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Auto measurement while drilling mud pulse signal recognition based on deep neural network

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ABSTRACT

The noise intensity of drilling mud pulse signal is large. It is difficult to recognize signal at once because of the low signal to noise ratio (SNR) of the detected signals. Moreover, the SNR has a low accuracy. A method which is called stacked wavelet autoencoder (SWAE) for recognizing mud pulse signals based on deep learning is proposed in this paper. The model is composed of wavelet neural network and autoencoder, which are trained for mud pulse signal classification specifically. Combining with the drilling mud pulse signal, the recognition performance of the typical data set is analyzed and tested. SWAE enhances the SNR of output signal by using signal detection method. And then the output detected signal is considered as a signal classification attribute. Finally, experimental results show that SWAE is suitable for mud pulse signal recognition, and it has strong ability to extract features from samples automatically and robustness. Experimental results confirm that the performance of SWAE is better than the methods in the state of the art under the same SNR.

1. Introduction

During the process of the petroleum exploration and development, the downhole information transmitted to the ground by mud pulse signals should be denoised and recognized in real time in measurement while drilling (MWD). In order to ensure the accuracy and clarity of the obtained information, how to recognize mud pulse signals effectively is a key problem (Chin et al., 2014; Chin and Ritter, 1998).

Presently, the researchers mainly focus on how to remove noises from signals, a series of methods of signal denoising have been put forward, such as the digital filtering method (Väisänen and Renfors, 2001); the wavelet transform denoising method (Xu et al., 2005); and empirical mode decomposition (EMD) algorithm (Huang et al., 1998; Zheng et al., 2012). With regard to mud pulse signal recognition, Tu et al. (2011) proposed a phase feature recognition algorithm for pulse signal recognition based on Manchester modulation, which has a good recognition rate for mud pulse signals. Zhao et al. (2011) applied the comparison of threshold method and neighborhood method, which finds the position of the pulse by the method of mixed peak detection. A method called mode similarity measure was used to recognize pulse waveform, and the three of Euclidean distance, nip angle cosine and Tanimoto are regarded as the standard of measurement (Tu et al., 2012). Li et al. (2013) used the principle of the maximum principle of judging and sliding window area to identify the pulse signal, it improve the accuracy of data decoding effectively. Method of combination of various methods to recognize mud pulse signal laid the foundation for the accurate identification and extraction of the signal (Zhang et al., 2014; Tu et al., 2013). Fang and Gong (2011) applied Costas phase locked loop technology and numerical control oscillator for signal recognition. Although it is an effective way to screen out the noise based on the denoising methods in the recognition models, the current methods of the recognition accuracy will be greatly reduced, when the original signal is completely covered by noise and the SNR is low after denoising.

The artificial neural network can realize multidimensional nonlinear recognition of sample data. When it combines the improved adaptive fuzzy system, it can achieve more effective prediction for the target object (Singh et al., 2012), such as the estimation of strength of rocks (Sharma et al., 2017a, 2017b); predicting CO2 permeability of bituminous coal (Sharma et al., 2017a, 2017b). But in recent years, in view of an effective pattern recognition method to imitate the human brain recognition process (Hinton et al., 2006), researches focusing on how to use deep learning to improve accuracy rate in various fields witness an upward trend. Deep learning is often used in signal recognition, the most common includes the EEG (electroencephalograph) signal recognition (Jirayucharoensak et al., 2014), mechanical fault detection (Lu et al., 2017), sound signal recognition (Deng et al., 2013), radar signals recognition (Işık and Artuner, 2016), etc. Researches show

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that deep learning is becoming to be an effective method for the recognition of mud pulse signal.

On the basis of studies mentioned above, we propose a new deep neural network, named stacked wavelet autoencoder (SWAE), which combines wavelet neural network and autoencoder. The first layer of the hidden layer of the network uses wavelet neural network, and the second to third layers of the hidden layer adopt autoencoder. Finally, the Softmax layer is used to classify the output signal categories. After finishing the layer by layer pre-training, the whole model is fine-tuned by back propagation algorithm. The pre-training can alleviate the problem of local optimal solution (Ding et al., 2017; Hinton et al., 2006), and the fine-tuning can optimize the parameters of the model to improve the recognition effect. Experiments show that SWAE performs better than the stacked autoencoder (SAE) model, and it is also more efficient than traditional machine learning methods.

2. Stacked wavelet autoencoder (SWAE)

The signal that are transmitted downhole to the surface equipment need to be intercepted to the proper length and then pre-processed. After the above steps, the signal can be rectified and extracted features to be recognized. The proposed classification pipeline is illustrated in Fig. 1.

The reason of low recognition accuracy is not only the limitation of the recognition methods, but also the inadaptability of the data after noise reduction. These reasons described above have resulted in changes of accurate rates. Therefore, the wavelet neural network and autoencoder are combined into a new deep learning model which is called SWAE. The framework of SWAE is reported in Fig. 2 in details. The model consists of four parts: the input layer, the signal rectify layer, the feature extraction layer and the Softmax layer. As to signal rectify layer, one wavelet neural network forms it. As to feature extraction layer, 3 autoencoders are cascaded to form it.

2.1. Signal rectify

In order to enhance the potential ability of wavelet to denoise, we adopt wavelet neural network in signal rectify layer to correct the input of the model, as shown in Fig. 3. The difference between normal feedforward neural network and wavelet neural network is that a wavelet base function is selected as the activation function of wavelet neural network (Hu et al., 2002; Lu et al., 2010). For a mapping from multiple input to multiple output f: $R^m \to R^m$, the realization of its network equation can be expressed as:

$$y_i = f(\boldsymbol{x}) = \sum_{j=1}^{J} w_{ij} h_{a_j,b_j} \tag{1}$$

And the wavelet base function is:

$$h_{a_j,b_j} = \psi\left[\left(\sum_{k=1}^{K} w_{jk} x_k - b_k\right)/a_k\right] \tag{2}$$

where $\boldsymbol{x} = (x_1, x_2, ..., x_K)$ is an input sample, $\boldsymbol{y} = (y_1, y_2, ..., y_I)$ is an output sample, J is the number of wavelet base, that is to say, the number of neurons in the hidden layer. a is the scaling factor of wavelet transform, and b is the translation factor of wavelet transform. The activation function from the unit k of the input layer to the unit j of the hidden layer is the Morlet wavelet function $\psi\left(\frac{z-b_k}{a_k}\right)$, and the weight value is w_{jk}. w_{ij} is the weight value from unit j of the hidden layer to the unit i of the output layer. The parameters w_{jk}, w_{ij}, a_k, and b_k should be trained throughout the network.

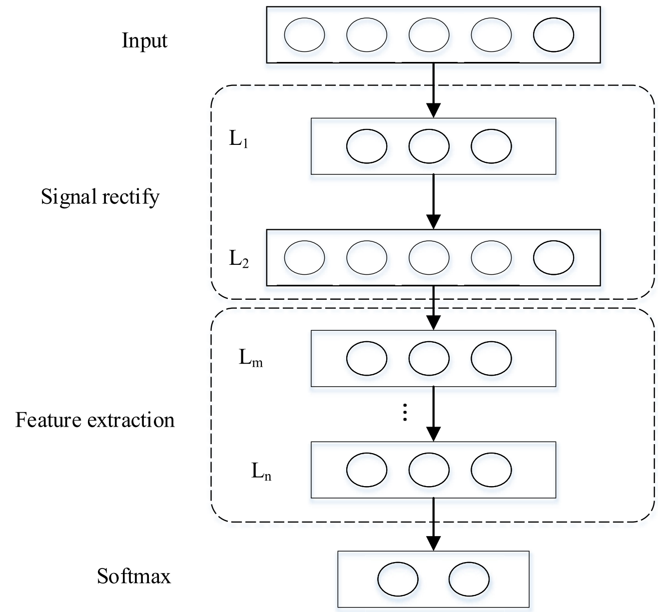

Fig. 2. Structure of stacked wavelet autoencoder model.

When training the signal rectify layer, the current output error of the network is calculated after each training step is completed. If the output error is greater than the output error at the previous time, the learning rate is reduced, otherwise, the learning rate is increased.

2.2. Feature extraction

PCA (principal component analysis) can solve the high-dimensional problem of data, and try to use data dimensionality reduction to extract features automatically, but the effect of PCA is better only for linear data. In order to realize the feature extraction function for mud pulse signal, autoencoder is used to build the underlying network (Wang et al., 2015). A feature extraction layer is formed by cascading multiple autoencoders, and the corresponding network structure is shown in Fig. 4. The output of the signal rectify layer is the input of the first layer of the autoencoder, and the output of the first layer of the autoencoder is the input of the next layer. Each autoencoder can learn the key features of their input layer well, then it can achieve feature extraction (Sun et al., 2016) eventually. If the reconstructed samples are $\boldsymbol{r}$, we can obtain the equation as follows:

$$\boldsymbol{r} = g_{\boldsymbol{W}'}(\boldsymbol{h}) = s(\boldsymbol{W}'\boldsymbol{h} + b') \tag{3}$$

The autoencoder takes minimized reconstruction error to realize model training, that is

$$\min_{\boldsymbol{W}} \|s(\boldsymbol{W}' s(\boldsymbol{W}\boldsymbol{x} + b) + b') - \boldsymbol{x}\|_2 \tag{4}$$

where $\boldsymbol{W}$ is weight matrix of coding process, and b is bias value of coding process. $\boldsymbol{W}'$ is weight matrix of decoding process, and b' is bias value of decoding process. s is a nonlinear activation function.

The reconstruction error is defined by cross entropy, $L_H(\boldsymbol{x}, \boldsymbol{r}) = -\sum_{k=1}^{n} [\boldsymbol{x}_k \log \boldsymbol{r}_k + (1 - \boldsymbol{x}_k)\log(1 - \boldsymbol{r}_k)]$. In order to make the reconstructed sample as a substitute for the original input sample as

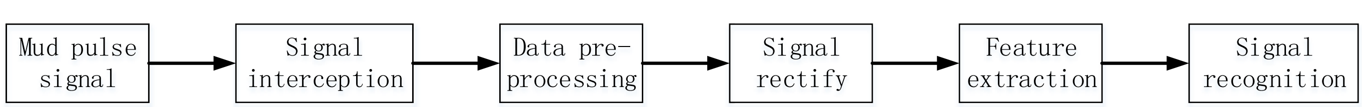

Fig. 1. Simplified mud pulse signal classification pipeline.