The Eleventh International Conference on
Engineering Computational Technology
23–25 August, 2022 | Montpellier, France

Proceedings of the Eleventh International Conference on
Engineering Computational Technology
Edited by B.H.V. Topping and P. Iványi
Civil-Comp Conferences, Volume 2, Paper 6.1
Civil-Comp Press, Edinburgh, United Kingdom, 2022, doi: 10.4203/ccc.2.6.1

A Deep Learning Based Real-Time Computational Method for Transcranial Focused Ultrasound Guidance System

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Abstract

In this paper, we present a method for surrogate model of transcranial focused ultrasound (tFUS) propagation problem using deep learning technique. The trained neural network outputs an acoustic source position of transducer placement. The training datasets are generated by forward tFUS simulation using finite-difference time-domain method. The performance of the proposed method was evaluated through three examples of ex vivo human calvaria. The results show that the deep learning based model can provide an accurate acoustic field solution in real-time. Through this study, we proved the effectiveness of the deep-learning based surrogate model of tFUS propagation problem and its applicability in practical clinics.

Keywords: deep neural network, surrogate model, wave propagation, transcranial focused ultrasound, finite-difference time-domain, real-time.

1 Introduction

Focused ultrasound (FUS), which concentrates acoustic energy to highly localized area of a few millimeters in biological tissue, has been gaining momentum as a non-invasive therapeutic device [1-2]. It has attracted attention from scientific and medical community, with potentials for treating neurological diseases such as epilepsy [3], brain tumors [4], Alzheimer's [5], and Parkinson's disease [6].

Computational simulation has been widely applied to estimate location of focus, intracranial pressure field, induced temperature distribution, and unexpected reverberation effects in steps of treatment planning and retrospective analysis [7-10].

However, the simulation is computationally expensive, often requiring computational time that is impractical for the use in clinical setting [11, 12].

Deep learning, a class of machine learning algorithms in artificial intelligence, is an emerging technology has been applied in various research fields [13-16]. In the computational mechanics area, various efforts has been made to prove that data-driven computation has the leverage to improve the conventional physics/mechanics-based numerical procedure [17-19].

Motivated from the previous studies fusing computational mechanics and machine learning technique, we developed deep learning-based surrogate model of transcranial FUS propagation problem. We construct a neural network to generate the FUS focus on the target regions for the position and orientation of the transducer given as input data.

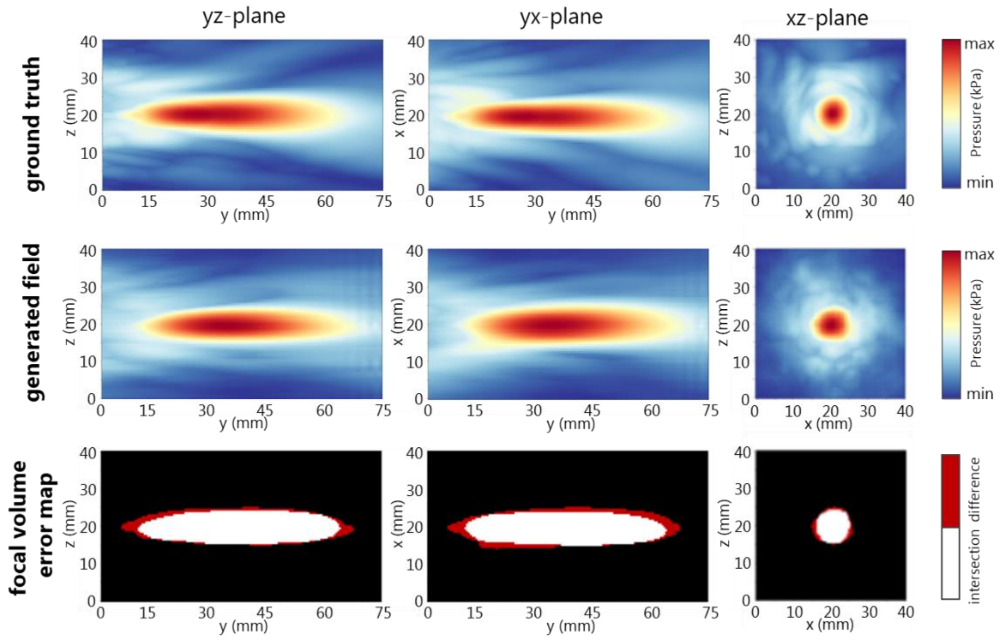

Figure 1. Sample accuracy evaluation result for the focal volume(projected to yz-, yx-, xz-planes) using GAN network. From top to bottom, the three rows represent the ground truth, generated field from the network, and focal volume error map that show the intersection (white region) and union (red region).

2 Methods

The training dataset consisting of the transducer placement and the corresponding acoustic pressure map were generated using the forward transcranial FUS simulation. To reduce amount of training data, the transducer maneuvering space was defined as a restricted field of 20 × 20 × 20 mm3. In the maneuvering space, the forward simulations were performed by translating the position with 5 mm interval (i.e., at -10, -5, 0, 5, 10 mm location from the center) along x, y, and z directions as well as adjusting the orientation to -5°, 0°, and 5° along the binormal and tangential directions, respectively. The resultant pressure distribution for the respective placement of the transducer was acquired in the region of interest (ROI) ranged 50 × 50 × 50 mm3 (i.e., 101 × 101 × 101 voxels with 0.5 mm resolution).

The input of the constructed neural networks is the position and orientation of the transducer while the output is the pressure field binarized and approximated in the ROI. We demonstrated three different network architectures constructed by using (1) autoencoder(AE) (2) generative adversarial networks(GAN) (3) variational autoencoder(VAE).

3 Results

The performance of the three different network structures (AE, GAN, and VAE) across the three calvaria ('HS1', 'HS2', and 'HS3') was compared to each other. The ultimate goal of the proposed network is to achieve accurate FUS focus on the placement of transducer. So, we evaluated conformity between the targeted region and the FUS focus obtained by binarizing the pressure field predicted from the forward simulation using the network. Intersection over union (IoU) of ground truth and predicted FUS focus on the desired target region was evaluated for the respective test data as shown in Figure 1.

4 Conclusions and Contributions

In this paper, a surrogate model of wave propagation problem utilizing deep learning technique was presented for accurate delivery of FUS focus through the cranium. The proposed neural network can provide a real-time solution with high accuracy in terms of IoU depending on the position and orientation of the transducer for producing the FUS focus on the given target region.

A surrogate model has been widely used to solve various engineering and scientific problems. Unlike a simple problem, a challenging problem demands heavy computation time involving an iterative solution scheme. Such extended simulation time brings difficulty in using computational methods in a practical application, especially in medical applications with lots of unexpected situations. Since the deep-learning based surrogate model presented in this study has the capability for providing real-time feedback, it is expected to be serve as a key technology to open an avenue for new applications.

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