Image Reconstruction Algorithm in Electrical Impedance Tomography Based on Improved CNN-RBF model

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Abstract— **Electrical Impedance Tomography (EIT) is a noninvasive and real-time medical imaging technique, which means more potential applications for clinical diagnosis and treatments. However, EIT reconstruction problem is a highly nonlinear and ill-posed problem which will lead to poor reconstruction quality. Since neural networks have been proven to fit any nonlinear mapping theoretically, there are significant advantages of neural networks for EIT reconstruction. Convolutional neural networks (CNN), as one of the most famous neural networks, have powerful spatial feature extraction capabilities. Radial basis function (RBF) neural networks represent local approximators to nonlinear mapping, which has the significant advantage of short training time. In this paper, we proposed a two-part solver for the EIT reconstruction problem based on deep learning. RBF neural networks are used to solve the EIT reconstruction problem while CNN are used for feature extraction.**

Keywords— **Deep Learning; Electrical Impedance Tomography; Image Reconstruction**

I. Introduction

Electrical Impedance Tomography (EIT) is a low-cost and noninvasive medical imaging method that reconstructs the images of a specific region of human tissue. It injects a low-frequency safe current on the surface of the body then measures the boundary voltages to obtain the conductivity distribution inside the human body. Since the conductivities of body tissues in different state are different, we can reconstruct the conductivity distribution of a tissue to reflect its pathological function. Due to the advantages of its low-cost, noninvasive and real-time imaging, EIT is widely used in clinical applications, such as real-time detection for pneumothorax [1].

EIT reconstruction is the process of solving the mapping from the conductivity distribution to the boundary voltages of the field (EIT inverse problem), which is a highly nonlinear and ill-posed problem. According to whether data driven is needed, the reconstruction algorithms are divided into two classes: non-intelligent algorithm and intelligent algorithm [2]. The non-intelligent algorithms, such as Newton-Raphson (N-R), D-bar method, etc., solve the EIT forward problem and inverse problem based on mathematical physics methods and electrodynamics theory. Intelligent algorithms often fit the non-linear mapping of EIT reconstruction problem using machine learning or deep learning method with a series of suitable datasets, such as Multilayer Perceptron (MLP) and Convolutional Neural Networks (CNN), etc., which can obtain more accurate images of reconstruction [3].

With the development of the deep learning in image processing, signal processing and medical imaging, especially the convolutional neural networks, it gradually shows significant advantages for inverse problem in imaging [4]. Although training a deep neural network usually takes a lot of times, it takes less time to map the boundary voltages to the conductivity distribution since the trained model just need one forward calculation instead of complicated calculations in solving inverse problem by numerical method, which means it has more potential in real-time imaging.

However, many data-driven and learning-based model are just committed to improving the predication accuracy (or other evaluation standard) but ignore the interpretability of the model. In this paper, we proposed a novel deep learning-based method to solve the EIT reconstruction problem step by step so that each part of the model is only considered to implement a certain function of the solver.

II. Method

A. Electrical Impedance Tomography (EIT)

The EIT forward problem can is to calculate the conductivity distribution based on the boundary potential as in (1), where $\sigma(x, y)$ is the conductivity distribution, $\varphi(x, y)$ is the boundary potential, F is a mapping from the conductivity distribution to boundary potential.

$$F: \sigma(x, y) \rightarrow \varphi(x, y) \tag{1}$$

The inverse problem is to find the conductivity distribution using the boundary potential which can be usually represented by F^{-1} , the inverse mapping of F.

In practical, the conductivity distribution is usually discretized into a vector of conductivity. Every component will represent the conductivity of a specific small area. The boundary potential is also represented by a vector whose dimension depends on the number of electrodes. Since linear approximations can produce satisfactory result [5], the linearization model is commonly used, which is given by

$$F: \mathbb{R}^N \rightarrow \mathbb{R}^M: \\ V = J\sigma \tag{2}$$

where σ is the conductivity distribution in vector form, V is the vector of the boundary potential, N and M is the dimension of σ and V respectively, J donates the Jacobian matrix.

B. Preparing Data

Since neural network has shown high performance on fitting nonlinear mapping, in our work, we will improve the basic Convolutional Neural Network (CNN) to fit the nonlinear relationship between V and σ. We use eidors in MATLAB for solving the forward problem of 16-electrode EIT circular model, which is triangulated into 576 triangular elements. The field background simulates the brain parenchyma with conductivity of 0.15S/m, while the imaging target simulated the focal area of cerebral hemorrhage with central conductivity of 0.7S/m. The imaging target in the model was set as a hexagon, the conductivity of which decreased according to the distance from the center, as shown in Fig. 1.

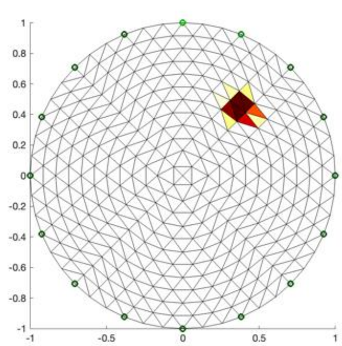

Fig. 1 Simulation result

After the simulation, we obtained almost 25441 sets of simulation data, which will be used for network training and evaluating. Each data includes:

1) A 192-dimensional of vector representing the boundary voltages in all 16 times injecting
2) A 576-dimensional of vector representing the conductivity in every element of the field.

Then split them into a training set and a test set by 8:2.

C. Network Architecture for EIT reconstruction

As shown in Fig. 2, the model can be divided into two sections, feature extraction and image reconstruction.

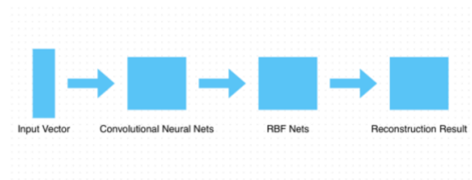

Fig. 2 The Architecture for EIT reconstruction

In this work, we extract the deep features of the original boundary voltages by a convolutional neural network, since there is a certain correlation between different dimensions of boundary voltages (see Result: Correlation analysis of boundary voltages).

This section first contains an input layer of 192 neurons which correspond to each of the dimensions of the boundary voltages respectively. Next There are 6 convolutional layers applying 3 × 3 convolutional kernel with a max pooling in each step. The last two layers apply 3×3 convolutional kernel with a 2 × 2 convolutional kernel average pool, as shown in Fig. 3. Exponential Linear Unit (ELU) is used as an activation function after each convolutional layers, Since ELU is. Since each element of the output from the convolutional layers contains the spatial features of the original data, the output layer contains 512 neurons which represent the deeper level of the feature.

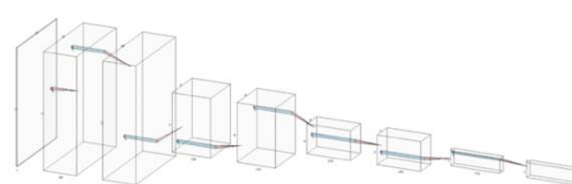

Fig. 3 CNN Architecture

The part of the image reconstruction contains a Radial Basis Function Neural Networks (RBFNN) with input layers of 512 neurons and output layers of 576 neurons, which represent conductivity of every element respectively.

As we know, Multilayer Perceptron contains dot products (between inputs and weights) and activation (non-linear) functions (such as ReLU, Sigmoid Functions). Network training is usually done through backpropagation for all layers. Unlike MLP, RBFNN uses Euclidean distances (between inputs and weights, also named as centers) and

Gaussian activation functions, which makes neurons more locally sensitive. RBF net has the similar input layer and output layer as MLP. What's diffident is that each neuron in the hidden layer has a prototype vector and a bandwidth denoted by μ and σ respectively, which computes the similarity between the input vector and its prototype vector, as shown in (3),

$$\phi_i = e^{-\frac{\|x-\mu_i\|^2}{2\sigma_i^2}} \quad (3)$$

where x is the input vector, μ_i is ith neuron's prototype vector, σ_i^2 is the ith neurons' bandwidth, and ϕ_i is the output of this neuron.

III. Result

A. Evaluation Metrics

The relative error (RE) of the image reconstruction measures the error between the reconstructed conductivity distribution σ^* and the real conductivity σ, which is an intuitive indicator to measure the quality of the reconstruction image, as expressed in (4).

$$RE = \frac{\|\sigma - \sigma^*\|}{\sigma} \quad (4)$$

The correlation coefficient (CC) measures the similarity between the reconstructed conductivity distribution σ^* and the real conductivity σ, which is defined by (5)

$$CC = \frac{\sum_{i=1}^{N}(\sigma_i^* - \overline{\sigma^*})(\sigma_i - \bar{\sigma})}{\sqrt{\sum_{i=1}^{N}(\sigma_i^* - \overline{\sigma^*})^2 \sum_{i=1}^{N}(\sigma_i - \bar{\sigma})^2}} \quad (5)$$

The mean square error (MSE) measures the average of the squares of the errors of the prediction and the groundtruth, as expressed in (6)

$$MSE = \frac{1}{N}\|\sigma - \sigma^*\|^2 \quad (6)$$

where σ_i^* is the ith reconstructed conductivity, $\overline{\sigma^*}$ is the mean of the reconstructed conductivity distribution σ^*, σ_i is the ith real conductivity, $\bar{\sigma}$ is the mean of the conductivity distribution σ.

B. Correlation Analysis of boundary voltages

Before reconstructing, we first analyzed the correlation between voltages measured at each projection angle, as shown in Fig. 4. We take 1000 samples from the dataset to do correlation analysis, where each sample contains 12 measured voltages from 16 projection angles. Then we calculate the Pearson product-moment correlation coefficient (PPMCC) between every voltage vector from every projection angle which equals to 0.4249. We find that the vectors are significantly correlated, which means the dimensions of the boundary voltages are not independent.

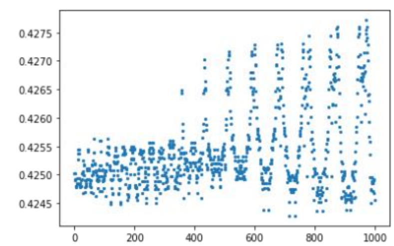

Fig. 4 the correlation between every two sets of measured voltages

According to the Cover's theorem on the separability of patterns, a pattern that is transformed into a higher-dimensional space with nonlinear transformation is more likely to be linearly separable. Depending on that, we use the CNN to map the boundary voltages into higher-dimensional space to get deeper features, which would be less correlated with each other.

C. Training and evaluating the model

During training, we tried different optimizers and learning rate. After training several models, we got the following result of correlation coefficient and relative error as shown in Table 1. The MSE loss is shown in Fig. 5. The reconstruction result from One data randomly obtained from the data set is shown in Fig. 6.

Table 1 Network evaluation with RE and CC

Model type	Learning rate	CC	RE ($\times 10^{-5}$)
CNN + RBFNN (Adam)	0.0001	0.9567	4.3771
	0.0005	0.9595	5.0552
	0.001	0.9555	4.5635
CNN + RBFNN (SGDM)	0.0001	0.2263	13.8964
	0.001	0.4520	15.0586
	0.01	0.7232	12.2693
	0.1	0.8360	10.5889
	0.5	0.8678	8.4608
	0.8	0.9020	7.2939
	1.0	0.8821	8.3368
CNN (Adam)	0.0005	0.3694	15.0147

Among all, the CNN + RBFNN using Adam as the optimizer with learning rate equals to 0.0005 is the best model, since it got the highest correlation coefficient and lowest relative error, which means the conductivity reconstructed by this model is most similar to the groundtruth.

The same result is obtained in loss curves. In

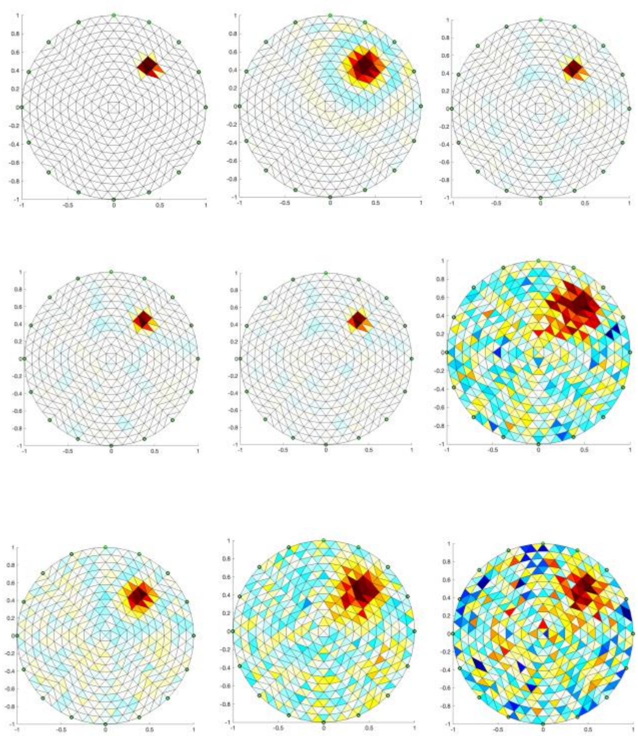

Fig. 5 The reconstruction result. The first image in the first row is the groundtruth. The other two are reconstructed by N-R method and CNN + RBFNN (Adam) with learning rate = 0.0005 model respectively. The first two images in second row are reconstructed by CNN+ RBFNN (Adam) with learning rate = 0.0001 and 0.001. Next one is reconstructed by CNN (Adam) without RBFNN. The third row contain 3 images reconstructed by CNN + RBFNN (SGDM) with learning rate = 0.8, 0.01, 0.0001 respectively.

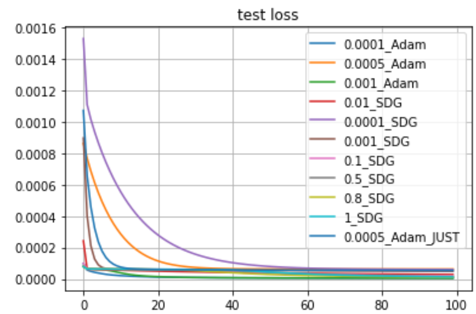

Fig. 6 Loss curve

IV. Disscussion

According to the experiment, CNN + RBF model can always obtain significantly better reconstruction result than original CNN. Adam optimizer can always achieve lower RE and higher CC than SDGM, which means higher reconstruction quality. However, for data driven model, what we want model to learn is a mapping from the boundary voltages to the inner conductivity, which means that the value of the conductivity in the data set should have a certain difference. Therefore, in the future experiment, we can explore the impact of data set on the model reconstruction result. And then determine whether the network fits the mapping well.

V. Conclusions

In our work, we proposed a novel learning-based model for Electrical Impedance Tomography reconstruction problem which contains the feature extraction part and the reconstruction part. After the comparison of the original CNN model in simulation data, different parameters and different optimizers, we got the most potential reconstruction model using CNN and RBFNN with optimizer of adaptive moment estimation (Adam), which has a significant performance improvement over the others.

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