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NUMERICAL FRAMEWORK FOR DEEP LEARNING PHOTOACOUSTICS IMAGE RECONSTRUCTION

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ABSTRACT

Photoacoustic Imaging (PAI) combines optical excitation with ultrasound detection to produce high-quality molecular images of intact biological tissues. Conventional systems rely on Class IV [1] pulsed lasers, which limits clinical translation. This work explores the use of pulsed semiconductor diodes for their portability, versatility, and low-cost. However, their lower peak power decreases PAI signal amplitude. Implementing deep learning techniques trained with realistic synthetic data is a promising technique to increase PAI image quality [2]. Here we create a framework which simulates real scenarios taking into account acoustics and optical properties, ultrasound transducer characteristics and fiber bundles features, crucial to optimize reconstruction performance with a Neural Network. The simulated experimental setup included an array of optical fibers connected to semiconductor diodes parallel to a 128-element transducer array which registers the signal generated by the absorbed light. Optical properties were simulated in MCX Monte Carlo software using GPU parallelization. k-Wave software was used for acoustic simulations and Time-Reversal (TR) image reconstruction. Finally, a Neural Network model implemented using Tensorflow enhanced the reconstruction, recovering up to 3 cm depth and 200 µm of resolution, delivering exceptional vascular imaging quality.

Keywords: *Photoacoustic Imaging, Ultrasound, Medical Physics*

1. INTRODUCTION

Photoacoustic imaging (PAI) is an emerging biomedical imaging modality that combines optical excitation and ultrasound detection to generate high-contrast structural and molecular images of biological tissues. Its underlying mechanism relies on the thermo-acoustic effect, mathematically represented by:

$$p_0 = \Gamma \mu_a \phi, \tag{1}$$

Where p_0 is the initial pressure rise, Γ is the

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Grüneisen parameter, μ_a is the tissue absorption coefficient, and ϕ is the local optical fluence.

State-of-the-art PAI systems typically utilize Class IV pulsed lasers, which, despite providing sufficient optical power, present substantial drawbacks such as high costs, large size, and significant regulatory restrictions, limiting clinical translation. To overcome these challenges, semiconductor diode lasers have emerged as a compact and cost-effective alternative. However, their lower optical output power substantially reduces fluence, negatively impacting image quality and clinical applicability.

Recent advances in computational imaging, specifically deep learning techniques integrated with conventional reconstruction algorithms, offer promising pathways to compensate for reduced fluence and improve reconstruction accuracy. In this study, we develop and evaluate a neural network model trained using realistic numerical simulations of our experimental setup, meticulously accounting for relevant acoustic and optical properties of biological tissues. By improving image reconstruction quality, this approach aims to mitigate the intrinsic limitations associated with diode-based illumination, thereby enabling the development of clinically viable, handheld PAI systems.

2. METHODOLOGY

Training neural networks effectively requires extensive datasets. To meet this requirement, we developed a computational framework to generate realistic synthetic data closely replicating our experimental setup. This framework integrates acoustic and optical simulations using accurate physical parameters, thereby producing synthetic pressure distributions that closely mimic real-world scenarios. The resulting data is subsequently used to enhance the quality and effectiveness of signal post-processing and reconstruction.

2.1 Optical simulations

An array comprising five semiconductor diodes is arranged to uniformly illuminate the acoustic transducer acquisition plane, as illustrated in Fig. 1A. Optical simulations were conducted using MCX Monte Carlo software [3] to calculate the two-dimensional fluence distribution at the transducer acquisition plane. The simulated medium was water, selected due to its low scattering and absorption coefficients [4], facilitating clear evaluation of the optical fluence pattern.

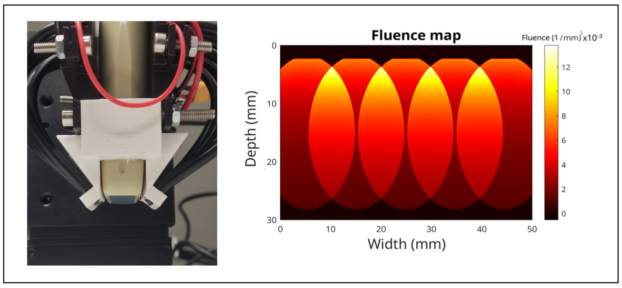

Figure 1. a) Experimental setup simulated. b) Fluence map in the transducer plane corresponding to the acquisition area.

2.2 Phantom generation

Phantoms with realistic vessel structures were generated using a 3D stochastic algorithm informed by real vessel data from coronary arteries [5]. Three distinct projections were created for each generated phantom, producing a comprehensive set of 2D images. By applying various geometric transformations and deformations, a diverse dataset comprising 2000 phantom images was compiled. Each phantom image was subsequently combined with the simulated fluence map to yield the corresponding initial pressure distribution. The ground truth used for neural network training was defined by an ideal, uniform fluence map, representing optimal illumination conditions with a perfectly homogeneous light source.

2.3 Acoustic simulations

Acoustic simulations were conducted using the k-Wave software [6], which addresses both the forward and inverse acoustic propagation problems. The forward simulation involved propagating the initial pressure distribution through water by solving the acoustic wave propagation equation. Signals were captured using a simulated 128-element ultrasound transducer array with a central frequency of 7.5 MHz, considering the acoustic properties of the medium and the geometric arrangement of the transducer elements [7].

Subsequently, the inverse acoustic problem was solved using the classical Time-Reversal (TR) reconstruction algorithm. This method reconstructs the initial pressure distribution by temporally reversing and re-emitting the recorded signals from each transducer element, effectively back-propagating the acoustic waves to their original spatial locations.

2.4 Neural network

The neural network framework developed for this study employs two distinct architectures, as depicted in Fig. 2. The first network is a U-Net designed to process the raw signals simulated with k-Wave under realistic fluence conditions and output signals corresponding to an ideal uniform fluence scenario. This step effectively corrects for fluence heterogeneities inherent in diode illumination.

Subsequently, a Y-Net architecture is utilized, receiving as inputs both the fluence-corrected signals from the U-Net and the initial reconstruction produced by the TR algorithm. The Y-Net generates an enhanced reconstructed image by combining the preliminary reconstruction information (TR) with additional data contained in the fluence-corrected signals, capturing potentially lost details during the initial reconstruction phase. All pressure maps and signals were normalized to their respective maximum values before neural network processing to ensure consistent training conditions and optimize network performance.

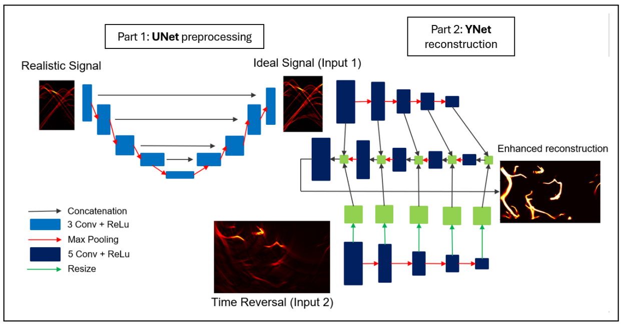

Figure 2. Neural Network workflow scheme.

3. RESULTS

3.1 Image reconstruction

The semiconductor diode illumination setup generates a non-uniform fluence distribution, as depicted in Fig.1, achieving a maximum imaging depth of approximately 30 mm. This depth represents the practical imaging limit for the current photoacoustic configuration, beyond which the fluence intensity decreases by 20% compared to the maximum. When comparing reconstruction techniques, the TR algorithm achieves effective reconstruction only up to approximately 20 mm, beyond which the image quality significantly deteriorates due to insufficient fluence and limitations in the algorithm, with the reconstruction pressure dropping to less than 20% of the maximum peak. In contrast, the combined approach utilizing the TR algorithm followed by the neural network (TR + Neural Network) successfully reconstructs images across the entire depth range enabled by the fluence distribution, demonstrating superior capability in compensating for the non-uniform illumination inherent in diode-based setups.

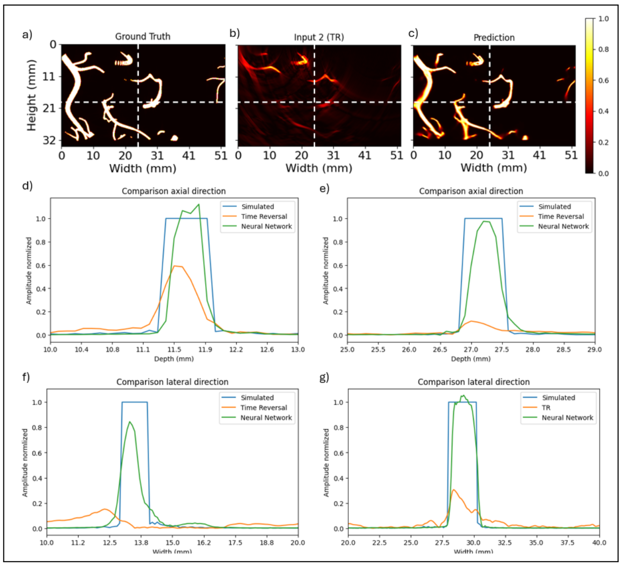

Figure 3. Enhanced image analysis. a) Ground truth. b) TR reconstruction. c) Neural Network reconstruction. d,e) Axial profiles. f,g) Lateral profiles.

3.2 Image enhancement and artifact reduction

Further evaluation of axial and lateral profiles in the reconstructed images provides insights into the effectiveness of signal recovery and artifact mitigation, as illustrated in Fig. 3. Axial profiles demonstrate the neural network's capability to compensate for fluence-induced signal loss at increased depths, effectively maintaining higher contrast compared to the TR reconstruction (Figs. 3d and 3e). Lateral profiles highlight the neural network's proficiency in reducing limited-view artifacts present in the TR method, which typically manifest as data loss along axial vessel structures. The neural network enhances the contrast and clarity of these structures, significantly improving overall image quality (Figs. 3f and 3g).

However, despite notable improvements, the neural network occasionally reconstructs vessel-like structures absent from the ground truth, introducing artifacts. This phenomenon likely arises from model overfitting due to limited variability in the training dataset. Expanding the training set size and diversifying case scenarios could mitigate such artifacts and further enhance reconstruction accuracy.

4. CONCLUSIONS

The integration of classical reconstruction algorithms with neural network-based approaches demonstrates significant potential for improving the image quality of low-cost, handheld photoacoustic imaging systems. This combined methodology effectively compensates for the inherent limitations of semiconductor diode-based illumination, such as reduced and non-uniform fluence, by enhancing both image depth and contrast. Crucially, accurate and realistic simulation environments are essential for the successful training and performance optimization of neural networks. By employing meticulously characterized synthetic datasets that closely replicate experimental conditions, neural networks can achieve reliable reconstruction capabilities, leading to improved clinical viability and diagnostic utility of compact photoacoustic devices. Future efforts should focus on expanding the variability and size of training datasets, addressing artifacts introduced during reconstruction, and validating performance against experimental data to ensure robust clinical translation.

5. ACKNOWLEDGMENTS

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