

Mapping of Breast Tissue Dielectric Properties Using T1-Weighted MRI Data

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Abstract—This study introduces a method for developing realistic numerical two-dimensional (2D) microwave breast models from T1-weighted MRI data, integrating anatomical features, such as: shape, size, and density. This method contributes a new perspective in enhancing noise reduction, tissue segmentation, nonlinear mapping of electromagnetic attributes, and the authentic depiction of breast contours for precise tissue categorization. It follows a comprehensive four-phase procedure: denoising MRI data by estimating and mitigating bias field in each slice, after which the breast tissue is segmented in two main categories: adipose (fat) and fibroglandular. Furthermore, using the distribution of MRI pixel intensities, a nonlinear mapping functions are generated, which allow each MRI pixel to map corresponding electromagnetic properties. The efficiency of proposed method is assessed through Dice-Sorensen Coefficient statistic, juxtaposing the categorized images against reference standards set by radiologists. The method achieved an average Dice Similarity Coefficient of 74.66% for class A, 85.12% for class B, 78.77% for class C, and 85.56% for class D breast densities.

Index Terms—Biomedical imaging, microwave breast imaging, tissue segmentation, dielectric mapping of breast, MRI processing.

I. INTRODUCTION

Breast cancer, primarily affecting women, has been a significant health concern for many years. Studies such as the 2019 report by the American Cancer Society (ACS) emphasize the critical role of early detection in lowering cancer mortality rates [1], [2]. Progress in medical imaging, especially for cancer detection, is crucial. Microwave imaging is emerging as a safe, non-ionizing, and cost-effective method for breast examinations [3], [4]. Our research centers on utilizing T1-weighted MR images to develop realistic 2D numerical breast models, with the aim of developing essential experimental tools for use in microwave imaging sessions to facilitate early breast cancer screening and diagnosis.

Previous studies, including those by [5], [6], have aimed to advance microwave breast cancer detection using sophisticated 3D modeling and MRI-based realistic breast phantoms. However, a significant gap remains: these studies lack a unified metric to validate their methods' accuracy. Addressing this critical gap, our work stands

out by incorporating correlation tests to enhance our approach. We rigorously quantify the effectiveness of our method using the Dice similarity coefficient, comparing our segmentation results directly against the 'ground truth' established by radiologists. This metric-based evaluation is a key differentiator of our study, ensuring our advancements are not only innovative but also verifiably accurate.

Our work unfolds through a series of concise steps: We begin by introducing an image preprocessing pipeline aimed at enhancing image quality via noise filtering and bias field correction. This is followed by the segmentation of breast tissue to distinguish between fat and fibroglandular tissue. The culmination of our process is the generation of a detailed dielectric breast map, where dielectric properties, derived from the Cole-Cole model, are assigned to each MRI image pixel. This streamlined approach outlines the core components of our methodology.

II. METHOD

A. Noise Filtering and Bias Field Corrections

MRI scans are often affected by noise, especially from low-reflectivity pixels on the breast's outer surface, which complicates tissue differentiation. To address this issue, we utilize triangle thresholding along with morphological operations, including erosion and dilation, to remove background noise and isolate the breast region.

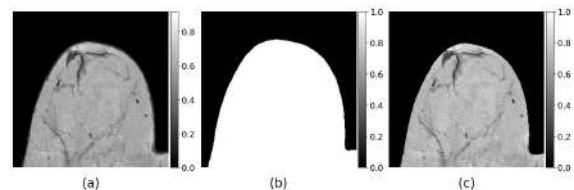


Fig. 1. Denoising of breast exterior: (a) Raw MRI data, (b) Binary mask generated using triangle thresholding combined with morphological erosion and dilation, (c) Final result after applying the mask.

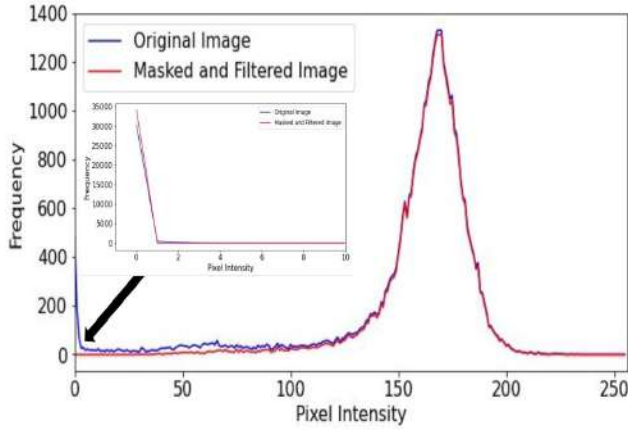


Fig. 2. The graph highlights the shift in low reflectance values following the application of masking, demonstrating the impact of the background removal process. The blue curve represents the histogram of the original image, while the red curve corresponds to the histogram after background removal.

The process start by selecting the region of interest (ROI), as illustrated in Fig. 1(a). The triangle thresholding method is utilized to normalize the height and dynamic range of the pixel intensity histogram within the ROI, thereby removing background noise [7]. Erosion and dilation filters are subsequently applied to preserve the original size of the breast and enhance the clarity of its boundaries (Fig. 1(b)). Finally, low-intensity background artifacts are eliminated by applying the smoothed binary mask to the noisy MRI data, as demonstrated in Fig. 1(c). Any noise, such as background artifacts or bias field, can disrupt the distribution of pixel intensities (Fig. 2), leading to inaccurate tissue differentiation. Therefore, these steps are crucial in ensuring well-defined breast borders, which facilitate further analysis.

After denoising operation (Fig. 3(a)), we proceed with bias field correction, to further enhancing the contrast between breast tissues. Accurately identifying adipose tissue samples is essential for precise bias field estimation. To select adipose pixel samples, we first define a moving window of 5x5 pixels to retrieve the local maxima within each window region at each step. After the sampling operation, we apply spatial filtering to eliminate any remaining samples that belong to non-adipose tissue. In this process, each selected point ($i_{max}(rc)$) within the moving window must satisfy a condition [8]:

$$i_{max}(rc) > \max(i_{max}) \cdot p \quad (1)$$

where the threshold operator p is set to 0.85. The adipose tissue pixels retained after this filtering process are shown as red dots (Fig. 3(b)). To model the bias field, we use thin plane spine interpolation to fit the smooth surface to the adipose pixels [9]. The estimated bias field is then removed from the corresponding slice through element-wise division.(Fig. 3(c).) After removing the bias field, we apply a sharpening operator to further enhance the contrast between adipose and fibroglandular tissues. The processed MRI data (Fig. 3(d)) is now ready for the segmentation

phase. This process ensures that the final image accurately reflects the underlying anatomical structures, enabling precise tissue differentiation.

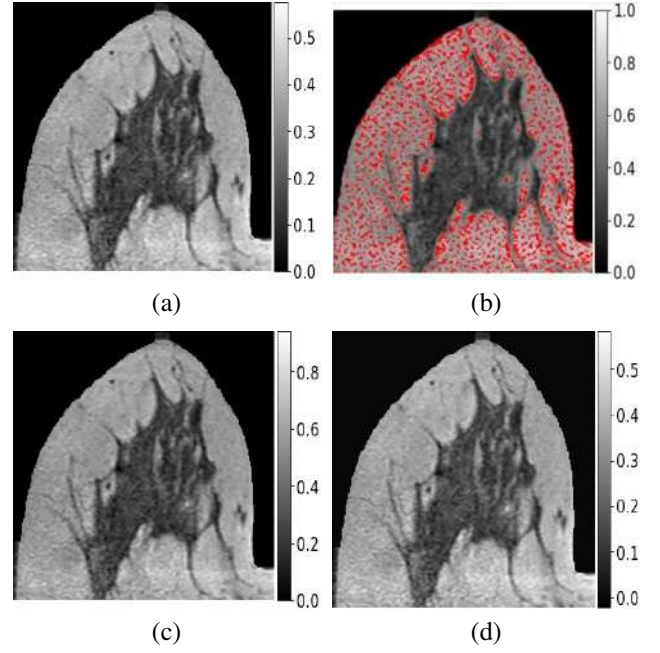


Fig. 3. Process of enhancing contrast between breast tissues: (a) Raw MRI data affected by bias field, (b) Sample pixels from adipose tissue, indicated by red dots, (c) Image after bias field removal, and (d) Final image obtained after applying bias field correction and sharpening filter.

B. Segmentation

T1-weighted MR scans effectively highlight the contrast between fibroglandular and adipose breast tissues, mainly due to the higher water and blood vessel content in fibroglandular tissues. Adipose tissue pixels typically display a Gaussian distribution in the grayscale image histogram, making histogram-based thresholding suitable for tissue segmentation. In our approach, we utilize histogram-based thresholding, assuming that the adipose tissue follows this Gaussian distribution. This automatic thresholding method leverages the characteristic distribution of adipose tissue pixels for effective segmentation.

In the segmented images, fibroglandular tissues appear black due to their lower reflectance, while adipose tissues are displayed in white, reflecting their higher reflectance. The reliability of our segmentation approach is validated by comparing our segmentation results (Fig. 4(a, c, e, g)) with the ground truth established by radiologists (Fig. 4(b, d, f, h)), employing the Dice similarity coefficient as a quantitative measure [10]. The similarity analysis is an important part of the segmentation process, as it not only highlights the effectiveness of our method but also aligns our findings with established medical standards.

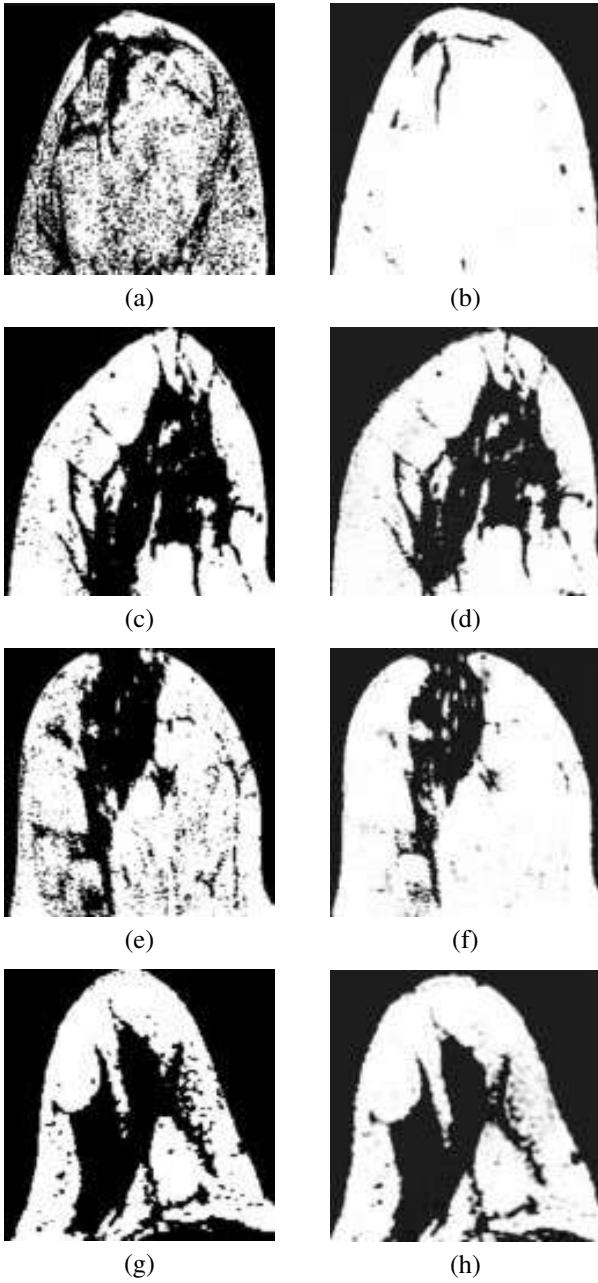


Fig. 4. Segmentation results for all breast types across the four ACR categories: (a) and (b) correspond to breast type A, (c) and (d) to type B, (e) and (f) to type C, and (g) and (h) to type D. In each pair, the first image (a, c, e, g) represents the binary segmentation obtained by the proposed method, while the second image (b, d, f, h) shows the ground truth segmentation validated by an expert.

C. Mapping of Breast Tissue Dielectric Properties

TABLE I
COLE-COLE MODEL PARAMETERS FOR 5 BREAST TISSUE GROUPS

Group	ϵ_∞	$\Delta\epsilon$	σ_s (S/m)	τ (ps)	α
Maximum	1.000	66.310	1.370	7.585	0.063
1	7.821	41.480	0.713	10.660	0.047
2	5.573	34.570	0.524	9.149	0.095
3	3.140	1.708	0.036	14.650	0.061
Minimum	2.293	0.141	0.002	16.400	0.251

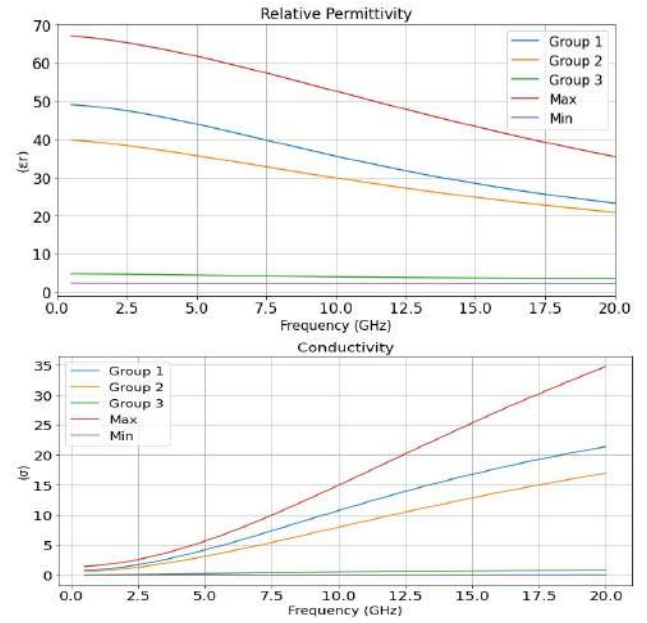


Fig. 5. Frequency-dependent relative permittivity (ϵ_r) and conductivity (σ) curves for various breast tissue groups.

The electromagnetic characteristics of breast tissues were thoroughly examined in the study by Lazebnik et al., where tissues were classified into three categories based on their adipose content: 1) group 1 with 0-30% adipose, 2) group 2 with 31-84% adipose, and 3) group 3 with 85-100% adipose content. Using the Cole-Cole parameters given in Table 1, we calculated the average relative permittivity and conductivity for each group, along with their minimum and maximum limits [11]. Fig. 5. shows the frequency-dependent behavior of the permittivity and conductivity predicted by the Cole-Cole model between 0 and 20 GHz. At a specific frequency—10 GHz in our study—the permittivity values are labeled as $p_{\min}$, p_1 , p_2 , p_3 , and $p_{\max}$ and conductivity values; $c_{\min}$, c_1 , c_2 , c_3 , and $c_{\max}$. Correspondingly, the pixel intensity values in MRI images are labeled as $I_{\min}$, $I_{\mu g}$, I_m , $I_{\mu f}$, and $I_{\max}$, defined as follows [8]:

$$I_{\min} = \mu_g - 3\sigma_g \quad (2)$$

$$I_{\mu_g} = \sum_{x=0}^T x f(x) \quad (3)$$

$$I_{\mu_f} = \sum_{x=T}^{\infty} x f(x) \quad (4)$$

$$I_T = T \quad (5)$$

$$I_{\max} = \mu_g + 3\sigma_g \quad (6)$$

To accurately map MRI voxel intensity variations to the electromagnetic properties of tissues, we first establish key pairs correlating MRI intensity values with tissue permittivity; $(p_{\min}, I_{\min})$, $(p_1, I_{\mu g})$, (p_2, I_T) , $(p_3, I_{\mu f})$, $(p_{\max}, I_{\max})$ and with tissue conductivity; $(c_{\min}, I_{\min})$, $(c_1, I_{\mu g})$, (c_2, I_T) , $(c_3, I_{\mu f})$, $(c_{\max}, I_{\max})$. In formulas 1 and

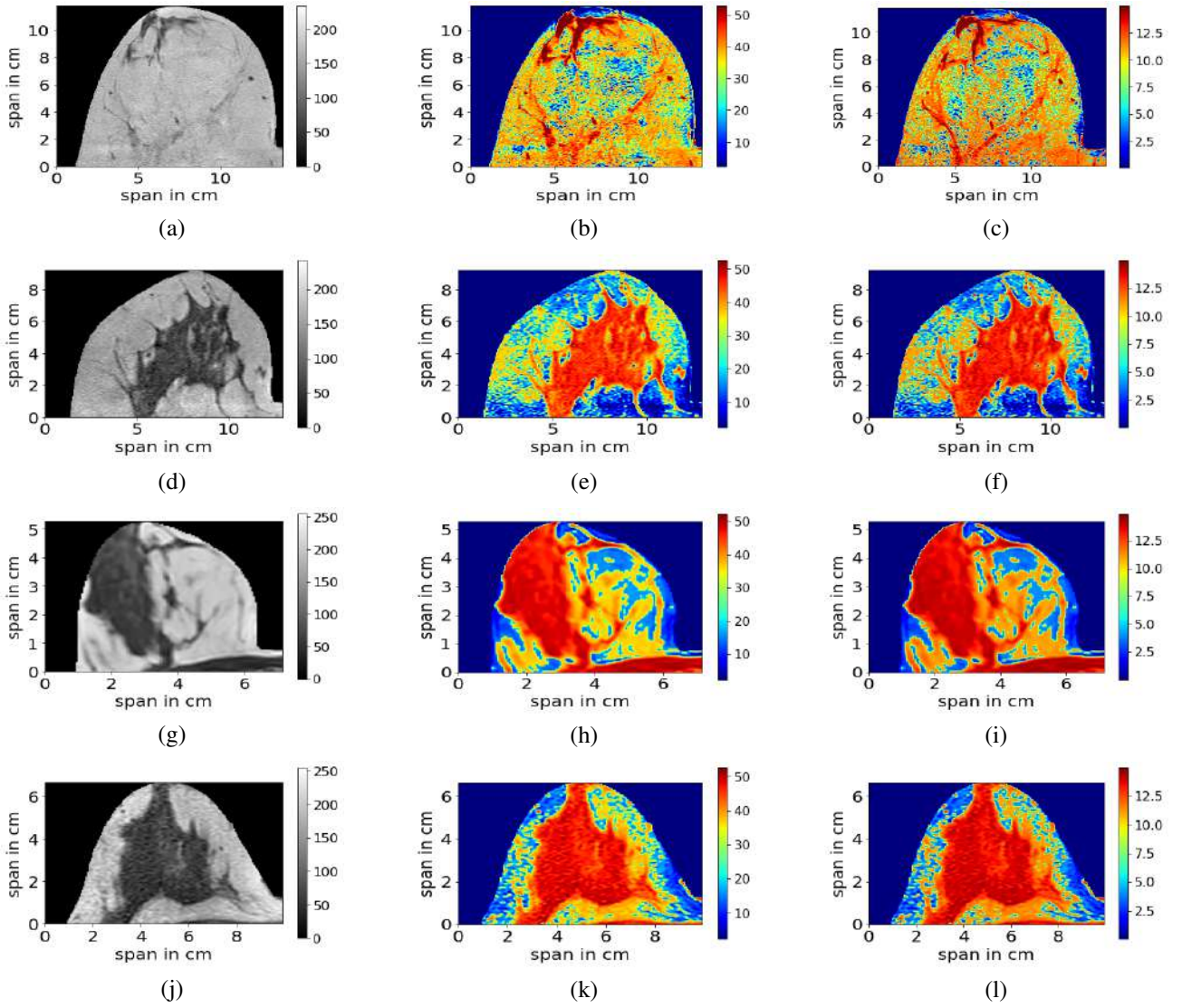


Fig. 6. Mapping of dielectric properties for all breast types across the four ACR categories: The first image (a, d, g, j) represents breast tissue-enhanced images, after bias field removal and denoising process are applied. Corresponding permittivity maps are shown in the second image (b, e, h, k), while the corresponding conductivity maps for each type are presented in (c), (f), (i), and (l).

5, the variables ' μ_g ' and ' μ_f ' represent the mean, while ' σ_g ' and ' σ_f ' denote the standard deviations of the pixel intensities, for adipose and fibroglandular tissues, respectively. These pairs enable an effective point-wise mapping from MRI intensity values ($I_{\min}, I_{\mu_g}, I_T, I_{\mu_f}, I_{\max}$) to permittivity values ($p_{\min}, p_1, p_2, p_3, p_{\max}$) and conductivity values ($c_{\min}, c_1, c_2, c_3, c_{\max}$) [8]. To cover the full spectrum of MRI pixel intensities, Hermite interpolation [12] is used to create a continuous mapping function for relative permittivity (ϵ_r) and conductivity (σ) intersecting the five established points ($p_{\min}, p_1, p_2, p_3, p_{\max}$) and ($c_{\min}, c_1, c_2, c_3, c_{\max}$). This methodology results in the generation of an anatomically realistic permittivity and conductivity map.

III. RESULTS

In this study, we analyzed T1-weighted MR images corresponding to breast density categories (A, B, C, and

D) defined in [13]. The dataset comprised 40 images, with 10 images representing each breast density type. For each processed image, segmentation masks were generated and then validated against the 'ground truth' established by expert radiologists, leading to the creation of permittivity and conductivity maps for each breast density type. The effectiveness of the segmentation was assessed using the Dice similarity coefficient, with mean values for each density group—based on 10 slices per group—summarized in Table II. Type A density, with a lower Dice coefficient of 74.66%, showed less effective segmentation, whereas Types B, C, and D, with higher coefficients of 85.12%, 78.77%, and 85.56%, respectively, demonstrated more accurate segmentation performance. As observed, the Dice coefficient tends to increase in breast MR images as the breast density increases. Fig. 6 shows the examples of the permittivity (Fig. 6 (b, e, h, k)) and conductivity (Fig. 6 (c, f, i, l)) profiles for

each breast density type. Regions of high contrast (shown in red) indicate a predominant presence of fibroglandular tissue, while areas of low contrast (shown in blue) suggest a higher adipose tissue content. The contrast variation between these regions reflects the varying levels of adipose tissue distribution across different breast types.

TABLE II
DICE COEFFICIENTS FOR DIFFERENT BREAST DENSITY TYPES

Density Classes	Mean Dice Coefficients (%)
A	74.66
B	85.12
C	78.77
D	85.56

IV. CONCLUSIONS

This study presents a realistic two-dimensional (2D) microwave breast model based on T1-weighted MRI data. The proposed method, applicable to any breast type across the four ACR categories, follows a methodology that includes tissue contrast enhancement through bias field correction and noise filtering, tissue segmentation for differentiating fibroglandular and adipose tissues, and mapping of permittivity and conductivity values based on a nonlinear function, which assumes a nonlinear relationship between breast tissues and electromagnetic properties. The effectiveness of the proposed approach was validated using the Dice similarity coefficient, which demonstrated sensitivity to changes in breast density, as evidenced by increasing coefficient values with higher density levels. Preliminary results suggest significant potential, with plans for further validation using larger datasets across diverse tissue compositions.

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