Image Reconstruction Based on ResV-Net for Electrical Impedance Tomography

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Abstract

Electrical impedance tomography (EIT) is a nonlinear and ill-posed inverse mathematical problem. Due to the above problem, the reconstruction image suffers from serious artifacts. To overcome shortcomings, we proposed a residual V-shaped deep convolutional neural network (ResV-Net). It consists of the feature extraction module and image reconstruction module which are optimized by ResBlock. The residual connection method can effectively increase the number of the forward information flow and reverse gradient flow in deep CNN and alleviate the problem of non-convergence caused by gradient vanishing. The simulation and experimental results show that the ResV-Net has a better visualization effect than the related imaging method.

Keywords: electrical impedance tomography, inverse problem, V convolutional neural network, image reconstruction

1. Introduction

Electrical impedance tomography (EIT) is a new visual measurement technology. EIT takes advantage of the electrical characteristics of different media with different conductivity in the area. The potential distribution on the observation area boundary are measured by applying an alternating current excitation to the measurement field, and the conductivity distribution are reconstructed by using appropriate imaging algorithm. However, due to the ill-posed and nonlinearity of image reconstruction problems, most current algorithms approximate nonlinear problems to linear problems based on sensitivity matrix theory, which results in the loss of part of boundary information and the interference of some artifacts in reconstructed images. The Landweber[1] iterative method and regularization method[2] proposed in recent years have relieved the influence of nonlinearity and ill-condition on image reconstruction to a certain extent, but the spatial resolution of reconstructed images still needs to be improved.

At present, a convolutional neural network has given many satisfactory results in image processing of inverse problems, indicating that the deep neural network model has a good performance in expressing complex nonlinear relations. To improve the quality of reconstructed images effectively, an electrical impedance tomography method based on a deep convolutional neural network is proposed in this paper. In this method, feature extraction and image reconstruction of the V-Net network are adopted, and a residual connection information transfer channel is added into each block. The deep learning model of this supervised mode is named ResV-Net. This strategy can effectively alleviate the gradient disappearance problem that may occur in the deep CNN model, as well as reduce the difficulty of network training and improve the robustness and generalization ability of the network. The ResV-Net is used to reconstruct the image with fewer artifacts, higher spatial resolution and more clear boundary of inclusions.

2. Method

2.1. Mathematical method model

The working model of current excitation by adjacent electrodes is used as the EIT data collection mode. A pair of adjacent electrodes are selected to inject current excitation, and another two adjacent electrodes are selected to measure the voltage as the measurement electrode. Sixteen pairs of adjacent electrodes are successively used as excitation electrodes, and a total of 208 measurements are collected. The EIT simulation model measurement system is shown in Fig.1.

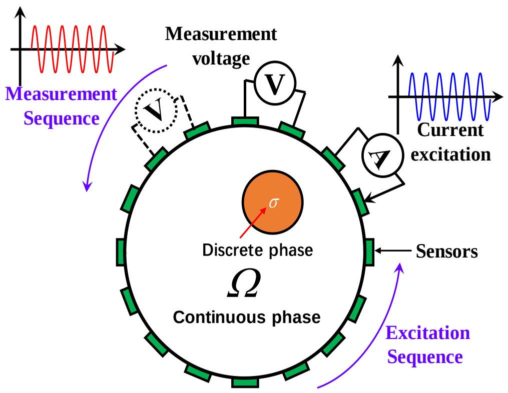

Fig.1. EIT simulation model measurement system

According to Maxwell equation[3], Neumann boundary conditions and complete electrode model[4], the mathematical model of EIT can be expressed as

$$\begin{cases} \nabla\cdot\sigma(\boldsymbol{r})\nabla\varphi=0, \boldsymbol{r}\in\Omega, \\ \varphi(x,y)=u(x,y),(x,y)\in\partial\Omega\setminus\bigcup_{L=1}^{16}e_L, \\ \varphi(x,y)+\sigma(r)\nabla_n\varphi(x,y)=U, \\ (x,y)\in e_L, L=1,2,\cdots,16. \end{cases} \tag{1}$$

Where $\boldsymbol{r}$ is the spatial position, $\sigma(\boldsymbol{r})$ is the conductivity distribution in the measurement field, $\varphi(x,y)$ is the potential distribution in the measurement field, $\boldsymbol{n}$ is the boundary unit normal vector, $\boldsymbol{\Omega}$ is the measurement field, e_L is the boundary attached electrode.

2.2. ResV-Net model structure

U-net has made a lot of satisfactory achievements in the field of computer vision in recent years, but the topological structure of the U-net cannot be directly applied to EIT imaging. Based on the above reasons, a V-shaped convolutional neural network with compression path as encoder and expansion path as the decoder isproposed in this paper. At the same time, in order to alleviate the problem of gradient disappearance caused by many hidden layers in the network, a residual connection is added in each module to avoid this problem. The network is named ResV-Net. It is composed of the feature extraction module and image reconstruction module. The feature transfer channel of residual connection is used between each block, and "skip connection" is used to connect the feature graph of the same dimension in the encoding module and decoding module. Residual information transmission mode is added in each block, and this connection method is made between of low-level features and high-level features. ResV-Net can improve effectively the training efficiency of the network and encourage the repeated use of features, as shown in Fig.2.

L1~L20 is a feature extraction module with the encoding function. The 16×16 voltage matrix is obtained by measurement sensors, and the input of ResV-Net is 32 × 32 pixel distribution which up-samples from the voltage matrix. Each block has two convolution layers with the 3×3 kernal and one residual connection layer realized by 1×1 convolution. The residual connection channel and the feature mapping layer are activated by 3 × 3 convolution and ReLU nonlinear function. The adjacent block are connected by 2×2 max-pooling layer, so that the complex image information can be expressed with less feature distribution. After feature extraction of 5 blocks, the 32×32 input features are mapped to a 2×2 feature map, and the number of feature channels is expanded from 1 to 256.

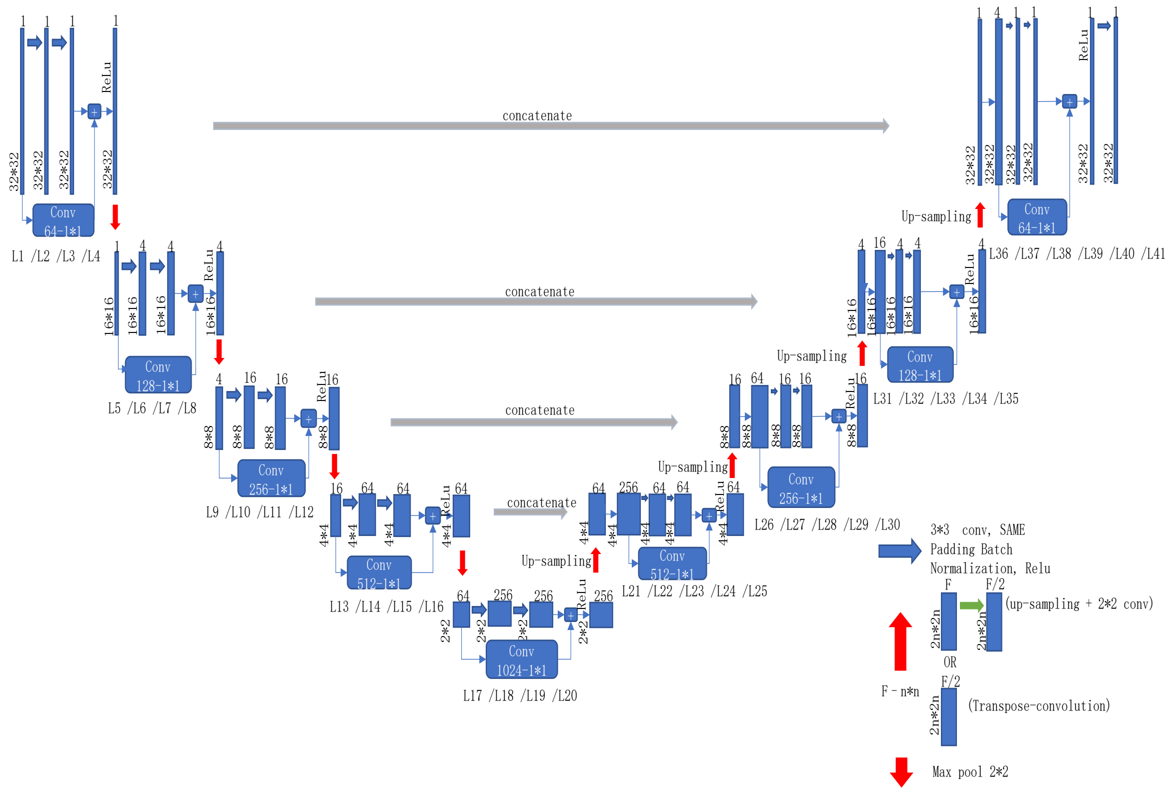

Fig.2. ResV-Net network topology

L21~L41 are image reconstruction module with the decoding function. Each block contains one feature compression layer, two convolution layers with the 3×3 kernal, one residual connection channel, and one feature mapping layer. The feature mapping layer is activated by 3×3 convolution and ReLU nonlinear function. An up-sampling layer with a convolution kernel of 2×2 was used to reconstruct a feature map of larger size between two adjacent blocks. After feature reconstruction of four blocks, the output feature is a feature map with the same size 32×32 as the input information, and the number of channels decreases gradually from 256 to 1. Finally, a convolution kernel with a convolution layer of 1×1 is used to eliminate the "checkerboard" effect caused by up-sampling, and the final result is taken as the output result of the network.

In ResV-Net, input features in each block are used to extract boundary features of parameter distribution by 1×1 convolution, and the constructed abstract features are fused with the output of a 3×3 convolution using a residual connection. The structure is shown in Fig.2. Meanwhile, the features of L4, L8, L12 L16 were spliced with L36, L31, L26 L21 respectively using a skip connection. Such connection mode, on the one hand, increases the repeated utilization of features and makes the deep network can learn more data distribution features. On the other hand, multi-channel feature connection can increase forward information flow and reverse gradient flow, avoid the problem of gradient disappearance in the deep network, make network training easier and increase the use efficiency of parameters.

2.3. Model training

The ResV-Net requires a large number of data samples, and the quantity and quality of data samples will affect the robustness and generalization ability of the network. During the simulation, a tank with a radius of 0.095m is set, and 16 electrodes are attached on the boundary of the tank with the same spacing and height. The water with the conducting of 0.6s /m is set as the homogenous background, and the conductivity of inclusions is set as the inhomogenous media. The finite element method in COMSOL Multiphysics is used to divide the observation domain into discrete triangular mesh, which solves the forward problem and obtains the boundary voltage. COMSOL Multiphysics and MATLAB are used to divide the measurement field into 32×32 mesh, and each pixel corresponded to the distribution of conductivity values in the field. The number of inclusion in the simulation database ranges from 1 to 4. The positions and sizes of inclusions do not overlap each other and are randomly set.

Due to the depth and complexity of the ResV-Net, a loss function is used to calculate the error between the predicted result $\hat{x}$ and the real result x. The loss function[7] is

$$Loss = \alpha \times l(\hat{x}, x) + \lambda \times \|\theta\|^2 \tag{2}$$

Where, $l(\hat{x}, x)$ represents the cross entropy of $\hat{x}$ and x. $\|\theta\|^2$ is a regular term, which can be used to constrain the solution of parameters to avoid the over-fitting problem of training. $\hat{x}$ and x are important optimization methods in the network. $\|\theta\|^2$ is auxiliary constraint factor, and their weight coefficients are α = 1 and λ = 0.01 respectively. The ResV-Net employs the mini-batch gradient descent method in training samples, which is expressed as

$$\theta_{t+1} = \theta_t - \eta \bullet \nabla_{\theta_t} Loss(\theta_t; V_{n,m+n}, \sigma_{n,n+m}) \tag{3}$$

The value of m is 120, and the initial learning rate is 0.01.

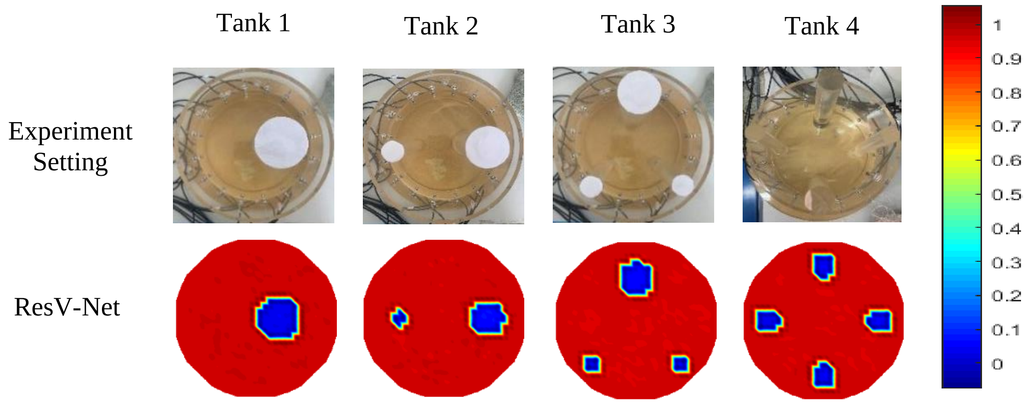

Fig.3. Simulation imaging results of RESV-NET network model

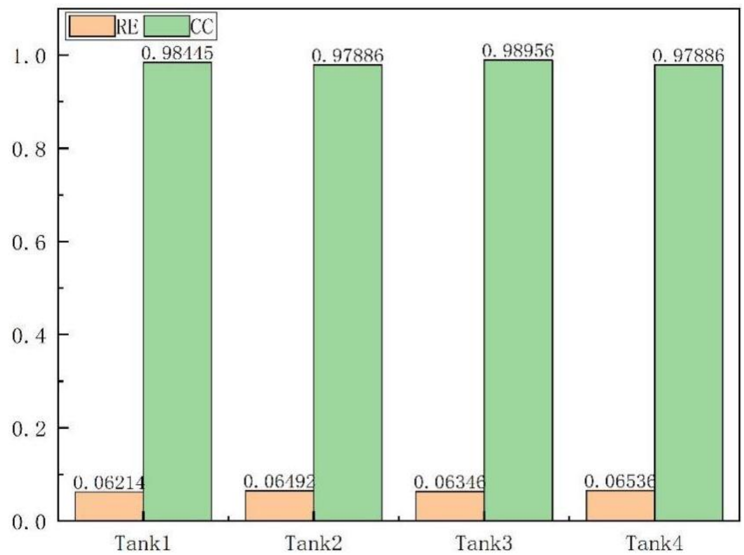

Fig.4. Evaluation index of simulation imaging of ResV-Net network model

The learning rate is reduced to 0.9 times before each update. This process is repeated until the ResV-Net converges. By using the mini-batch gradient descent method to update the parameters of the network, the loss function can reach the local optimum.

3. Results

The relative error (RE) and correlation coefficient (CC) are two general metrics for quantitative evaluation of reconstructed images[5,6].

In order to verify the performance of the proposed ResV-Net network model, the data in the test data set is used as the input of the network model for training. The training results are compared with the results of image reconstruction obtained by the commonly used algorithms such as NOSER, TR, CG and CNN. The comparison results verify the nonlinear ability of the ResV-Net network model to deal with EIT inverse problems. The ResV-Net model simulation imaging results are shown in Fig.3, and RE and CC are shown in Fig.4.

Fig.3 and fig.4 show that the ResV-Net has high RE and low CC, network in each image reconstruction using the characteristics of a residual connection between block transmission channels, at the same time use "skip connection" coding module and decoding module connection, the characteristics of the same dimension figure in the reconstruction image boundary clear, high spatial resolution and good visualization.

4. Conclusion

For EIT image reconstruction, the ResV-Net is proposed in this paper. The network consists of feature extraction module and image reconstruction module. The network adopts the feature transfer channel of residual connection, and uses the "skip connection" method to connect the feature maps of the same dimension in the feature extraction module and the image reconstruction module. It avoids the problem of gradient disappearance which may occur in the deep network, and increases the repeated utilization rate of features. The ResV-Net is superior to traditional imaging methods in terms of reconstructed image quality and quantitative evaluation indexes. And using this method in simulation and experiment can obtain good imaging results. However, the application of deep learning in image reconstruction still faces many challenges, such as incomplete simulation databases. This is also one of the problems to be solved in future research work.

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She is professor of Tianjin University of Science and Technology, graduated from Tianjin University with PH.D (2009), worked as a Post-doctor at Tianjin University (2009.5-2015.5). She had been in RPI, USA with Dr. Johnathon from Sep.2009 to Feb.2010 and in Kent, UK with Yong Yan from Sep-Dec.2012. She has researched electrical impedance tomography technology in monitoring lung ventilation for many years. She is in charge of the TUST-EIT lab and guides young researchers and graduate students to improve the electrical data acquisition hardware platform, to study the traditional and novel reconstruction algorithms with the prior structural information. Recently, her research team is focus on the novel methods through deep learning network models.