing

After the previous step identified probable islands (small and linear ellipses) that were supposed to be joined, there were still certain areas that should be joined and were not identified as small linear ellipses. The targeted region-growing algorithm was used to join these regions. It defines the distance between islands and searches for short ladder patterns and then classifies the ladder as part of the fibroglandular tissue. This step joined together separated islands that were located close enough to indicate that they should be connected. In order to address missing connections for regions that were larger than 50 pixels and not linear in shape, it was necessary to extend these regions under specific conditions such that the original shape and size of each region were essentially preserved by growing only under certain conditions. It was assumed that regions that should be joined would be relatively close together and there would be a specific short path between them. To find distances between regions, the MATLAB `bwdist` function was used to define a distance map for each binary axial slice of classified fibroglandular tissue. Ladderlike patterns in the distance map were searched for at 10° angular increments from -85° to 85° , such as

$$\begin{bmatrix} 1 & 2 & 3 & 2 & 1 \end{bmatrix}, \quad \begin{bmatrix} 1 \\ 2 \\ 3 \\ 2 \\ 1 \end{bmatrix}, \quad \text{and} \quad \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

If the pattern was found, it was classified as fibroglandular tissue. The maximum ladder distance was five pixels for the axial slices.

II.C.7. Volumetric processing

Up to this point, all of the segmentation has been performed only in axial planes. There may remain some discontinuities between slices due to the two-dimensional (2D) processing. In order to join the fibroglandular tissue volumetrically and smooth away the discontinuities between the axial slices, the MATLAB predefined morphological functions, ellipsoidal connection algorithm, and targeted region growing were performed on the coronal and sagittal slices. The MATLAB `bwmorph` function was used on the classified axial slices to fill in any small holes prior to processing in the coronal and sagittal directions. The values used for the different functions during volumetric processing were that the candidate region area for the ellipsoidal connection algorithm was 30 with eccentricity of 0.85, and the maximum ladder distance used for the targeted region-growing algorithm was 3.

FIG. 2. Surface rendering of the skin is shown on the left and an illustration of the inner structures is on the right.

II.C.8. Density differentiation

Although the breast is composed primarily of the three segmented tissue types, there is often a compositional marbling effect, where fibroglandular and adipose tissues are interspersed in varying degrees. This marbling effect is visible in the reconstructed data where some fibroglandular regions appear less dense and have a pixel value between that of adipose and fibroglandular tissues. The segmentation algorithm takes into account the varying levels of adipose content in the fibroglandular tissue by dividing the segmented fibroglandular tissue into three regions based on pixel value. The algorithm results in the breast segmented into five components: adipose, skin, and three varying levels of fibroglandular tissue.

After the volumetric processing step, the fibroglandular tissue had been classified as well as the skin. All pixels located within the predefined mask for the breast that were not skin or fibroglandular tissue pixels were classified as adipose tissue. The histogram of the fibroglandular tissue breast pixels was determined and divided into four segments. Because the fibroglandular tissue density visually appeared to consist primarily of less-dense tissue, the density differentiation was skewed toward the lower half. The first two segments were further classified as primarily adipose tissue with a low percentage (25%) of fibroglandular tissue. The third segment was classified as 75% fibroglandular tissue and the fourth segment was classified as 100% fibroglandular tissue. This differentiation incorporated the marbling property of the different breast tissues. Three fibroglandular levels were chosen because this provided a balance between simplicity and realism for the resulting segmented data; fewer levels would not provide a model with enough realism and higher levels were unnecessary because it complicated the final model and did not increase the realism of the final image.

II.D. Breast surface mesh-model creation

After the breast was segmented a polygon mesh model of each classified tissue was created using the MATLAB `isosurface` function, which renders isosurfaces in volumetric data. The `isosurface` function was used to generate initial polygon mesh objects for the skin, fibroglandular, and adipose tissues. Figure 2 shows an example surface rendering from this mesh model of the segmented breast CT data. The polygon mesh created for each structure using MATLAB serves as the initial mesh of a subdivision surface. The mesh can be iteratively subdivided and smoothed to create a smooth surface. Table I summarizes the methods we used to create the breast phantom.

TABLE I. Methodology to create breast phantom.

II.E. Simulated compression

To be applicable to many breast imaging modalities, the breast phantom created above must be able to simulate different compression levels. Currently, we use a simple model to simulate compression. The details of this algorithm have been presented in detail previously, but in general, the breast is compressed in one dimension (x) and extended in the other dimensions (y and z) simulating compression between stiff plates.⁴⁶ The breast is assumed to be incompressible (fixed volume) and isotropic. The mesh's node locations were determined to be inside or outside the compressed thickness of the breast. Each x value of the vertices located outside is multiplied by the compression ratio to give the new x values for the compressed vertex location. Each x value of the vertices originally located between the simulated compression paddles remained unchanged. The method is demonstrated in Fig. 3.

II.F. Simulated radiographic images

Once the phantom is defined, it can be combined with existing simulation packages to simulate imaging data. To demonstrate the application of the phantom, we simulate

FIG. 3. Illustration of breast compression geometry.

mammography and tomosynthesis data from the phantom as described below. Both of these modalities require compression of the breast.

The vertices of the mesh-model were input into our simplified compression algorithm in order to simulate the geometry of the breast for simulated mammographic imaging. The breast was compressed down to a thickness of 5 cm.

X-ray projection images were simulated directly from the surface mesh model using a technique developed by Segars *et al.*¹¹ The geometry of the system was equivalent to that of the Siemens Mammomat Novation System presented previously by the authors.⁴⁶ Attenuation coefficients for adipose, fibroglandular, and skin were derived from International Commission on Radiation Units and Measurements (ICRU) tissue data.⁴⁷ The three different levels of fibroglandular tissue were assigned attenuation coefficients between adipose and muscle in order to account for their relative amount of marbling. The most dense fibroglandular tissue was assigned the elemental composition of muscle for our purposes since fibroglandular tissue was not available in the database used. A custom polyenergetic spectrum was used to simulate a 50 μm rhodium filter with a tungsten target.⁴⁸ Images were simulated with 1000×1000 pixels at 250 μm resolution.

After a simulated projection was acquired, a sigmoidal correction function was applied in order to simulate a screen-film mammogram, similar to what is currently applied to digitally acquired mammograms. To validate the mammogram simulation, the fractal dimension (FD) was calculated for ROIs from the simulated mammogram and compared to typical FD values obtained from real mammograms.^{49–51} Ten different 150×150 ROIs located near the nipple were used for the FD measurement. The FD was estimated using the circular average power spectrum method^{52,53} that has been used successfully in prior mammography applications.⁵⁴ Initially, the two-dimensional power spectrum of the image was obtained using zero padding and a radial Hamming window to ensure better estimation of the power spectrum.^{55,56} The 2D power spectrum was then transformed into one dimension by linear averaging the spectrum as a function of the radial distance from zero frequency. The Fourier power spectrum was plotted on a log-log scale as a function of the frequency and linear regression was applied to estimate the slope of the fitted line. The slope was then transformed into a FD measure as described by Tourassi *et al.*⁵⁴

III. RESULTS

III.A. Image processing

Figure 4 illustrates the denoising algorithm's effect on the original images. It clearly removes a significant amount of noise and provides for clearer visualization of the fibroglandular tissue in the denoised data. Table II shows that the average standard deviation of ten 100×100 ROIs decreases as the number of denoising iterations increases, which demonstrates the noise reduction due to denoising. Figure 5 illustrates the signal that was subtracted from each slice in order to perform postreconstruction scatter correction to remove the cupping artifact.

FIG. 4. (A) The original reconstructed CT data. (B) The data with ten denoising iterations, as optimal for image review. (C) The data with 40 denoising iterations to perform maximum noise reduction for segmentation purposes only.

III.B. Tissue segmentation

Figure 6 shows the signal that contains the threshold during iterative histogram classification for each axial slice. Both the originally determined threshold level and the applied smoothed level values are shown.

Figure 7 is the binary data used during segmentation and illustrates the effect of using predefined morphological operations along with the ellipsoidal connection algorithm and targeted region growing to classify the fibroglandular data. Although subtle, there is improvement with the ellipsoidal connection algorithm and targeted region growing. These methods add noticeably to the high-resolution detail of resulting images simulated with the phantom without perturbing the overall shape and structure of the breast tissue.

Figure 8 illustrates the output of classification from the volumetric processing step of the described algorithm. Performing the segmentation steps volumetrically fills in holes between neighboring slices and further improves the classification performance.

Figure 9 shows the final segmented slice. The density differentiation is shown, which more closely represents the real data than using a single value to describe the fibroglandular tissue.

III.C. Simulated radiographic images

Figure 10 shows the characteristic curve that was used on simulated projection images in order to simulate screen-film mammogram appearance. Figure 11 shows a comparison of a mammogram of a real human subject with two simulated mammograms of the breast phantom. Figure 11(A) shows an actual mammogram of a real human subject that is different than the subject used for the phantom generation. Figure 11(B) shows a mammogram of the phantom using defined attenuation coefficients ranging from adipose to muscle for the differentiated fibroglandular tissue. Figure 11(C) shows a

TABLE II. Comparison of standard deviations for different levels of denoising.

Original data	Denoised data	Denoised data
(0 iterations)	(10 iterations)	(40 iterations)
0.119 ± 0.013	0.07 ± 0.011	0.057 ± 0.011

FIG. 5. Signal matrix subtracted from each slice to correct for the cupping artifact due to scatter.

FIG. 6. Signal of threshold points used for iterative histogram classification.

FIG. 7. (A) The initial binary slice after histogram classification. (B) The slice after the ellipsoidal connection algorithm. (C) The slice after targeted region growing. Arrows show regions added with the algorithm.

FIG. 8. (A) Result from iterative histogram classification. (B) Result from axial processing. (C) Result from sagittal processing. (D) Result from coronal processing.

FIG. 9. Final segmented slice showing five different tissue density classifications. From darkest to lightest: adipose, fibroglandular 1, fibroglandular 2, fibroglandular 3, skin.

FIG. 10. Characteristic curve used on simulated projection image in order to simulate mammogram.

FIG. 11. (A) An example of a real mammogram for comparison purposes of a different subject than used to generate the computerized breast phantom. (B) The mammogram with defined attenuation coefficients that are described with three levels of fibroglandular tissue ranging from adipose to muscle. (C) The mammogram with enhanced attenuation coefficient to demonstrate high-resolution detail of the phantom.

TABLE III. Comparison of the FD distributions calculated from simulations to published results observed from actual mammograms.

Fractal dimension (the mean and standard deviation are displayed)	Hamming window	Published results (Ref. 49)
Simulated mammogram [Fig. 11(B)]	2.23 ± 0.007	2.36 ± 0.10
Simulated mammogram [Fig. 11(C)]	2.18 ± 0.016	

mammogram of the phantom with artificially enhanced attenuation coefficients to illustrate the high resolution detail. The simulated mammograms subjectively demonstrate the realism of the phantom and the level of detail in the tissue structures appears similar to actual mammograms.

A quantitative validation of the breast phantom simulations was performed using the fractal dimension calculated from ROIs of the simulated mammograms [Figs. 11(B) and 11(C)]. The average results from the simulation are shown in Table III as compared to a study from Bakic *et al.* performed on actual mammograms.⁴⁹ The simulated results compare quantitatively to published findings. They also compare similarly to other studies by Caldwell *et al.*⁵⁰ and Byng *et al.*⁵¹ that have found the FD to be within the range of 2.25–2.6.

IV. DISCUSSION

The goal of producing a suitable breast phantom for research has been pursued by a number of investigators and presents many challenges. Physical phantoms are not adjustable and do not realistically mimic the complexity of breast anatomy. Computerized phantoms, on the other hand, have traditionally offered either improved realism or flexibility but often not at the same time. Computerized phantoms have been available in two types: voxelized phantoms and mathematical phantoms based on geometric primitives. Voxelized phantoms are based on real human data and are realistic; however, they are not flexible and are also limited by the parameters and environment used to acquire the images: such phantoms may include arbitrarily fashioned mastectomy specimens or low-resolution full body CT data. Mathematical phantoms allow for flexibility; however, the simplistic shapes used as their basis do not generate visually realistic images. The breast phantom created with this method differs from other breast phantoms in that it combines the realism of a voxelized phantom with the flexibility of a mathematical phantom.

Initial images generated using this new methodology demonstrate the realistic high-resolution detail available with this phantom. However, several areas remain that require further investigation. There are artifacts around the nipple region that may likely be due to the mesh creation or the image acquisition algorithm. Further optimization may be required for the final phantom to reduce the number of triangles in order to simplify and smooth the surface model. The goal of mesh optimization is to decrease the complexity while minimally perturbing the overall shape and improving the fit to the data. This optimized mesh will then become the input to

the subdivision surface algorithm that will generate the final mesh to be incorporated into the XCAT phantom.

Certain high-resolution detail structures such as Cooper's ligaments are not fully visible because the segmentation was not able to robustly classify these structures. Mathematically defined fine resolution structures can be incorporated in the future to artificially enhance the detail visible in the final acquired image without significantly affecting the phantom's realism.

Although fast and efficient, the image simulation method will be further improved to include models for noise, detector effects, and beam hardening. These steps will result in more realistic noise levels and statistics. The current model used a simplistic compression algorithm. This does not take into consideration the different mechanical properties of the different tissues. In the future, finite element methods will be implemented to realistically simulate the deformation of breast tissue under compression.

The similarity between the FD calculated from the simulated mammograms compared to the FD of real mammograms reported in the literature demonstrate the realism of the breast phantom and that the simulation methods used are capable of producing realistic imaging data. In addition, the phantom has visually demonstrated that there is a realistic level of detail that requires some additional tuning to further improve its utility.

The described phantom includes information from only a single patient. In the future, many additional models will be created from different human subject data and the final phantoms methodology will incorporate information from all of the models. We plan to incorporate adjustable size, density, and tissue distribution in order to simulate a large number of simulated subjects. Information from the multiple segmented data sets will be synthesized to create a generic base breast template that can be incorporated into the XCAT phantom. The base breast template can be manipulated to model a breast of any size or composition and deformed to simulate compression, essentially creating a source for an infinite number of simulated breasts to investigate existing and emerging breast imaging modalities.

V. CONCLUSION

Current breast phantoms have many limitations. The phantom presented in this work combines the flexibility of a mathematical phantom with realistic anatomy based on actual human data. This new phantom may provide an important tool for breast imaging researchers to optimize and improve different imaging techniques and to evaluate and compare various breast imaging modalities in terms of clinical performance.

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