

A Deep Neural Network-Based Inverse Solver for Electrical Impedance Tomography

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Electrical impedance tomography (EIT) is an imaging technique that reconstructs conductivity distributions to infer internal tissues within the human body. Despite its potential, EIT's ill-posed inverse problem is challenging for conventional inverse solvers, often leading to distortions and artifacts in reconstructions. In this study, a deep neural network (DNN)-based EIT inverse solver is proposed. Using EIT simulation data with targets with randomized positions and radius to train DNN, a DNN-based inverse solver enhances the accuracy of reconstructions and reduces artifacts compared to traditional inverse solvers. Clinical EIT data from stroke will be tested next.

Index Terms—Electrical impedance tomography; image reconstruction; multi-layer neural network; neural networks.

I. INTRODUCTION

ELECTRICAL IMPEDANCE TOMOGRAPHY (EIT) is a powerful non-invasive technique for imaging applications [1] widely applied in medical and industrial fields. The principle is that different living tissues have different electrical properties [2], by injecting current into the tissue boundary, measuring the voltage, and then estimating the conductivity distribution to reconstruct the image. However, The EIT reconstruction is a nonlinear and ill-posed inversion problem [3]. Various algorithms proposed in the literature can only approximate real conductivity distributions [4].

In the field of medical image reconstruction, a DNN has a stronger non-linear reconstruction ability than a shallow neural network [5]. In this study, we used EIT simulation data to train and evaluate the reconstruction results. A DNN-based EIT inverse solver is proposed and compared to the linear artificial neural network (ANN) and Long Short-Term Memory Neural Networks (LSTMNN) methods.

A. Training data

Fig. 1 shows the method of training a neural network with a flowchart. The training dataset was generated by EIDORS. A circular 2D finite element model (FEM) is defined with a homogeneous background conductivity ($=1$ S/m) and includes a homogeneous conductivity ($=2$ S/m) circular target. The radius of the target varied from 0.11-0.3 (unit: meter). Boundary voltage measurements were obtained by the forward problem solver model from EIDORS. A total of 5,000 samples were generated, where each sample comprised the EIT simulation measurement and the corresponding conductivity distribution reconstructed image.

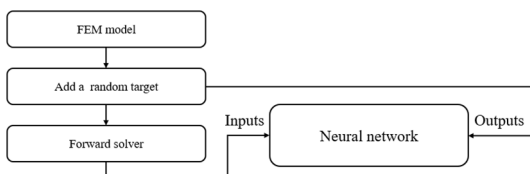


Fig. 1. Flowchart of the method for training neural network.

B. Deep neural network (DNN)

Fig.2 shows the deep neural network (DNN), designed to solve the inverse problem, processing EIT simulation measurements as the inputs and reconstructed images as the outputs. The network consists of convolutional blocks for feature extraction, transposed convolution blocks for up-sampling and reconstruction of the output, and dropout layers (with a probability of 0.2) were included to prevent overfitting. The details of the network are shown in Table 1.

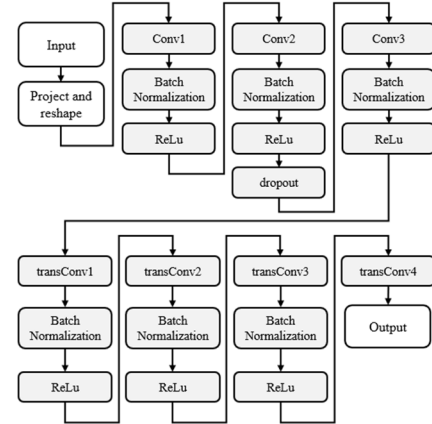


Fig. 2. The architecture of DNN.

	filtersize	numfilters		filtersize	numfilters
Conv1	(3,3)	128	transConv1	(3,3)	512
Conv2	(3,3)	128	transConv2	(3,3)	256
Dropout (probability 0.2)			transConv3	(3,3)	128
Conv3	(3,3)	64	transConv4	(3,3)	3

Table. 1. The details of DNN.

C. Training Procedure

The DNN was trained using the simulated dataset (80% training, 20% validation). The training process employed the root mean squared error (RMSE) and half-mean-squared error as loss functions, optimized using the adaptive moment estimation (Adam) optimizer with a learning rate of 0.001. The model was trained for 200 epochs with a batch size of 128, and early stopping was implemented based on validation performance.

II. RESULT

A Deep Neural Network (DNN) was designed to solve the inverse problem in EIT. The input is EIT simulation measurements (with 208 features) to output reconstructed images of size 128x128x3. The model was trained for a maximum of 200 epochs. However, early stopping was implemented, and training was halted after 99 epochs due to no significant improvement in the validation loss. The model achieved a final RMSE of 11.75 at the early stopping point.

The position and size of the circle target are randomly chosen to compare the performance of different EIT inverse solvers. The radius values range from 0.11 to 0.3. This random variation simulates diverse scenarios, providing a wide range of test conditions for evaluating the model's performance. Furthermore, white Gaussian noise (WGN) was added, changing the EIT simulation measurements to have a 20 dB signal-to-noise ratio. Fig. 4 shows the EIT simulation measurements.

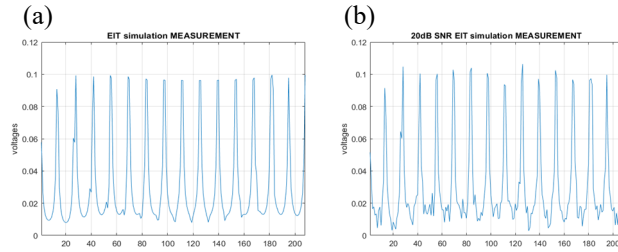


Fig. 4. EIT simulation.
(a) EIT simulation measurements (b) EIT simulation measurements with 20 dB signal-to-noise ratio.

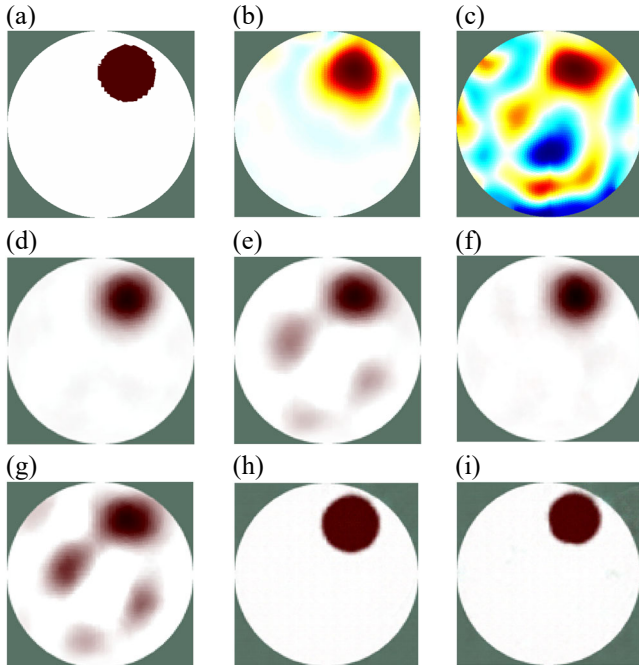


Fig. 5. EIT simulation reconstructed images from different inverse solvers. (a) Ground truth. (b) EIDORS inverse solver. (c) EIDORS inverse solver. (20 dB SNR measurement) (d) ANN-based inverse solver. (e) ANN-based inverse solver. (20 dB SNR measurement) (f) LSTMNN-based inverse solver. (g) LSTMNN-based inverse solver. (20 dB SNR measurement) (h) DNN-based inverse solver. (i) DNN-based inverse solver. (20 dB SNR measurement)

Fig.5. illustrates the reconstructed images from the EIDORS inverse solver and the NN-based inverse solvers. The EIDORS

inverse solver uses the default inversion method as specified in the EIDORS framework, which is typically based on the one-step Gauss-Newton (GN) method. The DNN reconstruction Fig.5(h) aligns more closely with the ground truth target location Fig.5(a) and exhibits significantly fewer artifacts. To evaluate the robustness of the DNN-based inverse solver, EIT simulation measurements with 20 dB SNR noise were inputted. As shown in Fig.5(c)(e)(g)(i), the EIT simulation reconstructed image from the EIDORS inverse solver, ANN and LSTMNN-based inverse solver containing more artifacts, while the DNN-based reconstructions remained highly accurate despite the presence of noise in the input data.

III. CONCLUSION

EIT has faced challenges in accurately diagnosing stroke [6]. EIT reconstructions often suffer from low resolution and are sensitive to noise, limiting their application in clinical settings due to the complexities of the inverse problem. This paper proposes a deep neural network (DNN)-based EIT inverse solver. The proposed method shows significant improvements over linear, artificial neural network (ANN), and long short-term memory neural network (LSTMNN)-based inverse solvers, particularly in terms of resolution and robustness to noise. These findings highlight the potential of deep learning to enhance the accuracy of EIT reconstruction. The full paper will employ the DNN-based inverse solver method to reconstruct 3D stroke targets using clinical EIT data from finite element brain models (Fig. 6).

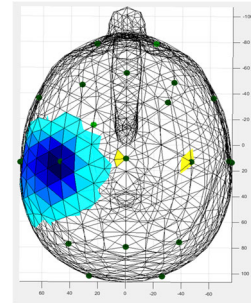


Fig. 6. EIT in stroke diagnosis

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