

# Renewal Request: Learning-based Image Reconstruction Methods for Quantitative Three-Dimensional Optoacoustic Tomography Breast Imaging

April 2, 2025

**Abstract:** In this renewed project, the primary objective remains the development of deep learning (DL)-based methods for estimating functional quantities in three-dimensional (3D) breast optoacoustic tomography (OAT). This will result in a powerful new bioimaging modality. The project will address new challenges that have emerged from progress made during the initial phase. Specifically, the 3D OAT virtual imaging framework, featuring a GPU-accelerated implementation, will be refined to improve its practical relevance. Building upon this foundation, DL-based acoustic and optical inversion methods will be investigated under more practical conditions. In addition, comprehensive performance assessment approaches for OAT image reconstruction will be established, providing essential guidance and supporting the advancement of DL applications in OAT.

**Science Objectives:** This renewed project builds upon the accomplishments of the initial project phase and retains the overarching goal of developing a DL-based two-step approach, (1) acoustic inversion to estimate the initial pressure distribution, followed by (2) optical inversion to estimate functional quantities, such as optical absorption coefficients and blood oxygen saturation ( $sO_2$ ), from acoustic measurements. It specifically addresses three new challenges that emerged from the execution of the individual tasks conducted during the initial phase.

First, the current 3D numerical breast phantoms (NBPs) include only malignant lesions but not clinically relevant benign ones. Incorporating benign lesions, which exhibit distinct functional and optical properties, will expand the scope of clinically relevant studies utilizing these phantoms, particularly those related to optical inversion. Second, to perform realistic virtual imaging experiments, it is necessary to incorporate transducer characteristics into virtual data acquisition process. This is crucial, as transducer response effects are inherently present in experimental measurement data. Ideally, these effects should be appropriately compensated during acoustic inversion. DL models trained on idealized synthetic data may otherwise exhibit reduced reconstruction accuracy when applied to real-world measurements. Third, since optical inversion follows acoustic inversion in the two-step approach, the optical inversion method must maintain robust accuracy when applied to images reconstructed via acoustic inversion, rather than idealized images.

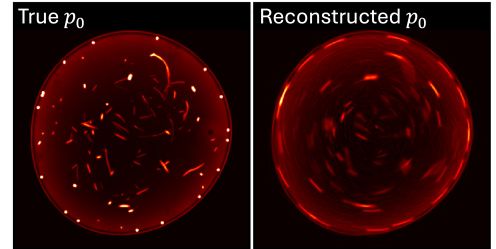


Figure 1: 2D true initial pressure distribution  $p_0$  (left) and the corresponding reconstructed distribution (right). Pressure measurements were simulated from the true distribution (left), incorporating both acoustic heterogeneity and SIR of 20 mm line transducers. Without compensation, the reconstructed image exhibits noticeable blurring and artifacts (right).

To address these challenges, the following tasks will be conducted: **Task 1:** Generation of 3D NBPs and virtual OAT imaging incorporating diverse lesion models and realistic transducer characteristics; **Task 2:** Development of DL-based acoustic inversion methods, accounting for acoustic

heterogeneity and transducer characteristics; and **Task 3**: Development of a DL-based optical inversion method using images reconstructed via acoustic inversion under more realistic acoustic conditions, aligned with practical imaging scenarios.

In **Task 1**, stochastic 3D models of benign lesions (cysts and fibroadenomas) will be integrated into the virtual OAT imaging framework based on an extensive literature review. To enhance the practical relevance of the framework, both the acousto-electric impulse response (EIR) and spatial impulse response (SIR) of transducers will be incorporated into the 3D virtual data acquisition process. Experimentally measured EIR signals, provided by our collaborator, TomoWave Laboratories (Houston, Texas), will be utilized. The SIR will be modeled by approximating the integral of the pressure field over the transducer’s detection surface. A preliminary two-dimensional (2D) SIR modeling result is presented in Fig. 1. As illustrated, image reconstruction without compensation for acoustic heterogeneity and the transducer SIR can lead to severe blurring and artifacts. As in the current framework, high-performance computing (HPC) resources, particularly multiple GPUs, will be utilized to expedite the dataset generation process, given the significant computational complexity involved in 3D simulations.

In **Task 2**, a DL-based SIR compensation model integrating both physics-based and data-driven features will be developed for accurate acoustic inversion. This work extends a prior study that investigated an end-to-end, data-domain convolutional neural network-based method (see accompanying progress report). In OAT imaging models, incorporating the spatially varying SIR corresponds to its temporal convolution with the pressure measurements. Leveraging this principle, the proposed method compensates for the SIR in the data domain through a combination of temporal deconvolution using learned SIR kernels and a learned weighted sum, as illustrated in Fig. 2. Additionally, the benchmarking study introduced during the initial phase will be continued and expanded to incorporate both acoustic heterogeneity and SIR in a 2D setting. Comprehensive performance assessment approaches will be established, including analyses based on linear operator theory for quantifying hallucinations and signal detection theory for evaluating lesion detectability.

In **Task 3**, a DL-based optical inversion method will be further developed to estimate 3D distributions of  $sO_2$  in blood vessels and lesions from multi-wavelength optoacoustic data. Following the completed study from the initial phase, where optical inversion was applied to idealized initial pressure distributions with colored noise, this renewal focuses on evaluating the model under more realistic conditions using images reconstructed via acoustic inversion. The pressure data used for reconstruction will be simulated under assumptions of acoustically lossy and heterogeneous breast tissue, with modeled measurement noise included. This setting more faithfully reflects the complexities of experimental imaging. As part of the per-

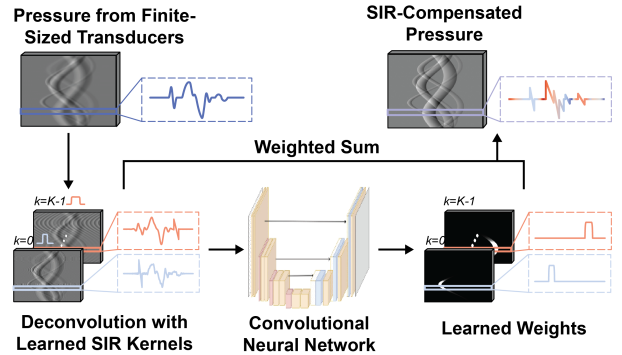


Figure 2: DL-based SIR compensation model integrating both physics-based and data-driven features.

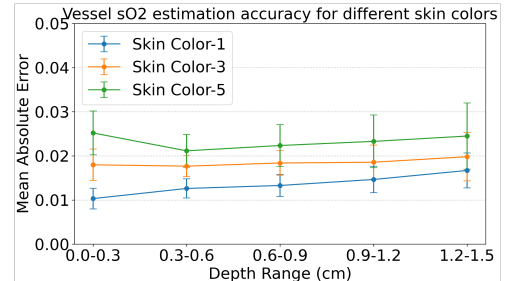


Figure 3: Depth-dependent accuracy of vascular  $sO_2$  estimation across three skin colors (1: lightest, 3: medium, 5: darkest). Estimation accuracy decreases with increasing depth and darker skin tones.

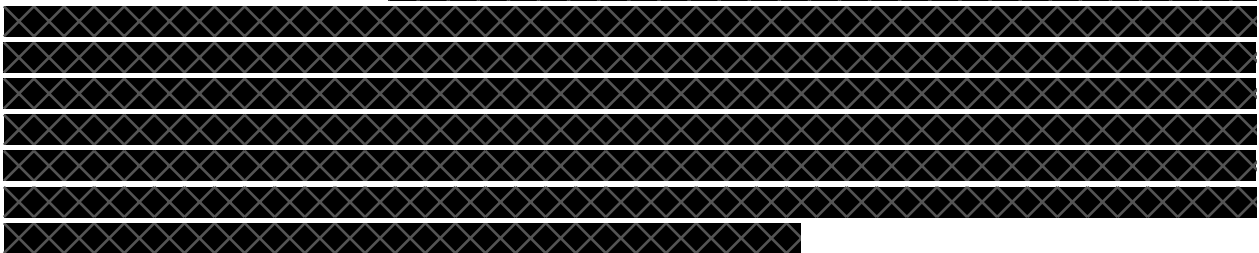
formance evaluation, variations in skin color will be considered, and model performance will be analyzed as a function of depth. Preliminary results shown in Fig. 3 reveal that the model’s estimation accuracy varies with both skin color and depth, highlighting the importance of this additional analysis to ensure reliability across diverse populations. Based on these investigations, the DL-based model will be further refined to improve its robustness and practical applicability in real-world optical inversion tasks.

**Estimate of Resources:** We request 2,998,587 ACCESS credits, equivalent to 44,976 NCSA Delta GPU-hours. We will begin with the 15 TB of previously allocated Delta storage. GPU-hour estimates are based on performance measured using NSCA Delta GPUs. In **Task 1**, new NBPs will be generated for two additional skin

tones, along with 180 NBPs featuring newly modeled benign lesions, complementing the previously created 1,500+ NBP pairs (lesion-absent and lesion-present) associated with the lightest skin tone. All new NBPs will be virtually imaged at three wavelengths, with an estimated processing time of 1.2 GPU-hours per NBP on a quad A100 GPU node. Existing NBPs for the lightest skin tone will be also re-imaged employing the updated virtual data acquisition tool, without repeating optical simulation. Each NBP and the corresponding simulated data will require  $\sim 7$  GB. In **Task 2**, 585 GPU-hours on a two-way A40 GPU node will be used for the SIR compensation study (7,000 training samples, 4.3 s/step, 70 epochs), and 1,111 GPU-hours on a quad A100 GPU node will support for the benchmarking study (8,000 samples, 5 s/step, 100 epochs). In **Task 3**, 667 GPU-hours will be required on a quad A100 GPU node (1,000 samples, 24 s/step, 100 epochs). Up to 12 models will be trained for each study in **Tasks 2** and **3** to explore various loss functions and network parameters. To manage storage efficiently, data not immediately required will be moved to local storage, and additional storage will be requested as needed. Final results will be stored on the UIUC Box cloud service. A detailed breakdown is provided in Table 1.

**Software & Specialized Needs:** The code in **Task 1** utilizes FEniCS, MPI, PvPython, and MCX, while in **Tasks 2** and **3**, PyTorch and TensorFlow are employed. Docker and Singularity will be used to package the applications and their dependencies into portable and isolated environments.

**Team and Preparedness:**



**Expected outcomes:** The project is expected to establish an enhanced end-to-end framework for quantitative 3D OAT image reconstruction, building on the outcome from the first project year. Source codes for network training will be made publicly available in separate GitHub repositories for each study in Tasks 2 and 3, along with the corresponding trained models. Several test datasets generated in Task 1 and used in Tasks 2 and 3 will be released via the Illinois Data Bank. Research findings will be presented at flagship conferences in the field. The renewed project is also expected to result in additional submissions to high-impact peer-reviewed journals.

Table 1: Breakdown of resource requirements

Task	Description	GPU-hrs
1	3,000 NBPs $\times$ 1.2 hrs $\times$ 2 STs 3,000 NBPs $\times$ 0.4 hrs (lightest ST) 180 NBPs $\times$ 1.2 hrs	8,616
2	12 models $\times$ 585 hrs $\times$ 2 GPUs $\times$ 0.5 SU 12 models $\times$ 1,111 hrs	20,352
3	12 models $\times$ 667 hrs $\times$ 2 GPUs	16,008
Total		44,976

STs: Skin tones; SU: Service unit