

Advanced Breast Tissue Tomography via Anatomical Prior-Informed Electrical Impedance Reconstruction

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ABSTRACT: Breast cancer is the most prevalent cause of mortality among women. Early diagnosis is critical because it can enhance survival rates and facilitate effective treatment. In classical breast cancer detection, mammography is the gold standard method. Because each traditional modality has limitations, researchers have studied alternative approaches for over a decade. Electrical impedance tomography is a portable, low-cost, noninvasive technique for screening, tracking, and remote monitoring. This study presents a novel image reconstruction framework that utilizes high-resolution anatomical information obtained from ultrasound tomography (UST) to enhance the spatial resolution and diagnostic accuracy of Electrical Impedance Tomography (EIT) for breast tissue evaluation. First, a high-fidelity forward model for both EIT and US was created, and the corresponding potential distribution and acoustic wave propagation were observed. Second, independent inverse solvers were created, using the Total Variation Primal-Dual Interior Point Method (TV-PDIPM) for EIT and the Attenuation-Weighted Bilinear Interpolation for UST, which revealed their limitations. A physics-informed reconstruction method is proposed, in which a grayscale segmented ultrasound image serves as a spatially variant anatomical prior. This prior technique is used to assign weights to the Total Variation (TV) regularization term in the EIT inverse problem. The integrated US-EIT system achieved an overall accuracy of 98.38%, sensitivity of 92.05%, and Dice coefficient of 0.93. The Relative Image Error (RIE) was reduced to 0.078, with a Localization Error of approximately 0.4 mm. These findings substantiate that physics-informed anatomical guidance significantly alleviates the ill-posedness of the EIT inverse problem. This study establishes a solid computational basis for an economical, non-ionizing, and highly precise multimodal imaging system intended for clinical use in breast cancer screening. The method demonstrated a robust correlation with ground-truth data and a low reconstruction error, achieving a Dice coefficient greater than 0.91.

1. INTRODUCTION

Breast cancer poses a significant challenge in modern oncology care and raises serious concerns regarding global public health. According to recent reports published by the World Health Organization, breast cancer remains the most diagnosed cancer among women worldwide. In 2022, approximately 2.3 million women were diagnosed with breast cancer globally, with nearly 670,000 associated deaths reported worldwide. In clinical practice, survival rates improve when cancer is diagnosed [1]. According to [2], patients commonly diagnosed with localized Stage I disease have a 5-year relative survival rate of about 99%. However, if cancer is identified only after it has progressed to Stage IV (distant metastasis), the survival rate falls sharply to 27%. This data emphasizes an important point in clinical care: the best way to reduce cancer deaths is not just through treatment, but by using high-sensitivity, early-stage screening. Despite the widespread use of X-ray mammography, significant diagnostic problems persist. Women with dense breasts are often misclassified because both dense tissue and tumours appear white on a mammogram [3]. The “masking effect” leads to a false-negative rate of nearly 50% among women with dense breast tissue [4]. Additionally, the ionizing effects of X-rays and discomfort from breast compression can lower

patient compliance [5]. This has led to the development of affordable, noninvasive imaging techniques, including electrical impedance tomography and ultrasound tomography [6, 7]. A study showed that combining a 3D-EIT system with ultrasound can enhance diagnostic accuracy, achieving a specificity of 89.6% compared to 80.1% for USG alone [8]. Ref. [9] explored integrating ultrasound structural information with EIT conductivity imaging and demonstrated that ultrasound-derived boundaries significantly improved the EIT reconstruction accuracy. Ref. [10] proposed a hybrid US-EIT imaging framework for soft tissue characterization, which improved spatial resolution and contrast recovery. The methodology was validated using simulation and phantom studies. Ref. [11] developed a multimodal imaging strategy combining ultrasound tomography and EIT. This approach incorporated acoustic property maps into the conductivity reconstruction. The results showed improved boundary detection and tumor contrast. Ref. [12] investigated an upstream data fusion framework combined with machine learning for improved breast cancer detection. Multimodal imaging data were integrated using automated image registration to accurately align heterogeneous sources. Ref. [13] proposed a Convolution Attention Network for dual-modal fusion of Electrical Impedance Tomography (EIT) and ultrasound (US) data to improve 2D image reconstruction quality.

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One effective way to improve EIT is to include prior anatomical information from other modalities. Soft-prior regularization studies in breast EIT showed that when the tumor region was constrained by prior spatial information, conductivity recovery became more accurate, and the tumor was better localized [14]. Similar ideas have been successful in other tomographic inverse problems, where spatial priors reduce ambiguity and improve reconstruction stability [15, 16]. Ultrasound is especially useful as a source of prior information because it can provide clear anatomical boundaries and lesion shape information in a non-ionizing and accessible manner. This makes ultrasound a suitable companion modality for EIT [17, 18].

This study proposes a physics-informed ultrasound-guided EIT framework for breast cancer detection. We simulated the forward problems for EIT and ultrasound tomography in COMSOL and performed the corresponding inverse reconstructions in MATLAB. A segmented ultrasound image is used as a spatially varying anatomical prior to weight the total variation regularization term in the EIT inverse problem. The objective is to improve conductivity reconstruction, tumor localization, and boundary preservation while maintaining the method computationally feasible and non-ionizing. This study extends earlier EIT and multimodal breast imaging studies by introducing ultrasound-derived prior weighting within the EIT reconstruction framework.

2. METHODOLOGY

This study was conducted as a simulation-based multimodal imaging study for breast cancer detection. The proposed framework combines electrical impedance tomography (EIT) and ultrasound tomography (UST), in which an ultrasound image is used as an anatomical prior to improve the EIT inverse reconstruction. This study was designed to compare three reconstruction settings: standalone EIT, standalone UST, and the proposed US-guided EIT fusion model. The main aim was to determine whether anatomical guidance from ultrasound could reduce the EIT ill-posedness and improve tumor localization, edge definition, and image fidelity [19].

2.1. Breast Phantom Model

A heterogeneous breast phantom with a radius of 7 cm was developed to represent main tissue classes relevant to breast imaging, including skin, adipose tissue, glandular tissue, and a malignant inclusion. The same geometric domain was used for both EIT and UST so that the two modalities could be reconstructed in a co-registered manner. This choice is important because the proposed fusion strategy depends on the accurate spatial correspondence between the anatomical map obtained from ultrasound and the conductivity map reconstructed from EIT. To thoroughly assess the performance and robustness of the proposed framework, the single-phantom evaluation was expanded to a dataset of different numerical phantom configurations. The dataset varied tumor radius (0.5, 0.75, and 1), position across four quadrants, radial depths, and conductivity contrast ratios (1.5 : 1 to 3 : 1 relative to glandular tissue). The model is consistent with prior breast phantom work used

in EIT soft-prior studies and multimodal breast imaging investigations. Sixteen Ag/AgCl electrodes were placed equidistantly around the surface of the breast model. These electrodes were chosen because of their stable electrochemical behavior and low contact impedance, which make them suitable for biomedical impedance measurements. This configuration employed 16 ultrasound PZT-4 transducers arranged in an alternating ring pattern, using a free triangular mesh with a maximum element size of $\lambda/6$. Figure 1 shows the geometry of the model used in this simulation study.

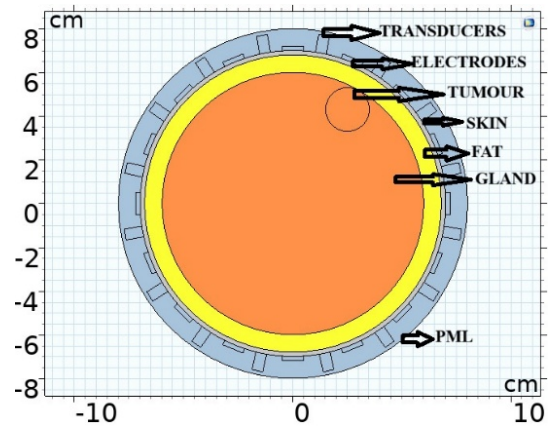


FIGURE 1. Geometry of breast model.

2.2. EIT Forward Modelling

The EIT forward problem was formulated under the quasi-static approximation of Maxwell's equations, which is the standard approach for low-frequency bioimpedance imaging. The fundamental relationship between the current density and electric field is provided by Ohm's law:

$$J = \sigma E \quad (1)$$

$$E = -\nabla U \quad (2)$$

Here, E is the electric field; U is the scalar potential distribution inside the field; and σ is the conductivity distribution. The following expression is obtained by combining the equations:

$$J = -\sigma(\nabla U) \quad (3)$$

If internal current sources are absent, it is given that $\nabla \cdot \sigma(\nabla U) = 0$, which results in EIT's partial differential equation and describes how current flows through breast tissues. In the proposed geometry, an adjacent current injection pattern is adopted. A maximum current amplitude of 1 mA was employed, consistent with recommendations of the IEC 60601-1 standard and in line with the values reported in [20]. Current injection was applied through surface electrodes positioned around the breast phantom, and the resulting potential distribution was computed using a complete electrode model (CEM). CEM was selected because it accounts for electrode size, contact impedance, and measurement configuration more accurately than simplified boundary models. Forward simulation was implemented in COMSOL Multiphysics using finite element analysis, and the resulting boundary voltage data were exported for inverse reconstruction using MATLAB. The boundary current source applied in COMSOL is mathematically gov-

erned by the following condition, which enforces a prescribed normal current density on electrode boundaries while ensuring zero current flow elsewhere:

$$n \cdot (J_1 - J_2) = Q_{j,s} \quad (4)$$

The mesh was designed to conform closely to curved tissue boundaries and electrode surfaces, ensuring an accurate numerical representation of field discontinuities near interfaces. Special refinement is typically applied in regions of high conductivity gradients, such as near tumors and electrode boundaries, where rapid spatial variations in electric potential are expected.

The experiment is repeated so that each electrode functions as a current source. Frequency domain analysis for Electrical Impedance Tomography (EIT) was performed at a chosen frequency of 50 kHz. The tissue-specific parameters, summarized in Table 1, are deemed critical for the accurate modelling of current flow and voltage distribution within the breast.

TABLE 1. Dielectric parameters used for EIT modelling.

Parameters	Conductivity (Sm^{-1})	Permittivity
Skin	0.0273	1130
Fat	0.0249	118
Gland	0.534	4020
Tumor (Malignant)	1.125	60
Tumor (Benign)	0.5	35
Ag/AgCl electrodes	61E6	1

Electrical and acoustic properties assigned to breast tissues were selected based on reported tissue-property ranges in the literature. The present model includes skin, adipose, glandular tissue, and tumour regions to represent the principal electrical and acoustic heterogeneity relevant to the proposed EIT-UST framework. Although the model captures major tissue contrasts, it does not reproduce the full anatomical variability of a real breast, including irregular glandular structures and patient-specific tissue distributions. This simplification was adopted to provide a controlled environment for evaluating the proposed multimodal reconstruction method.

2.3. EIT Inverse Reconstruction

The EIT inverse problem poses considerable challenges owing to its poorly defined characteristics and notable nonlinearity. The objective is to reconstruct the internal distribution of electrical conductivity, σ , based on a series of voltage measurements V , gathered at the edge of the domain. This is structured as a minimisation problem aimed at identifying the conductivity distribution that aligns most closely with the measured data, with regularisation applied to guarantee a stable and unique solution:

$$\hat{\sigma} = \arg \min \|V_m - V_c\|^2 + \lambda \int |\nabla \sigma| dx \quad (5)$$

λ is the regularization parameter that controls smoothness, and V_m and V_c are measured and calculated boundary voltages. To

address the inverse problem in EIT, the MATLAB-based EIDORS toolbox (Electrical Impedance Tomography and Diffuse Optical Tomography Reconstruction Software) was used with the Total Variation Primal-Dual Interior Point Method (TV-PDIPM). TV regularization was selected because it preserves sharp conductivity transitions better than smoothness-based methods, which is especially useful for breast lesion imaging. The TV-PDIPM algorithm addresses the non-linear, non-smooth inverse problem by reformulating it as a convex optimization problem. The PDIPM algorithm fundamentally involves the iterative resolution of a linearized form of Karush-Kuhn-Tucker (KKT) optimality conditions. This approach facilitates the effective management of the non-differentiable L1-norm associated with TV regularization. In the standalone EIT case, the inverse solution was obtained directly from the measured boundary voltages without anatomical prior information, providing a baseline reconstruction for comparison.

2.4. UST Forward Modelling

The ultrasound component was also simulated in COMSOL using the same breast phantom geometry. An acoustic forward model was used to estimate wave propagation through heterogeneous tissues and generate a pressure- or attenuation-based response map. Ultrasound tomography was chosen because it can provide a structural image of the breast with good boundary definition, which is useful for guiding EIT reconstruction[21]. The UST model captures the modality's complementary nature: ultrasound provides anatomy, while EIT provides electrical functional contrast. The total pressure $p_T(x, t)$ within a propagating pressure wave is defined as:

$$p_T(x, t) = p_0 + p(x, t) \quad (6)$$

where $p_T(x, t)$ is the dynamic acoustic pressure associated with the ultrasound wave. In the context of steady-state harmonic excitation, we established the forward problem within the frequency domain using the Pressure Acoustics, Frequency Domain interface in COMSOL. The acoustic pressure field is considered to change harmonically over time and represented as a complex quantity that encompasses both amplitude and phase details.

With these assumptions in place, the governing equation is simplified to a generalized Helmholtz equation, represented as

$$\nabla \cdot \left(-\frac{1}{\rho_c} (\nabla p_t - q_d) \right) - \frac{k_{eq}^2 p_t}{\rho_c} = Q_m \quad (7)$$

$$k_{eq}^2 = \left(\frac{\omega}{c_c} \right)^2 - k_z^2 \quad (8)$$

where ρ denotes the medium's density; q_d and Q_m represent monopole and dipole sources, respectively; k_{eq} denotes the associated wave number over the waveform velocity c_c in the fluid; k_z signifies the out-of-plane wave number; ρ_c pertains to the medium density; ω is the angular velocity; and c is the speed of sound. As the ultrasonic wave travels through a multiphase medium distribution, various attenuation mechanisms [22] — such as diffusion, scattering, and absorption occur at the interfaces of different media. Consequently, the ultrasonic

TABLE 2. Acoustic parameters used for UST in COMSOL.

Parameter	Density rho (kg/m ³)	Speed of sound (m/s)
Skin	1100	1600
Breast Fat	950	1480
Gland	1040	1580
Malignant Tumor	1100	1630
PZT4 Transducers	7500	4820

transducer at the receiving end captures the sound pressure signal attenuated at 1 MHz. Table 2 lists the acoustic parameters of the UST model used in COMSOL.

2.5. UST Inverse Reconstruction

Inverse UST problem was reconstructed in MATLAB using attenuation-weighted bilinear interpolation. This reconstruction strategy was used to obtain a grayscale ultrasound image that reflects anatomical structure and lesion boundaries. Attenuation weighting improves interpolation process by reducing artifacts and preserving spatial information in regions where the acoustic signal is weakened by tissue heterogeneity. The resulting UST image was then segmented using the k-means clustering algorithm to form a spatial prior for fused EIT reconstruction.

2.6. Ultrasound Guided Fusion

The central contribution of this study is using segmented ultrasound images as spatially varying priors for EIT reconstruction. In the proposed framework, the ultrasound image is converted into a grayscale anatomical map, and this map is used to weight the total variation regularization term in the EIT inverse solver. Regions identified as suspicious or structurally distinct in the ultrasound image are assigned lower regularization weights so that conductivity changes can be recovered more freely, whereas homogeneous regions are assigned higher weights to suppress artifacts. A significant technical hurdle is the resolution discrepancy. UST images rely on a pixel-based approach using a Cartesian grid, whereas EIT solvers use Finite Element Method (FEM) meshes composed of triangular elements. A mapping algorithm that determines the centroid of each FEM element and retrieves the associated K-means cluster value was formulated. Edges of the FEM elements were assigned weights, and when an edge intersects a boundary in the UST mask, the regularization penalty for that edge is diminished. In the process of iterative updates, we determine the search direction $\nabla \sigma$ by addressing the modified Karush-Kuhn-Tucker (KKT) system:

$$(J^T W_d J + \alpha G^T W_s G) \Delta \sigma = -r \quad (9)$$

where J represents the Jacobian; G denotes the discrete gradient operator; and r signifies the residual. Including W_s guarantees the update step inherently aligned with the anatomical

prior. The localization error (LE) is calculated as

$$LE = \sqrt{\{(x_{true} - x_{recon})^2 + (y_{true} - y_{recon})^2\}}$$

where x_{true}, y_{true} is the actual geometric center of the target tumor inclusion, and x_{recon}, Y_{recon} represents the centroid of the reconstructed tumor domain.

2.7. Sensitivity Analysis of Ultrasound-Prior Weighting

To examine the influence of the ultrasound-derived anatomical prior on EIT reconstruction, a sensitivity analysis was performed by varying the weighting factor applied to the spatial prior. The ultrasound-derived information was incorporated into the total variation regularization while keeping the breast geometry, electrode configuration, stimulation pattern, reconstruction algorithm, and other solver parameters unchanged. Different weighting values 0.1, 0.3, 0.5, 0.7, and 0.9 were applied to the same simulated measurement data, and the corresponding EIT reconstructions were obtained independently. The reconstructed images were subsequently evaluated using the same quantitative measures for the main reconstruction, including accuracy, sensitivity, specificity, Dice coefficient, mean squared error, peak signal-to-noise ratio, correlation coefficient, and relative image error. This analysis was performed to determine how changes in the ultrasound prior affect reconstruction quality.

2.8. Robustness Analysis of Ultrasound Segmentation

The robustness of the ultrasound-derived spatial prior was evaluated by introducing controlled changes to the segmented tumour boundary. Morphological erosion and dilation were applied to the segmented tumour region to simulate under-segmentation and over-segmentation, respectively. Different structuring-element sizes were used to produce small and large boundary perturbations. The modified segmentation masks were then incorporated into the ultrasound-guided EIT reconstruction without changing the remaining reconstruction parameters. The resulting images were compared with the reference reconstruction using the same quantitative evaluation measures. This procedure was used to determine whether moderate inaccuracies in the ultrasound segmentation substantially affect the final EIT reconstruction.

3. RESULTS

3.1. EIT Forward Problem

The EIT forward model was first solved in COMSOL to obtain the boundary voltage distribution corresponding to the prescribed current injection pattern. The simulated potential map in Figures 2(a)–(d) shows a clear dependence on the heterogeneous conductivity distribution of the breast phantom, with measurable voltage variation around the tumor inclusion. These forward data confirmed that the chosen phantom geometry and electrode arrangement were suitable for inverse reconstruction and consistent with the complete electrode model used

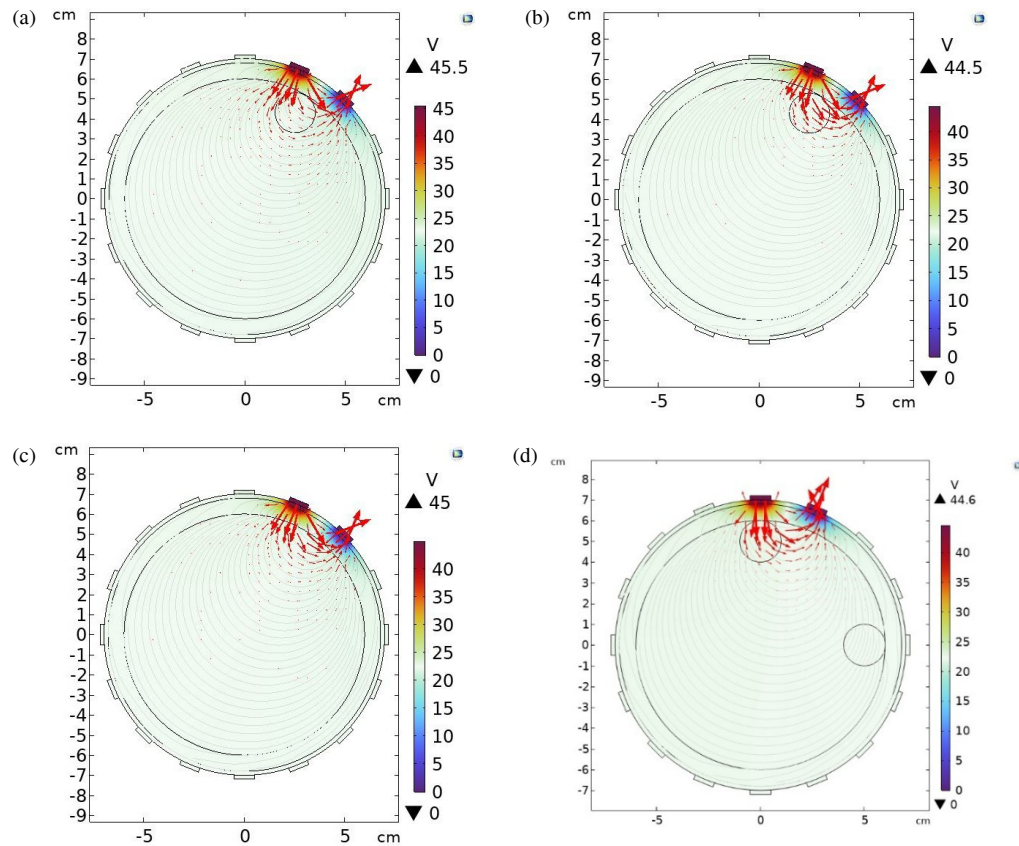


FIGURE 2. Electric potential distribution of (a) Benign tumor, (b) Malignant tumor, (c) Normal breast tissue, and (d) one benign and one malignant tumour.

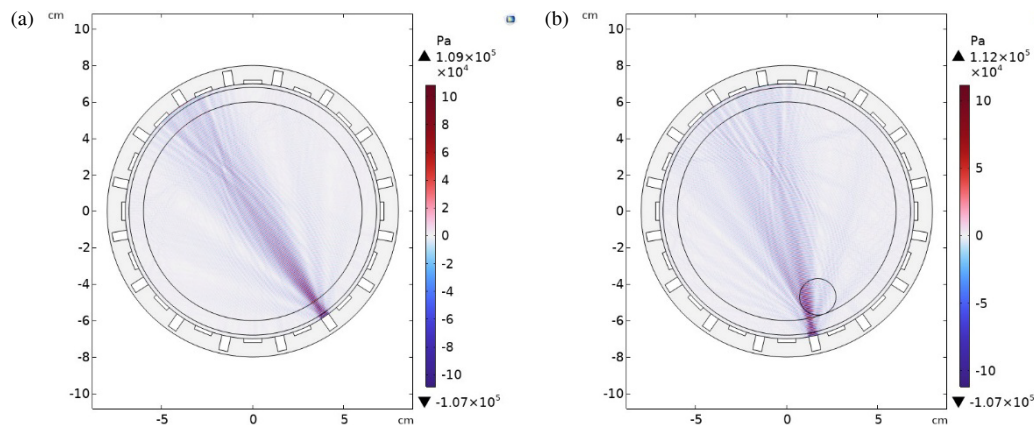


FIGURE 3. Acoustic pressure distribution in the frequency domain of (a) Normal breast tissue and (b) malignant tumour.

in breast EIT studies. The forward solution also provided a synthetic measurement set used for the subsequent inverse solver.

3.2. UST Forward Problem

The ultrasound forward model was simulated using the same breast phantom geometry to generate the acoustic propagation pattern and pressure response. The acoustic pressure is recorded from the other transducers functioning as receivers after the Pressure boundary condition applies 100 kPa to the first transducer. The experiment was conducted until all transduc-

ers functioned as transmitters. A study in the frequency domain was conducted at 1 MHz, with the corresponding acoustic pressure recorded and organized in a table. Figures 3(a) and (b) show acoustic pressure distributions of normal breast tissue and malignant tumor in the frequency domain. The resulting ultrasound field showed a structural contrast between the background tissue and the tumor region, which is important because ultrasound in this framework acts as an anatomical guide for EIT reconstruction. The simulated acoustic response produced a clearer spatial representation of the lesion than the EIT forward data, consistent with the ultrasound structural role in mul-

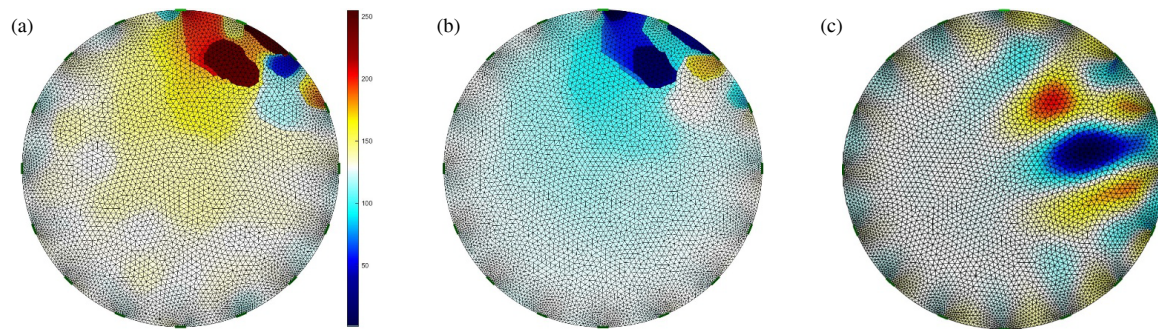


FIGURE 4. Reconstructed image showing (a) malignant tumour, (b) benign tumour, and (c) one benign and one malignant tumour.

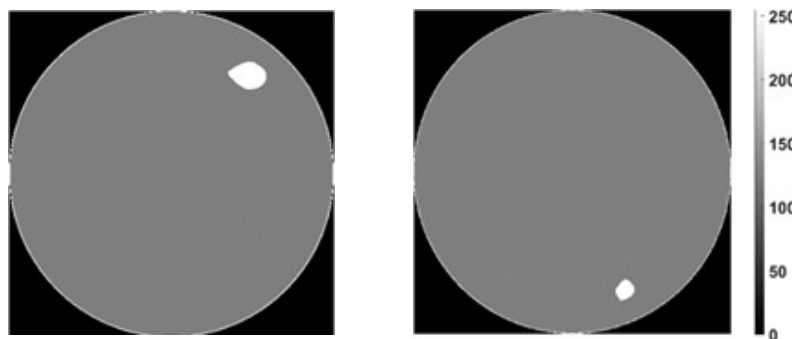


FIGURE 5. Segmented UST reconstructed image.

timodal breast imaging. This output was used as the basis for the inverse ultrasound reconstruction.

3.3. Standalone EIT Inverse

The standalone EIT reconstruction was performed in MATLAB using the TV-PDIPM algorithm. The reconstructed conductivity image identified the tumor region, but the lesion boundary remained somewhat blurred, and the background contained artifacts, which is expected in a strongly ill-posed inverse problem. This result shows the limitation of using EIT alone for breast tumor imaging, especially when anatomical prior information is not available. However, the reconstruction confirmed that the forward model generated meaningful input for the inverse solver. The EIT inverse solver creates a detailed map of the conductivity distribution, as shown in Figures 4(a)–(c), highlighting high conductivity areas, such as malignant tumors, in red, while low conductivity areas, representing benign or healthy tissues, are shown in blue. However, this colourmap representation is of a qualitative nature.

3.4. Standalone UST Inverse

Ultrasound inverse reconstruction was performed using attenuation-weighted bilinear interpolation. The resulting UST image provided a more distinct anatomical outline of the tumor region and surrounding tissue than the standalone EIT image. This is consistent with the established role of ultrasound tomography as a structural imaging modality with good boundary definition. However, UST reconstruction did not provide conductivity information; therefore, it could not

recover the electrical contrast associated with malignancy. Figure 5 presents the reconstructed and segmented tumour region using the UST reconstruction algorithm and k-means clustering algorithm.

3.5. Fused US-Guided EIT Reconstruction

After obtaining separate EIT and UST reconstructions, the segmented ultrasound image was used as a spatially varying anatomical prior in the EIT inverse problem. The grayscale ultrasound mask was used to weight the total variation regularization term so that tumor-related regions were allowed to vary more freely while homogeneous regions remained strongly regularized. This fusion produced the best overall reconstruction among the three cases, with a sharper tumor boundary, fewer artifacts, and improved alignment with the ground-truth phantom. The fused approach achieved an overall accuracy of 98.38%, sensitivity of 92.05%, Dice coefficient of 0.93, relative image error of 0.078, with a localization error of approximately 0.4 mm. Figure 6 compares ground-truth conductivity map, standalone EIT result, ultrasound-based segmentation, and proposed fused reconstruction. Figure 6(a) shows the reference phantom with a circular tumor region of higher conductivity. Figure 6(b) shows the EIT reconstruction, where the tumor is visible, but the boundary is blurred, and the contrast is reduced. Figures 6(c) and 6(d) show the segmented tumor regions obtained from the EIT and UST reconstructions, respectively. UST-based segmentation was sharper and more anatomically accurate than EIT-based segmentation. Figure 6(e) presents the fused conductivity image, where the ultrasound prior improves

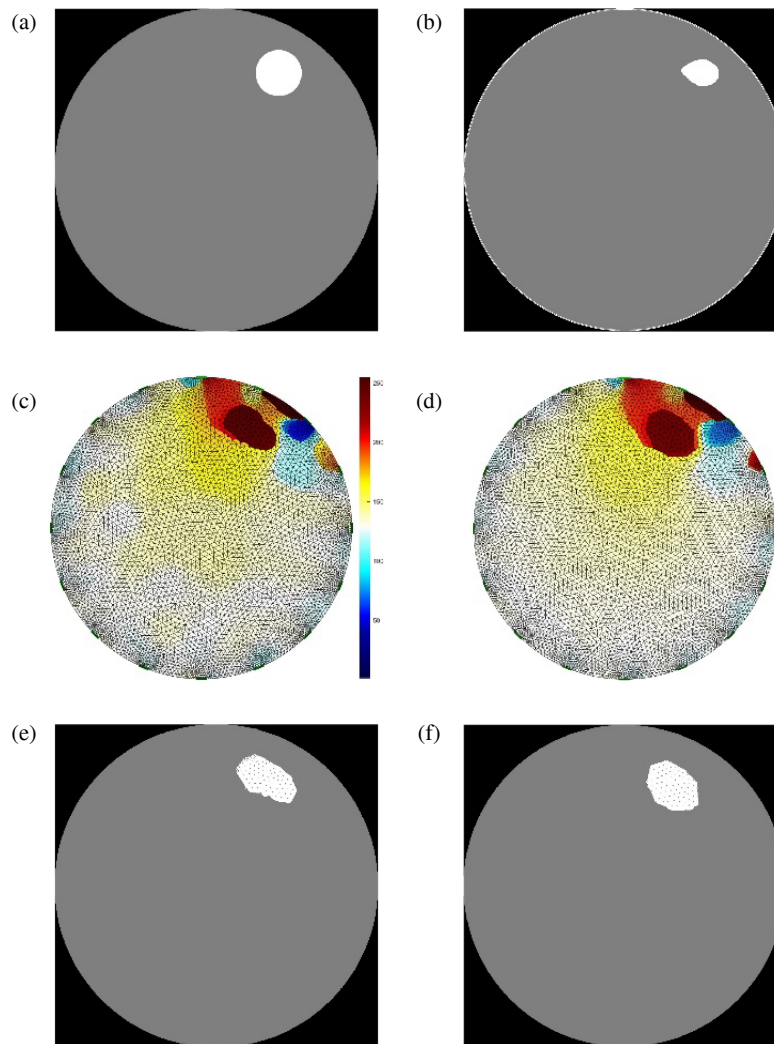


FIGURE 6. (a) Ground truth image, (b) reconstructed EIT image, (c) segmented EIT image, (d) UST segmented mask, (e) physics-informed fused image, and (f) segmented image of fusion.

boundary definition, contrast recovery, and background suppression. Figure 6(f) shows the final segmented tumor from the fused result, which aligns more closely with the ground truth.

Across the multi-phantom trial dataset, standalone EIT showed a mean LE of 3.85 ± 0.92 mm due to boundary-driven spatial blurring. Incorporating the high-resolution ultrasound spatial prior significantly reduced the ill-posedness, yielding a sub-millimeter centroid localization error of 0.42 ± 0.11 mm. This sub-millimeter precision reflects the anatomical positional fidelity imparted by the UST prior rather than the intrinsic spatial resolution of standalone EIT.

3.6. Sensitivity Analysis of Ultrasound-Prior Weighting

The effect of the ultrasound-prior weighting factor was investigated by reconstructing the EIT image using different values of the weighting parameter. All other simulation and reconstruction conditions were kept unchanged so we could examine the influence of the ultrasound prior independently.

Figure 7 presents reconstructed images for different weighting values. Table 3 summarizes quantitative results. The

analysis shows that the reconstruction quality changes with the contribution of the ultrasound-derived prior. Lower weighting provides a reconstruction that is closer to the standalone EIT solution, whereas increasing the contribution of the anatomical prior modifies the spatial regularisation and consequently affects tumour delineation and background reconstruction. The results demonstrate that the performance of the proposed method depends on the selected prior weighting and that the parameter should therefore be selected based on the reconstruction objective and characteristics of the available ultrasound information.

3.7. Robustness Analysis of Ultrasound Segmentation

The effect of inaccuracies in the ultrasound-derived tumour boundary was evaluated using controlled morphological perturbations. Erosion was used to represent an underestimated tumour region, whereas dilation represented an overestimated tumour boundary. Figure 8 shows reconstructed results obtained using perturbed masks.

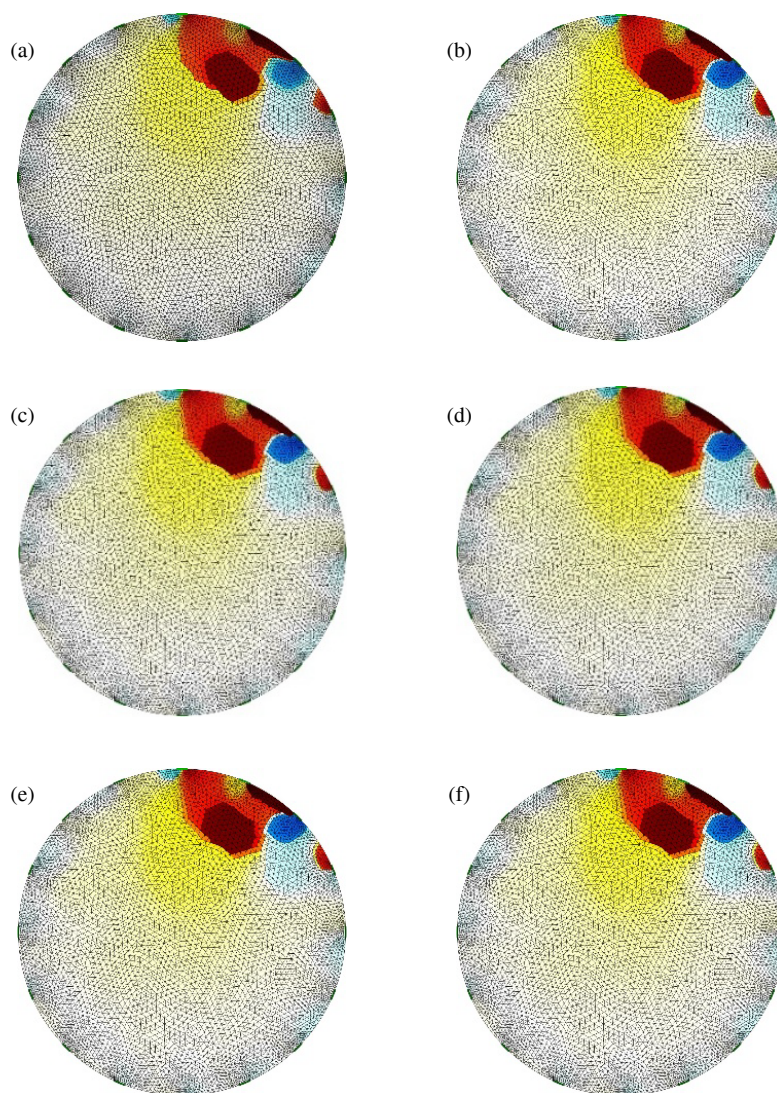


FIGURE 7. Effect of ultrasound-prior weighting factor (λ) on the reconstructed EIT images: (a) $\lambda = 0$, (b) $\lambda = 0.1$, (c) $\lambda = 0.3$, (d) $\lambda = 0.5$, (e) $\lambda = 0.7$, and (f) $\lambda = 0.9$.

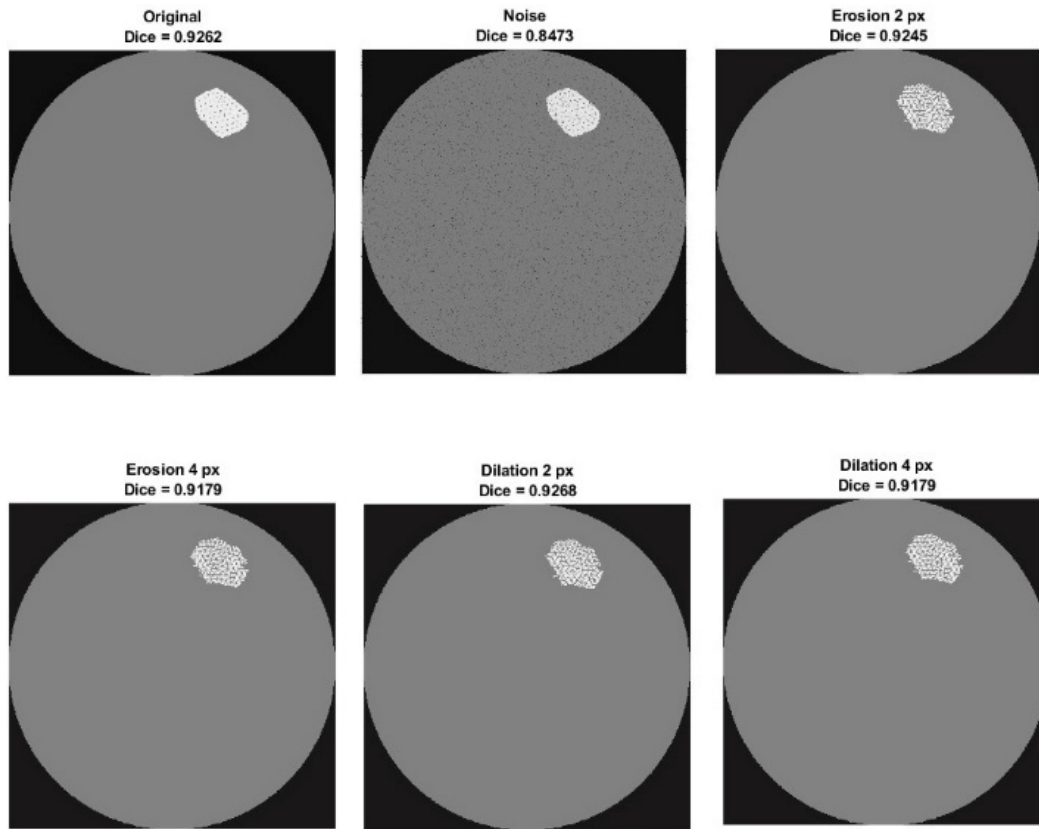
TABLE 3. Sensitivity analysis of the ultrasound-prior weighting factor.

Case	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice	MSE	PSNR (dB)	CC	RIE
Original	98.380	92.048	99.166	0.926	0.004	24.252	0.962	0.078
$\lambda = 0.1$	98.629	92.470	99.394	0.937	0.003	24.979	0.968	0.070
$\lambda = 0.3$	98.699	92.827	99.428	0.940	0.002	26.025	0.975	0.059
$\lambda = 0.5$	98.528	91.546	99.395	0.932	0.003	24.661	0.965	0.073
$\lambda = 0.7$	98.528	91.545	99.395	0.932	0.003	24.660	0.965	0.073
$\lambda = 0.9$	98.528	91.545	99.395	0.932	0.003	24.659	0.965	0.073

Table 4 gives corresponding quantitative results. The reconstruction remained capable of identifying the tumour region under the applied boundary perturbations, although changes in the segmented prior resulted in corresponding variations in the reconstruction metrics. This observation indicates that the proposed fusion framework is influenced by the accuracy of the ultrasound prior, while moderate boundary variations do not completely prevent tumour localization.

3.8. Comparative Analysis across Multiple Phantom Configurations

Table 5 presents the quantitative evaluation of standalone EIT, standalone UST, and the proposed US-guided EIT fusion framework averaged over 30 simulation configurations. The fused model consistently outperformed standalone modalities across all metrics.

**FIGURE 8.** Robustness analysis showing Dice for segmentation.**TABLE 4.** Robustness analysis under segmentation perturbations and noise.

Conditio	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice	MS	PSNR (dB)	CC	RE
Original	98.3	92.0	99.1	0.9262	0.0038	24.2	0.9618	0.0778
Nois	96.4	88.5	97.4	0.8473	0.0106	19.7	0.8944	0.1431
Erosion 2 px	98.3	90.5	99.3	0.9245	0.0036	24.4	0.9630	0.0741
Erosion 4 px	98.2	89.6	99.2	0.9179	0.0039	24.0	0.9595	0.0749
Dilation 2 px	98.4	91.0	99.3	0.9268	0.0033	24.7	0.9660	0.0721
Dilation 4 px	98.2	89.6	99.2	0.9179	0.0039	24.0	0.9595	0.0749

3.9. Computational Complexity and Execution Time Analysis

To evaluate the practical feasibility of the proposed reconstruction framework for clinical applications, computational complexity, memory usage, and execution time were benchmarked across 30 test configurations on an Intel Core i7-workstation (3.60 GHz CPU, 32 GB RAM, MATLAB 2023b). Standalone EIT reconstruction using the Primal-Dual Interior-Point Method (PDIPM) for total variation regularization operates with an asymptotic computational complexity of $O(N_{elem}^{1.5})$, where N_{elem} is the finite element mesh count. This required an average execution time of 1.15 ± 0.08 s with a memory footprint of approximately 120 MB. Standalone UST attenuation map reconstruction using bilinear interpolation functions with a complexity of $O(N_{px} \log N_{px})$ on a 256×256 grid required 1.85 ± 0.12 s and 210 MB of memory. The proposed US-guided

EIT fusion framework combines prior matrix construction with regularized iterative EIT inversion, resulting in an overall complexity of $O(N_{elem}^{1.5} + N_{px})$. The combined pipeline achieved a mean execution time of 3.42 ± 0.18 s per slice with a peak memory allocation of approximately 280 MB

4. DISCUSSION

The results show that ultrasound guidance improves EIT reconstruction by reducing image blur and improving tumor boundary definition. Standalone EIT provides functional conductivity contrast, but the image is affected by the ill-posed nature of the inverse problem. In contrast, ultrasound provides clearer anatomical information but does not directly show electrical properties. When the ultrasound prior is added to EIT, the final image becomes more stable, accurate, and closer to the ground

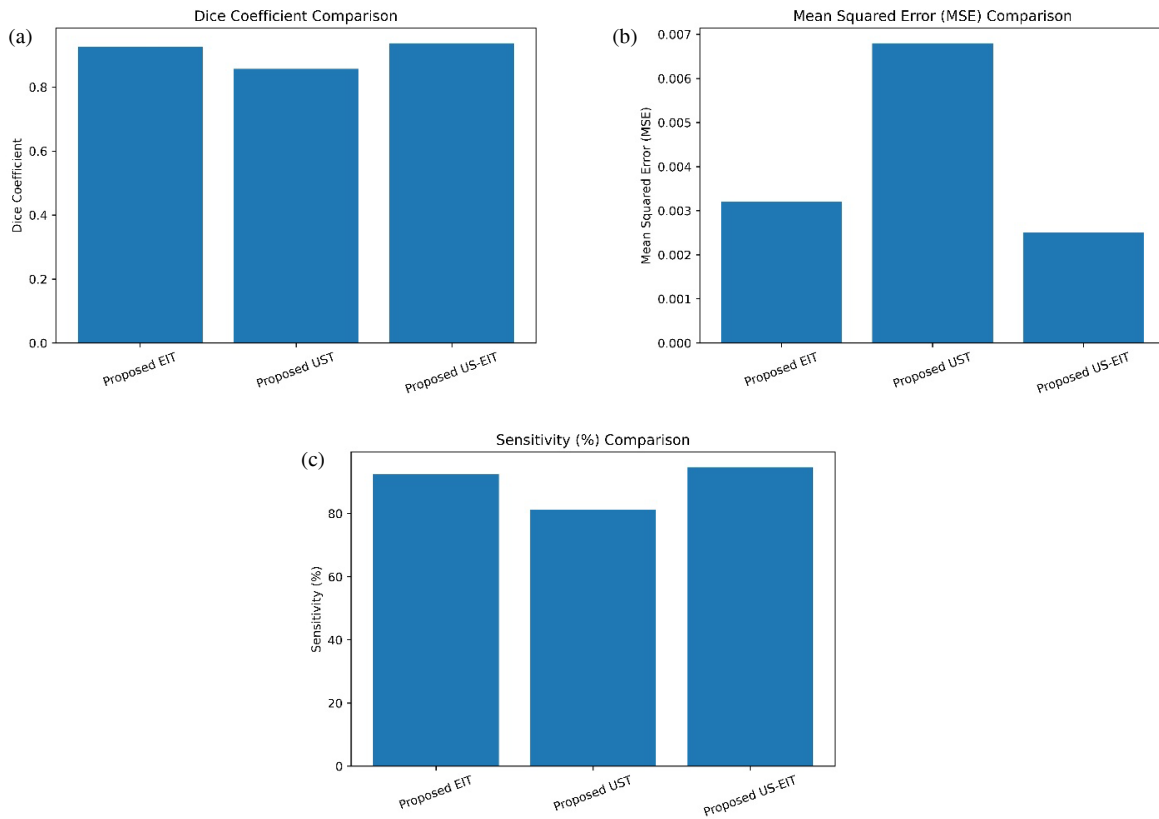


FIGURE 9. (a) Comparison of the Dice coefficient, (b) comparison of the mean squared error, and (c) comparison of sensitivity.

TABLE 5. Quantitative comparison across different phantom configurations.

Metric	Standalone EIT	Standalone UST	Proposed US-EIT Fusion
Accuracy (%)	92.1 ± 1.82	85.6 ± 2.15	98.2 ± 0.45
Sensitivity (%)	84.3 ± 3.10	81.1 ± 3.40	92.1 ± 1.15
Specificity (%)	93.8 ± 1.45	88.2 ± 2.05	99.1 ± 0.28
Dice Coefficient	0.83 ± 0.04	0.79 ± 0.04	0.92 ± 0.01
MS	0.0092 ± 0.0018	0.0145 ± 0.0022	0.0031 ± 0.0006
PSNR (dB)	20.4 ± 1.12	18.3 ± 1.35	24.5 ± 0.58
Correlation Coeff.	0.88 ± 0.02	0.81 ± 0.03	0.96 ± 0.00
Relative Image Error	0.18 ± 0.02	0.24 ± 0.03	0.07 ± 0.00

truth. This improvement is consistent with earlier prior-based EIT studies, which reported better tumor recovery when structural information was used during reconstruction. In this study, ultrasound segmentation acted as a spatial constraint and helped the EIT solver focus the conductivity update in the correct region. Consequently, both the reconstructed image and the segmented tumor became more reliable.

The sensitivity analysis further showed that the ultrasound-prior weighting has a direct influence on the reconstructed conductivity distribution. Changes in the weighting factor modify the balance between the measured EIT information and the anatomical constraint provided by ultrasound. Therefore, the weighting parameter should not be considered independent of the quality of the ultrasound-derived prior.

The segmentation robustness experiment also showed the effect of imperfect anatomical information on the fused reconstruction. Erosion and dilation of the tumour region introduced controlled boundary errors into the prior, allowing the reconstruction behaviour under inaccurate segmentation to be examined. Although variations of quantitative measures were observed, the tumour region remained identifiable for tested perturbations. These results indicate that the quality of the ultrasound segmentation is an important factor in the performance of the proposed multimodal reconstruction framework. With an overall processing throughput of approximately 3.42 s per 2D slice, the physics-informed fusion framework adds minimal computational overhead compared to standalone algorithms. This low memory footprint and fast execution speed confirm

that integrating the ultrasound spatial prior does not hinder real-time performance, establishing the method's practicality for low-cost, point-of-care clinical breast imaging.

The present study is limited to a two-dimensional numerical breast phantom and simulated EIT and ultrasound measurements. Although this controlled environment enables systematic evaluation of the proposed reconstruction framework, it does not account for measurement noise, electrode-skin interaction, patient motion, and the anatomical variability encountered in experimental or clinical measurements. The experimental validation using tissue-mimicking breast phantoms and measured multimodal data is therefore required to further assess the practical performance of the proposed method. Extension of the framework to three-dimensional breast models is also planned as a subsequent development. Figures 9(a)–(c) show a summary of the quantitative performance comparison for the proposed methods with the most important evaluation metrics.

5. CONCLUSION

This study presents a physics-informed multimodal framework for breast-tumor detection using EIT and UST. The proposed ultrasound-guided fusion method improved reconstruction quality, achieving 98.38% accuracy, 92.05% sensitivity, a Dice coefficient of 0.93, and a relative image error of 0.078. These results indicate that anatomical priors from ultrasound can strengthen EIT reconstruction and improve tumour localization. Future work should focus on experimental validation using 3D breast phantoms, automatic extraction of ultrasound priors using machine learning, and extension to full 3D volumetric reconstruction.

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