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AN IMAGE RECONSTRUCTION FRAMEWORK BASED ON DEEP NEURAL NETWORK FOR ELECTRICAL IMPEDANCE TOMOGRAPHY

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Introduction

Electrical impedance tomography (EIT) is a novel noninvasive imaging technology in which electrodes are placed on the surface of the unknown object and the interior impedance of an object is reconstructed from voltage data arising from currents applied on the electrodes. Due to the advantages of being non-radiant and non-intrusive, rapid response and low cost, EIT has wide foreground for application in the field of clinical monitoring and industrial measurement.

Since the main difficulties of EIT are the limited number of sensing electrodes and the non-linear property of the field, the image reconstruction for EIT is a typical non-linear and ill-posed inverse problem. Traditional methods of image reconstruction for EIT include Landweber iteration method , the conjugate gradient (CG) method, Tikhonov regularization method and so on. Compared with the traditional methods, the shallow neural network is easier to implement and has lower computational demands, such as Hopfield neural network , Radial Basis Function neural network and Back Projection (BP) network have been widely used for image reconstruction. Because the ability of deep neural network (DNN) to represent complex functions is stronger than that of shallow neural network, there have been a number of initial attempts at using DNN for medical image reconstruction in recent years, such as in CT and MRI .

In this paper, we propose a new image reconstruction framework based on DNN for EIT. A 4-layer DNN based on the stacked autoencoder (SAE) is trained to establish the nonlinear mapping between the voltage measurements and the inner conductivity distribution. Thus we can directly use voltage measurements through the trained DNN model to estimate conductivity distribution which is used to reconstruct image of EIT. In this way, the DNN can simplify the mathematical formulation without requiring any approximate linearization.

The theory of EIT problem includes the forward and the inverse problem. The forward problem is to calculation of voltage measurements according to the known conductivity distribution of given object and applied current value. The most common method to obtain numerical solution of EIT forward problem is Finite Element Method (FEM). And the deterministic observation model of EIT can be expressed as

$$V = U(\sigma; I) = R(\sigma) I \tag{1}$$

Where V is a vector of the voltage measurements, $U(\sigma; I)$ is the forward model mapping the conductivity distribution σ and injected current vector I to the boundary voltage vector V, $R(\sigma)$ is the model mapping conductivity σ to resistance.

The inverse problem is also called image reconstruction. When the changes in conductivity distribution are small, this problem can be estimated by considering the linearized equation system as follows:

$$\delta U = J \delta\sigma \tag{2}$$

Where $\delta U \in R^m$(m is the number of independent voltage measurements) is the change of perturbation of boundary voltage, $\delta\sigma \in R^n$ (n is the number of pixels of the reconstructed image), and $J \in R^{m \times n}$ is the Jacobian matrix. As the matrix J in (2) is usually neither square nor full rank, image reconstruction for EIT is a typical ill-posed inverse problem, in which a solution either does not exist or is not unique or unstable. This is a reason we choose DNN to avoid solving the Jacobian matrix.

Reconstructed Method

Information Extension

In this section, the SAE combined with the logistic regression (LR) layer constitutes the entire DNN model. The working principle of imaging reconstruction for EIT based on DNN contain two parts, one is using training set to train the DNN model, another one is using test set through the trained DNN model to obtain the test result which is used for image reconstructions, as illustrated in Fig. 1.

The stacked autoencoder, referred to as the SAE in this paper, consists of a series of autoencoders which are stacked on top of each other. A typical autoencoder is a neural network consisting of three fully connected layers which are the input layer, the hidden layer, and the output layer, as shown in Fig. 2(a). Given a set of training samples as the input $X = \{x^{(1)}, x^{(2)}, x^{(3)}, \dots, x^{(M)}\}$ (M is the number of training samples), where $x^{(k)} \in [0,1]^m$ (m is the number of input layer neurons). The j^{th}input value can be represent by x_j , and the weight matrix components expressed as $\{w_{ij}\}$ with $j = 1,2,3,\dots,m$ and $i = 1,2,3,\dots,n_h$, where n_h is the number of hidden layer neurons. The autoencoder transforms input vector x to hidden vector y via the encoder f. In this study we used the logistic sigmoid function as follow:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

The hidden layer neurons output, called encoding, is obtained by the following formula:

$$y_i = f(\sum_{j=1}^{m} w_{ij} x_j + b_i) \tag{4}$$

where b_i is the bias of the hidden layer neuron i . The autoencoder attempts to reconstruct input vector x via the decoder f to produce reconstruction vector z . The output layer values, also called the decoding, is given by

$$z_j = f(\sum_{j=1}^{m} w_{ij}^T y_i + b'_j) \tag{5}$$

here, b'_j is the bias of the output layer neuron j, The parameters of this neural network are optimized to minimize the average reconstruction error

$$J(w,b) = \frac{1}{M} \sum_{k=1}^{M} L(x^{(k)}, z^{(k)}) \tag{6}$$

here, L is a loss function. The Gradient Descent method used to update weight matrices and bias vectors according to formulas (7), where α represents the learning rate.

$$b = b - \alpha \frac{\partial L(x,z)}{\partial b} \qquad b' = b' - \alpha \frac{\partial L(x,z)}{\partial b'} \qquad w = w - \alpha \frac{\partial L(x,z)}{\partial w} \tag{7}$$

The DNN model based on SAE used in our study is constructed by several autoencoder layers and a LR layer. The working principle of the SAE is illustrated in Fig. 2(b).

A SAE is a network combining together the hidden layers of subsequent autoencoders, that is, the output layer of the previous autoencoder is discarded after training, and the output of the hidden layer as the input of another autoencoder. Each hidden layer is a higher-level abstraction of the previous layer, therefore the last hidden layer contains high-level structure and representative information of the boundary voltage measurements, which are more effective for estimating the conductivity distribution.

To employ the DNN model based on SAE for estimating the conductivity distribution, the real-value of conductivity must be added on the top layer. In this paper, a logistic regression (LR) layer is embedded as an output layer into the network for estimation of the true conductivity distribution.

The new method

The training procedure contains the SAE pre-training and fine-tuning steps. Before the pre-training step, we have to do some preparation, first, we obtain the training set by the finite element simulation model, the training set consists of samples of voltage measurements and samples of corresponding conductivity distributions. The input samples for training the model are a set of normalized voltage measurements, which is denoted by $U = \{V^{(1)}, V^{(2)}, \dots, V^{(M')}\}$ (M' is the number of training samples), where $V^{(k)} \in [0,1]^{m'}$ (m' is the number of independent voltage measurements). The output samples for training the model are a set of normalized corresponding conductivity distributions, which is expressed as $R = \{\sigma^{(1)}, \sigma^{(2)}, \dots, \sigma^{(M')}\}$,in which $\sigma^{(k)} \in [0,1]^n$ (n is the number of pixels of the reconstructed image). So that we can get the relationship between the voltage measurements and the inner conductivity distribution. Then the number of hidden layers is preset to l layers, the number of nodes is preset in each hidden layer, and the network parameters including the training epochs, the learning rate, the batch-size and the number of iterations are initialized. At last, some prior information (shape, size, position of the object, etc.) is added to the network. The training procedure is based on the studies by Hinton et al. and Bengio et al. In the pre-training stage, we initialize the weight matrices and bias vectors randomly. Then U is used as input to train the first hidden layer, the successive hidden layers are trained in a greedy layer-wise manner while using the output of the previous hidden layer as the input of the next hidden layer. In the fine-tuning stage, we use the output of the last hidden layer as the input for the LR layer and randomly initialize $\{w^{l+1}, b^{l+1}\}$. The backpropagation (BP) algorithm with the gradient-based optimization technique is used to update the whole network's parameters in a top-down manner.

In order to obtain the reconstructed image of the EIT, the test set is used to verify the validity of the trained DNN model. The test set includes the untrained samples of voltage measurements, and is expressed as $u = \{V'^{(1)}, V'^{(2)}, \dots, V'^{(N)}\}$ (N is the number of test samples), in which $V'^{(k)} \in [0,1]^{m'}$ (m' is the number of independent voltage measurements). u is the input for testing the trained DNN model, and the test result is regarded as the estimations of conductivity distributions. This result can be expressed as $r = \{\sigma'^{(1)}, \sigma'^{(2)}, \dots, \sigma'^{(N)}\}$,where $\sigma'^{(k)} \in [0,1]^n$ (n is the number of pixels of the reconstructed image) is used to reconstruct image by a mesh with square elements, as shown in Fig.1(b) and (c).

An EIT system with 16 electrodes is employed to reconstruct the interior conductivity distribution. Numerical simulations were carried out to evaluate the performance of the proposed framework. In this paper, we used COMSOL software to create a set of models of different conductivity distributions based on Finite Element Method (FEM) and to obtain boundary voltages, as shown in Fig.1 (a). Due to the measured voltages were simulated using the complete electrode model and adjacent current patterns, there are 208 measured voltages, which constitute the input vector for the DNN model. The image is reconstructed with 812 pixels digitized image in a grid with 32×32 square elements.

In order to verify the validity of the new framework for EIT imaging, we used the geometry of object as a priori information for the DNN model. We designed two kinds of simulation models with circular and square objects. Each kind of objects have 2000 different positions, which are evenly distributed in the field. Therefore, each kind of simulation model has 2000 different impedance distribution models for training. Furthermore, objects of each shape have 100 different conductivity distribution models for testing, whose positions are without in the training set. The finite element simulation method is used for numerically simulate the data sets for DNN. Before training, we added the Gaussian noise to voltage measurements and normalize the data sets first. The DNN based on SAE was created and trained using Deep Learning Tolbox in MATLAB.

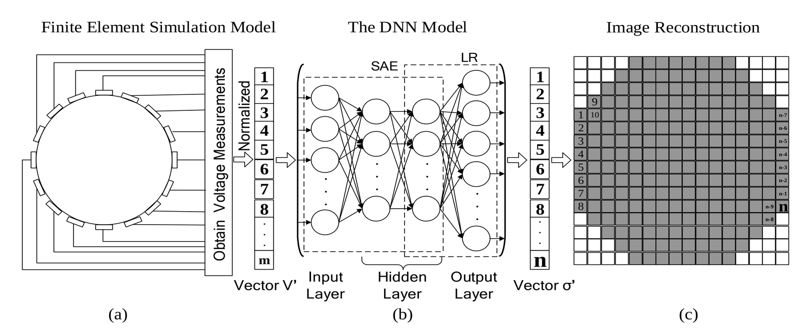

Fig. 1. The working principle of imaging reconstruction for EIT based on DNN. (a) Finite element simulation model is used for numerically simulate the data set. (b) The DNN model based on SAE. (c) A test result is used to reconstruct the image of EIT

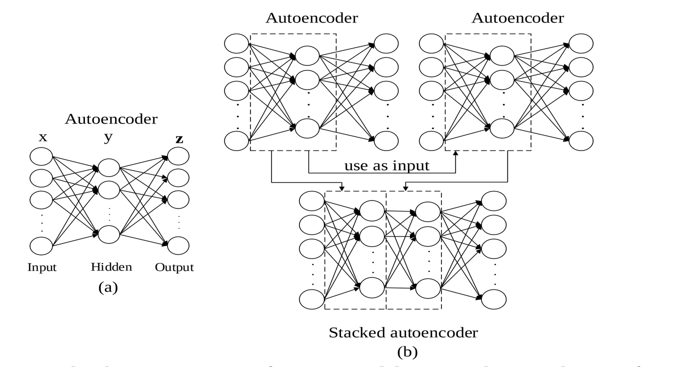

Fig. 2. The basic structure of DNN model. (a) A basic schema of an autoencoder. (b) The structure of the SAE used in this study. It contains an input layer, two hidden layers, and an output layer.

Results

Simulation Results

In this paper, we used the proposed framework to estimate the conductivity distribution of two kinds of simulation models. The DNN model was trained with four layers, and the number of nodes in each layer was {208,150,150,812}. In the pre-training stage, the learning rate was set to 1 for each layer, the training epochs was 100 and the batch-size was 10. In the fine-tuning stage, the learning rate was set to 2 for each layer, the batch-size was 40 and the number of iterations was 100. The test sets were used to obtain the estimations of the conductivity distribution through the trained network. The reconstructed images presented the conductivity distribution by using a mesh with 812 square elements. The performance of this reconstruction technique is compared with the CG method and BP network method on simulated data, as shown in Figure 3.

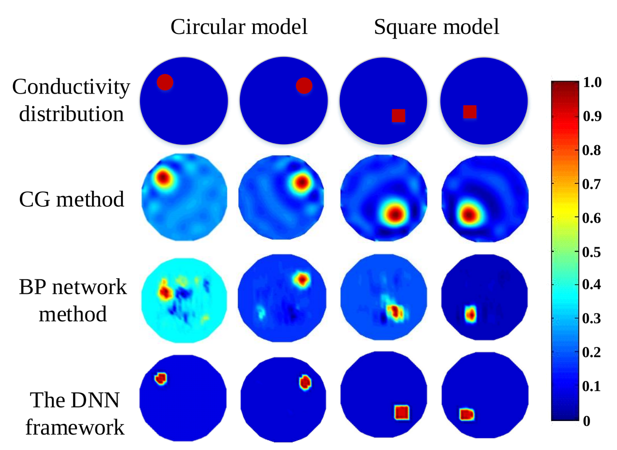

Fig. 3. Reconstructed images of different shape objects by using the three methods.

From Fig. 3 we can see that, reconstructed images based on the CG and BP network methods contain a lot of artifacts, by contrast, the new framework we proposed is much better. In addition, the results indicate that the new framework can more clearly reflect the edge of the object compared with BP network method, while the reconstructed images based on the CG method can not accurately reflect the edge contours of the object inside the sensing field.

To evaluate the performance of the proposed model, we adopted the mean-squared error (MSE), which is calculated as follows:

$$MSE(\sigma^*) = \frac{\| \sigma^* - \sigma \|_2^2}{N} \tag{8}$$

Where σ^* denotes the true conductivity distribution and σ denotes the estimation of the conductivity distribution. The average mean-squared errors of the three methods are shown in Table I.

Table I. Average MSEs of different methods for simulation

Simulation model	Average MSEs		
	CG method	BP network method	The DNN framework
Circular object	0.0968	0.0327	0.0083
Square object	0.0529	0.0304	0.0271

The simulation results displayed in Table I also demonstrated that the DNN framework performs best.

Results

Experimental Results

An experimental study was performed using the EIT system with 16 electrodes. In the experiment, The EIT imaging domain was set up by using a cylindrical container filled with tap water. A plastic rod was placed at 100 different positions in the imaging region, therefore 100 samples of voltage measurements are obtained as a new test set. The radius ratio of the cylindrical container to the plastic rod was consistent with the above circular simulation model. We used the new test set to test the DNN model, which was trained by the training set of the circular simulation model described in section 4.1 above, and the reconstruction results compared with CG method are shown in Fig. 4. Experiments show that the DNN model can obtain reconstructed results of the experimental data by training the simulation data.

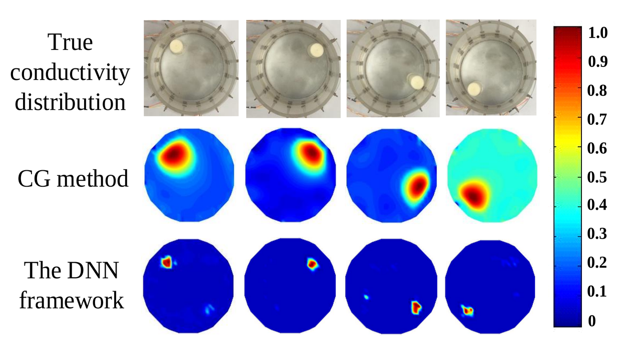

Fig. 4. Reconstructed results of the plastic rod.

Conclusion

In this paper, a new image reconstruction framework for EIT based on DNN with SAE is implemented. Simulation and experimental results have shown that the DNN model trained with simulation data not only can be used to obtain the reconstruction results of the simulation data, but also can be used to obtain reconstruction results of the experimental data. In addition, compared with other methods in this paper, the proposed framework has an obvious advantage in quality of reconstructed images. In the future work, we will increase the training samples and find the optimal parameter settings to compare the new framework with other methods.

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