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Electrical resistivity imaging inversion: An ISFLA trained kernel principal component wavelet neural network approach

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ABSTRACT

The traditional artificial neural network (ANN) inversion of electrical resistivity imaging (ERI) based on gradient descent algorithm is known to be inept for its low computation efficiency and does not ensure global convergence. In order to solve above problems, a kernel principal component wavelet neural network (KPCWNN) trained by an improved shuffled frog leaping algorithm (ISFLA) method is proposed in this study. An additional kernel principal component (KPC) layer is applied to reduce the dimensionality of apparent resistivity data and increase the computational efficiency of wavelet neural network (WNN). Meanwhile, a novel ISFLA algorithm is adopted for improving the learning ability and inversion quality of WNN. In the proposed ISFLA, a hybrid LC mutation attractor is used to enhance the exploitation ability and a differential updating rule is used to enhance the exploration ability. Four groups of experiments are considered to demonstrate the feasibility of the proposed inversion method. The inversion results of the synthetic and field examples show that the introduced method is superior to other algorithms in terms of prediction accuracy and computational efficiency, which contribute to better inversion results.

1. Introduction

Electrical resistivity imaging (ERI) is one of the most commonly used geophysical exploration methods. It is widely used in hydrogeological, environmental, archeological and geotechnical field, which calculates and analyses the apparent resistivity from a large number of resistance measurements made from electrodes. During the last several decades, various approaches to the interpretation of geoelectrical resistivity data have been published, based on linear or quasi-linear inversion techniques (Lesur, Cuer, & Straub, 1999; Loke & Barker, 1995, 1996; Shima & Sakayama, 1987). However, the inverse problem is a classical nonlinear and ill-posed parameter estimation problem. These linear inversion algorithms are mostly linear approximations of nonlinear problems and critically depend on the initial parameters chosen for them (El-Qady & Ushijima, 2001).

In recent years, nonlinear inversion methods have been introduced into resistivity inversion due to the global optimization ability, such as artificial neural network (ANN) (El-Qady & Ushijima, 2001), particle swarm optimization (PSO) (Shaw & Srivastava, 2007), simulated annealing (SA) (Sharma, 2012), and genetic algorithm (GA) (Liu, Li, Nie, Wang, & Zhang, 2012; Schwarzbach, Börner, & Spitzer, 2005). ANN performs an intelligent nonlinear mapping between input ("Apparent resistivity") and output ("True resistivity") data, allowing the network to acquire information and learn about the problem while it is being solved. A few researchers have studied the applicability of back propagation neural network (BPNN) to solve geophysical inverse problem for 1D vertical electrical sounding data (El-Qady & Ushijima, 2001; Maiti, Erram, Gupta, & Tiwari, 2012). However, even in moderately complex areas, the 1D approach is not sufficiently accurate. So 2D direct current investigations and resistivity data inversion using BPNNs have been launched and significant results have been obtained (Jiang, Dai, & Dong, 2016a, b; Singh, Tiwari, & Singh, 2010). 3D resistivity surveys are widely used in areas with complex geology, and the BPNN interpretation models have used in 3D ERI inversion and given the most accurate inversion results as all geological structures are 3D in nature (Ho, 2009; Neyamadpour, Abdullah, & Taib, 2010; Neyamadpour, Abdullah, Taib, & Niamadpour, 2010). Although BPNN makes the interpretation more general and accurate than linear inversion approaches, it also has some limitations: slow convergence, low accuracy and over-fitting phenomenon in training, etc. Al-Abri and Hilal (2008). Nonlinear and complex direct current resistivity data require more efficient ANN models and more intensive optimization procedures for better results and interpretations.

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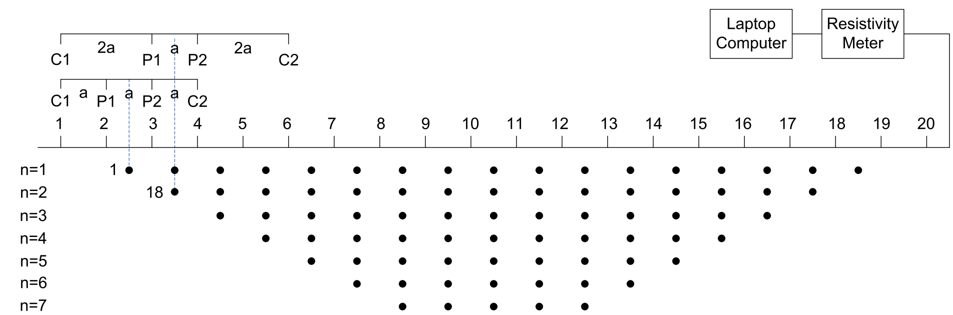

Fig. 1. The arrangement of electrodes for Wenner–Schlumberger configuration and the sequence of measurements collected. C1 and C2 are two current electrodes, P1 and P2 are two potential electrodes, n is the number of measurement level, the laptop microcomputer is used to automatically select the relevant four electrodes for each measurement, and the resistivity meter is used to calculate the ground resistivity.

Wavelet neural network (WNN), which has strict theory base and high nonlinear mapping capability, is a combination of wavelet theory and neural networks. Nguyen et al. (2012) developed a WNN algorithm for electroencephalogram artifact. Kasiviswanathan, He, Sudheer, and Tay (2016) presented and compared WNN and ANN for streamflow forecast, both of which were combined with the ensemble method using block bootstrap sampling, in terms of the forecast accuracy and precision at various lead-times on the Bow River, Alberta, Canada. Duan, Liu, Jiao, Zhao, and Zhang (2017) proposed a SAR image segmentation method based on convolutional-wavelet neural networks and Markov Random Field. Compared with traditional neural networks, WNN shows better prediction accuracy, convergence rate and fault tolerance to the complex nonlinear, uncertain and unknown system (Zhang, 1994).

In ERI inversion, the apparent resistivity data are always high dimensional samples, so the construction of a wavelet basis in the hidden layer is computationally expensive. Principal component analysis (PCA) is a useful dimensional compression technology whose feature is based on the minimum mean square error. Recently, some hybrid architectures which incorporated PCA into the framework of neural network have been studied. Gross and Luttermann (1993) first proposed a hybrid architecture combining PCA with a multilayer perception for face recognition; Ghosh-Dastidar, Adeli, and Dadmehr (2008) used PCA technology to enhance radial basis function neural network for robust epilepsy and seizure detection. Ravi and Pramodh (2008) applied principal component neural network to bankruptcy prediction. Reddy and Ravi (2013) proposed a differential evolution trained kernel principal component WNN and differential evolution (DE) trained kernel binary quantile regression for bankruptcy classification. However, in spite of the architecture simplicity and guaranteed convergence, the PCA neural networks have not been investigated for ERI inversion.

In this study, we investigate a kernel principal component wavelet neural network trained by an improved shuffled frog leaping algorithm (denoted ISFLA-KPCWNN) in 2.5D ERI inversion. Firstly, an additional KPCA layer is applied to extract the features of high dimensional apparent resistivity samples. Secondly, the shuffled frog leaping algorithm is used to improve the learning procedure of WNN. Thirdly, a hybrid LC mutation attractor is used to enhance the local search process of SFLA and a differential updating rule is applied to enhance the diversification and the global search ability of SFLA. Finally, a synthetic example and a field example are used to verify the feasibility and effectiveness of the proposed inversion method. The inversion performance of the proposed method is compared with several different kinds of SFLAs and WNNs, and it has been found to be better in computational efficiency, convergence stability and inversion accuracy.

The remainder of the paper is organized as follows. Section 2 introduces the electrical resistivity imaging technology. Section 3 reviews the theories of WNN and SFLA. Section 4 proposes the ISFLA-KPCWNN algorithm for ERI inversion. Section 5 presents the experimental evaluations and result discussions. Section 6 gives some concluding remarks and suggestions for the future work.

2. Electrical resistivity imaging technology

2.1. Wenner–Schlumberger configuration

Electrical resistivity technique involves measurements of electrical resistance of subsurface structure. For a measurement, a direct current is injected into the ground between two current electrodes and a voltage is measured through other two potential electrodes. The ratio of the voltage to the current is referred to as the electrical resistance of the ground. Such surveys are usually carried out using a large number of electrodes connected to a multicore cable. As an example, Fig. 1 shows a possible sequence of measurements for the Wenner–Schlumberger configuration with 20 electrodes. The basic spacing between adjacent electrodes is "a". The first step is to make all the possible measurements with electrode spacing of "1a". After completing the sequence of measurements with "1a" spacing, the next sequence of measurements with "2a" electrode spacing between current and potential electrodes is made. The same process is repeated for measurements with "3a", "4a", "5a" and other spacing. All the possible measurements are made finally.

2.2. 2.5D forward problem

The apparent resistivity values for Wenner–Schlumberger configuration with 42 electrodes are calculated using forward modeling method. In each synthetic profile, 18 layers and 396 datum points can be gathered. The finite volume approach with cell centered and variable grid is applied (Pidlisecky & Knight, 2008). The forward problem can be described as follows:

The 3D potential field due to a known input current is related to the conductivity structure. It is governed by the Poisson equation:

$$-\nabla \cdot \sigma(x, y, z)\, \nabla\phi(x, y, z) = I\delta(x - x_s)\, \delta(y - y_s)\, \delta(z - z_s) \quad (1)$$

where ϕ is the electric potential field; I is the current source strength from a dipole; σ is the electrical conductivity structure; $\delta(x - x_s)\, \delta(y - y_s)\, \delta(z - z_s)$ are the Dirac delta functions, which are non-zero only at the locations of the current sources and sinks.

In 2.5D geological situations, the subsurface conductivity structure is invariant in one dimension, we assume $\left(\frac{\partial}{\partial y}\right) \sigma(x, y, z) = 0$, then Eq. (1) can be rewritten as follows:

$$-\nabla \cdot \sigma(x, z)\, \nabla\phi(x, y, z) = I\delta(x - x_s)\, \delta(z - z_s)\,. \quad (2)$$