A Deep Learning Framework for Magnetotelluric Impedance Tensor Reconstruction

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SUMMARY

Magnetotellurics (MT) is a geophysical method that infers subsurface conductivity distributions by measuring natural variations in the Earth's electromagnetic field. Therefore, obtaining high-quality impedance tensors is crucial for accurately resolving subsurface structures. This paper introduces a method for reconstructing impedance tensors based on deep residual neural networks (ResNet). The network leverages multi-layer convolutions and residual connections to harness the continuity of the impedance tensor and the interrelationships between different tensor elements, extracting valuable information from noisy impedance tensors to recover the original impedance tensor. Noise-free samples are generated via 3D forward modeling of both actual models and manually designed models. The training set is then augmented by rotating the impedance tensors and finally adding noise. After testing various approaches, logarithmic apparent resistivity and unwrapped phase were chosen as the optimal data combination for training. Additionally, a specialized ResNet model is trained for phase unwrapping. The test results indicate that this method can accurately reconstruct noisy impedance tensors. Furthermore, we applied the reconstructed impedance tensors to enhance M-estimation data processing. In each iteration of the M-estimation process, the reconstructed impedance tensor replaces the impedance tensor from the previous iteration, reducing the impact of outliers introduced by strong noise. The experimental results show that the ResNet-based reconstruction method significantly improves data processing performance, especially when dealing with complex geological structures and high-noise environments. This study highlights the profound potential and broad application prospects of deep learning in magnetotelluric data processing.

Keywords: Magnetotellurics, Impedance Tensors, ResNet, Phase Unwrapping, M-estimation

INTRODUCTION

Magnetotellurics (MT) is a widely applied geophysical technique used to infer subsurface conductivity distributions by measuring natural variations in the Earth's electromagnetic field. A critical component of MT data is the impedance tensor, which reflects the electrical conductivity structure of the subsurface. However, obtaining high-quality impedance tensors directly is often challenging due to factors such as complex measurement environments, data noise, and instrument errors (Bahr, 1991).

In recent years, deep learning technologies have demonstrated remarkable performance in addressing complex nonlinear problems, particularly in the domains of signal processing and image reconstruction. The impedance tensor in magnetotellurics typically exhibits continuity and inter-component correlations. By leveraging these underlying relationships, it is possible to identify and suppress noise within the impedance tensor. Therefore, this paper proposes a novel method for reconstructing magnetotelluric impedance tensors based on deep learning, aiming to enhance the quality and reconstruction accuracy of MT data.

METHODS

ResNet

We adopted the deep residual neural network (ResNet) as the core model, which consists of multiple residual layers (Residual Blocks), each comprising several convolutional layers(He et al, 2015). The convolutional layers are designed to capture dependencies between adjacent frequencies and extract valuable information from noisy data. Through the operation of multiple convolutional layers, the network can efficiently extract features at various scales.

ResNet employs a residual learning mechanism, utilizing skip connections and residual blocks to learn residual functions, as shown in Figure 1. This approach allows the network to focus on learning the residual functions rather than directly mapping the input to the output, thereby facilitating the effective training and optimization of deep networks. ResNet has demonstrated exceptional performance and scalability across various domains, including image recognition.

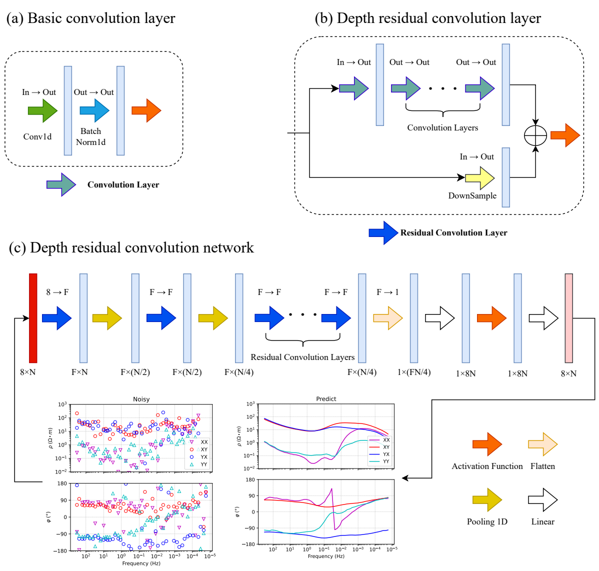

Figure 1: The basic structure of ResNet

Training Process

To construct the training dataset, we utilized multiple existing measured data three-dimensional (3D) inversion models and manually designed three-dimensional models, totaling forty distinct models. Each model comprises 2500 sites, from which noise-free impedance tensor samples were obtained through 3D forward modeling. Subsequently, we rotated the impedance tensors at each site ten times, thereby expanding the dataset by a factor of ten. Following this, we introduced varying degrees of noise randomly into the noise-free impedance tensors to simulate real-world noise conditions during measurements.

We conducted training tests on various data combinations, including the real and imaginary parts of impedance ($\Re[Z]$ & $\Im[Z]$), impedance magnitude and phase ($|Z|$ & $Arg(Z)$), apparent resistivity and phase (ρ & φ), logarithmic apparent resistivity and phase ($lg(\rho)$ & φ), and logarithmic apparent resistivity and unwrapped phase ($lg(\rho)$ & unwrapped φ). The results indicated that training with $|Z|$ & $Arg(Z)$ and ρ & φ did not converge, while training with $\Re[Z]$ & $\Im[Z]$ showed poor performance. Ultimately, the combination of $lg(\rho)$ and unwrapped φ performed the best during training. Therefore, we selected this combination strategy for the final training.

For the data combination of $lg(\rho)$ & unwrapped φ, we first needed to address the phase unwrapping of noisy data. To achieve this, we trained a specialized ResNet model designed for phase unwrapping. The phase unwrapping problem was simplified into a three-class classification task, categorizing data points into clockwise, uncoupled, and counterclockwise wrapping states. The network primarily used the tanh activation function, while the softmax activation function was employed at the output layer. After testing the network with different parameters, we determined the optimal configuration: 20 convolutional kernels, 4 residual layers, and 16 convolutional layers. The final Recall-Precision curve achieved an Area Under Curve (AUC) of 0.979, indicating very high accuracy in phase unwrapping.

In the ResNet used for impedance tensor reconstruction, we tested different network parameter combinations. Eventually, ReLU was chosen as the activation function, and the optimal configuration was determined to be 400 convolutional kernels, 2 residual layers, and 4 convolutional layers. Subsequently, we continuously trained the network with these parameters until the loss function no longer decreased.

Impedance Tensor Reconstruction Test

We tested the trained ResNet network, as shown in Figure 2. The network effectively denoises and corrects noisy impedance tensors, reconstructing impedance tensors that closely approximate real impedance data, and demonstrates strong adaptability in handling out-of-quadrant phase data.

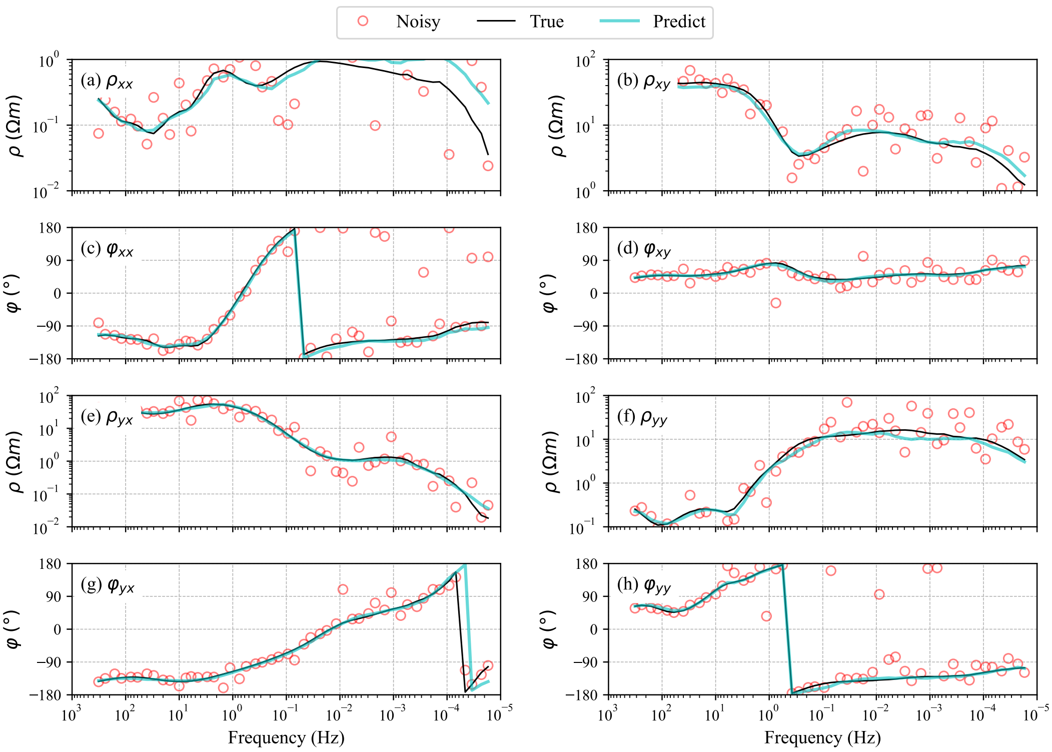

Figure 2: The reconstructed impedance tensor performance at a certain measurement point in the test set

Applications

ResNet M-estimation

Reconstructed impedance tensors are not entirely equivalent to real impedance tensors. To avoid potential unknown issues associated with directly using reconstructed impedance tensors, we propose a novel approach using reconstructed impedance tensors to enhance the processing of M-estimation data. Traditional M-estimation methods are susceptible to strong noise during iteration, leading to the presence of outliers in the results. Our approach involves substituting the ResNet-reconstructed impedance tensors for the previous iteration's results in each iteration of M-estimation, before updating residuals and weights. This process guides the M-estimation iterations towards a more reasonable direction, mitigating the impact of noise-induced outliers on the final results.

Method Testing

We tested this method using both synthetic and field-measured data. The test results of field-measured data, as shown in Figure 3, demonstrate that reconstructing impedance tensors based on ResNet effectively enhances the quality of M-estimation data processing. In scenarios without a remote reference channel, strong short-term noise near 1Hz adversely affected M-estimation, resulting in very low apparent resistivity (beyond the displayed range) and phase disorder. In contrast, the proposed method yielded reasonable apparent resistivity and phase estimates. Although the remote reference method can mitigate such short-term noise, our method performs better in situations where remote references is unavailable.

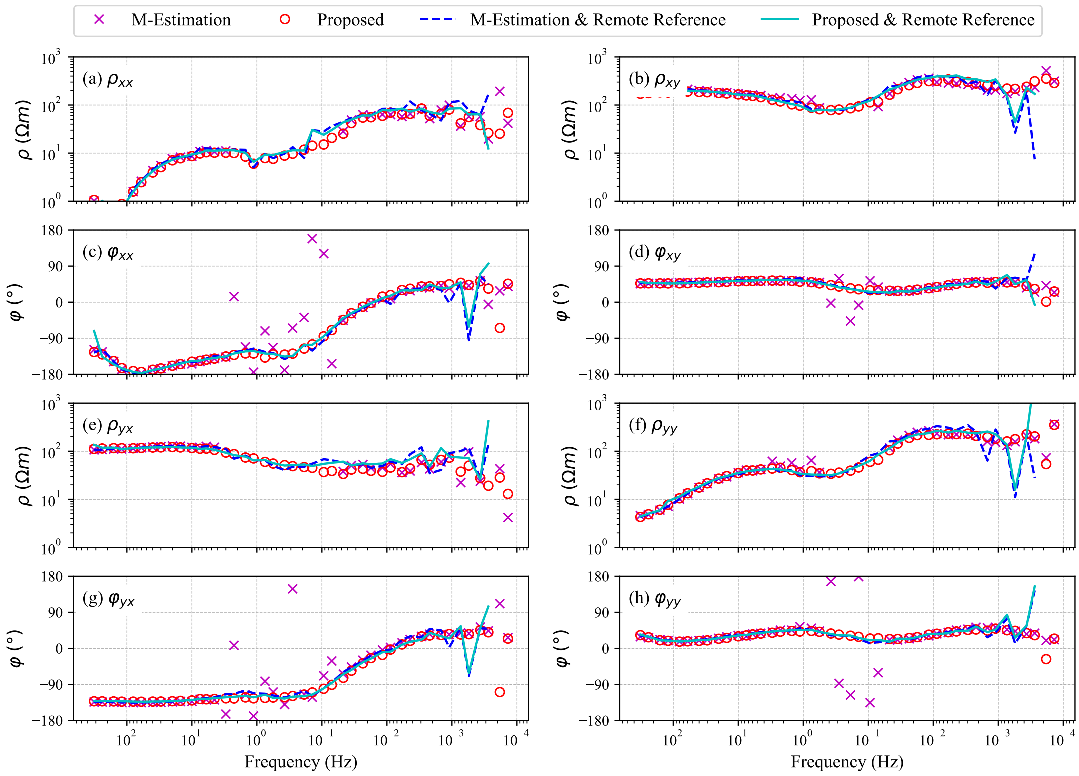

Figure 3: Comparison of processing effects between traditional M-estimation and proposed method on certain measured data

CONCLUSION

This paper presents a method for reconstructing magnetotelluric impedance tensors based on deep residual neural networks (ResNet). Through careful network construction and fine-tuning, this method accurately reconstructs noisy MT impedance tensors. It guides the iteration process of M-estimation to enhance data processing accuracy. Test results demonstrate its excellent performance in handling high-noise data and complex geological environments, suggesting broad application prospects. Future research will focus on further optimizing the model and exploring its application in larger-scale geophysical exploration tasks.

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