SDA-based Neural Network Approach for MWD Mud Pulse Signal Recognition

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Abstract. The low signal to noise ratio (SNR) of the detected mud pulse signal leads to difficult to recognize signal at once. The recognize accuracy is low. So a stacked denoising autoencoder recognition model was constructed. Combining with the drilling mud pulse signal, the recognition performance of the typical data set is analyzed and tested. The proposed method of recognizing mud pulse signal enhances the SNR of output signal by using signal detection method. And then we take the output detected signal as signal classification attribute. Test results also show that the proposed method is suitable for mud pulse signal recognition, and it has strong ability to extract features from samples automatically and robustness. Performance is better than pattern matching and support vector machine and other recognition methods under the same SNR.

Introduction

In the process of measurement while drilling (MWD), the experts need to know the downhole information in real time, and make accurate judgment to the next operation. And underground information is transmitted to the ground through the mud inside the drill string. Then the equipment on the ground receives a series of transmitted signals according to the prior agreed protocol and processes the signals to extract the final useful parameters. So, it is essential to process signals, which determines the decision of the expert guidance, but also is now the focus of research and difficulty problem [1, 2].

In recent years, many mud pulse signal recognition methods have been proposed. Tu et al. [3] suggested a phase feature recognition algorithm for pulse signal recognition based on Manchester modulation. In Ref. [4], Zhao et al. applied the comparison of threshold method and neighborhood method, which finds the position of the pulse by the method of mixed peak detection. In Ref. [5], Li et al. used the principle of the maximum principle of judging and sliding window area to identify the pulse signal, and effectively improve the accuracy of data decoding. Method of combination of various methods to recognize mud pulse signal laid the foundation for the accurate identification and extraction of the signal [6]. In Ref. [7], Fang et al. applied Costas phase locked loop technology and numerical control oscillator for signal recognition. At present, the recognition methods mainly rely on the denoising methods can screen out the noise effectively, but when the original signal is completely covered by noise and the SNR is low after de-noising, the current methods of the recognition accuracy will be greatly reduced.

As an effective pattern recognition method, deep learning is often used in signal recognition, such as the EEG signal recognition [8], mechanical fault detection [9], and radar signals recognition [10].

On the basis of the study mentioned above, we use the depth neural network as classifier, properly speaking, we select stacked denoised auto-encoder (SDA) to recognize mud pulse signal, so as to achieve better feature representation in the process of signal recognition in MWD. The features extracted from multiple hidden layers can capture the main components of the input signal as far as possible to realize the signal reconstruction and attribute reduction. The recognition process of mud pulse signal based on SDA is divided into four continuous stages: firstly, the signals received on the ground are detected so as to remove low frequency component noise and random
Gauss white noise and improve output SNR. Secondly, the detected signals are divided into training set, validation set, and test set. Thirdly, a deep neural network model is constructed, and the greedy layer-by-layer training algorithm is applied to the model, and then the parameters of the model are adjusted by using the back propagation algorithm. Finally, the test data are used to verify the effectiveness of the proposed SDA model. The algorithm flow chart is shown in Figure 1. Compared with other methods, the recognition results show that the proposed method is more effective and robust, and has a strong practicability.

Mud Pulse Signal Recognition Based on SDA

Since the depth neural network has been proposed, stacked denoising autoencoders (SDA), deep belief network (DBN), convolutional neural network (CNN), and long short-term memory (LSTM) are proposed to be applied in different fields. SDA model is a kind of network model usually used in deep learning, because of its robust representation of the input signal, it has strong generalization ability, and it is better than DBN in many respects [11].

Denoising Autoencoder (DAE)

In order to make the model more robust, the original data can be superimposed with noise by a certain probability of binomial distribution, and it can get the similar characteristics with the signal when the signal is not superimposed, that is the function of DAE. The network structure of DAE is shown in Figure 2(a). For a data sample \( x = (x_1, x_2, ..., x_n) \), we can add random noise in terms of Eq. (1), that is to say, the value of the input node is 0 with a certain probability, we can get \( \tilde{x} \).

\[
\tilde{x} \sim qD(x | x)
\]  

Then after taking denoising autoencoder to samples added noise, we can obtain the equation as follows:

\[
h = f_w(\tilde{x}) = s(W \tilde{x} + b)
\]  

Where \( s \) function is nonlinear function, such as sigmoid function or tanh function, and \( W \) is weight matrix of input samples, \( b \) is bias value, \( h \) is encoding output. DAE decodes \( h \) and gets reconstructed sample \( r \), that is
\[ r = g_w(h) = s(W'h + b') \]

(3)

Where the \( W' \) is a weight matrix of encoded samples, \( b' \) is bias value of encoded samples.

The reconstruction error of DAE is \( L_H(x, r) = \|x - r\|^2 \). If the reconstruction error is defined by cross entropy, \( L_H(x, r) = -\sum_{k=1}^{x_i} [x_i \log r_i + (1 - x_i) \log(1 - r_i)] \). In order to make the reconstructed sample as a substitute for the original input sample as much as possible, we need to do as follows:

\[ \arg \min(L_H(x, r)) \]  

(4)

Training Steps of SDA

A SDA model is a neural network that makes up of multiple layers of SAE, the structure of SDA is shown in Figure 2(b), and SDA is able to abstract data from multiple levels, so it has better nonlinear expression ability than DAE, which can realize the automatic extraction of data’s features. The extracted features are inputted to the softmax classifier to achieve the classification recognition function. The implementation of SDA training can be realized by following five steps.

**Step1:** The weight matrix \( W \) and bias matrix \( b \) of the system are initialized, initialize the adding noise ratio which is called \texttt{corruption\_level}, initialize layer-by-layer epochs called \texttt{p\_epochs} and learning rate called \texttt{p\_lr} and fine tuning epochs called \texttt{f\_epochs} and fine tuning rate called \texttt{f\_lr};

**Step2:** We use \( X' \) which are got by adding the sample data \( X \) and noise by denoising coefficient as model’s input data to train the network parameters of the first hidden layer, and the output \( Y_i \) of the first hidden layer is calculated by using the trained network parameters;

**Step3:** We use \( Y_i' \) which are got by adding the \( i(i \geq 2) \) th output and noise by denoising coefficient as \( i+1 \) th layer’s input data, and use the same method as Step2 to train the network parameters of the \( i+1 \) th layer, this step is repeated until all the hidden layers are trained completely;

**Step4:** The output of the last layer of hidden layers is the characteristic of self-learning model, the output data and data labels are seen as input to the softmax layer in order to train the network parameters of classifier;

**Step5:** The weight matrix of getting by Step2 ~ Step4 are treated as model’s initial parameters of fine tuning, and the training samples \( X \) are treated as input data. The loss function of the whole model is calculated. And then we use the back propagation of softmax layer to spread the error to each layer, and the parameters of the whole network are fine tuned. Finally, the optimal parameters of the final model are obtained.

Mud Pulse Signal Recognition Experiment

Mud Pulse Signal Recognition Model Based on Deep Neural Network

After the collected mud pulse signal \( X_i = (x_{i1}, x_{i2}, ..., x_{iN}) \) (where \( i \in R^N \), \( N \) is the number of training samples) is detected, the training data \( X_i' = (x_{i1}', x_{i2}', ..., x_{iN}') \) (where \( i \in R^N \), \( N \) is the number of training samples) needed for the experiment were obtained. The training data and the corresponding class label value \( B' \in [0, 15] \) are inputted into signal recognition model to train the model. Taking all the detected signal data as the input layer of the model to train the first hidden layer \( L_1 \) of the model by SAE, the output of the first hidden layer is used as the input of the second hidden layer to train second hidden layer \( L_2 \). The output of the \( j-1 \) th hidden layer is used as the input of the \( j \) th hidden layer to train the \( j \) th hidden layer \( L_j (j \geq 2) \). Layer by layer training, the output of the last
hidden layer is used as the input layer of the softmax classifier, which forms the whole network model. As a result, the number of neurons in the input layer is 80, the number of neurons in each hidden layer is optimized by successive training so as to find the best one. And the number of neurons in the output layer is 16. Sigmoid function \((\text{sigmoid} = 1/(1+\exp(-x)))\) is selected as neuron activation function. Unsupervised pre training is layer-by-layer training, training epochs \(p\_epochs = 50\), training rate \(p\_lr = 0.001\). And the fine tuning training using supervised softmax regression, the training epochs \(f\_epochs = 1000\), training rate \(f\_lr = 0.005\). The whole training algorithm for the model is backpropagation algorithm. The adding noise ratio of the first hidden layer \(\text{corruption\_level} = 0.3\), the rest of the layer does not add noise.

**Experimental Result Analysis**

In this paper, the 2288 sets of data were used to verify the model of the mud pulse signal collected at drilling site after a period of time of well opening, which random selection of 2000 sets of data as a training set, and the remaining 288 sets of data were randomly selected 160 sets of data as validation set, and the remaining 128 sets of data were used as the test set. At the same time it is essential to ensure that the number of data sets of the various groups is without big difference. For the recognition method of mud pulse signal based on SDA, we make the following tests by using actual acquisition data.

**Performance Comparison of Different Methods**

Evaluation indicators using precision (PEC) which evaluation of the results in the identification of the proportion of the target results and recall ratio (REC) which recall target category ratio from the desired category as well as the test time, the purpose of this is to evaluate the performance of the identification method. We use the same test set, and the SNR of the test set is 10 dB after noise reduction treatment. After normalizing denoised data, recognition methods can be used to recognize data and analyzed results. Naïve Bayesian classification (Bayes) calculates the probability that a given entry belongs to a class, and selects the largest category as its class. For fuzzy C-means clustering (FCM), the number of categories is given, and the purpose is to find out the best analysis of the test set. Pattern matching method (PM) uses Pearson correlation coefficient method, the standard mud pulse signal template is established firstly, and then the recognition result is obtained by matching the test set. And SVM method uses RBF kernel function, the 5-fold cross-validation is used to select the penalty factor \(C\) and the relaxation variable \(\gamma\). The SDA method contains three hidden layers, and the number of network nodes is \([160, 80, 60]\), random 0-1 noise with a probability of 0.3 are added into the first hidden layer. We can see from Table 1 that the recognition REC and REC of the DAE method is the highest when the input SNR is uniform as the same number of test set, reached 89.84% and 91.87% respectively. And the shortest test time of recognizing methods is SVM method, which costs 0.12s. Although the test time of the DAE method costs 0.27s, the test time is longer than the SVM method, but it still can satisfy the requirement of the real-time performance of the system.

<table>
<thead>
<tr>
<th>test set</th>
<th>Bayes</th>
<th>FCM</th>
<th>PM</th>
<th>SVM</th>
<th>DAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>test set</td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
</tr>
<tr>
<td>SNR/dB</td>
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<td>10</td>
<td>10</td>
<td>10</td>
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<tr>
<td>REC%</td>
<td>76.56</td>
<td>71.88</td>
<td>86.72</td>
<td>85.94</td>
<td><strong>89.84</strong></td>
</tr>
<tr>
<td>PEC%</td>
<td>75.78</td>
<td>65.63</td>
<td>88.66</td>
<td>87.71</td>
<td><strong>91.87</strong></td>
</tr>
<tr>
<td>test time/s</td>
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<td>0.48</td>
<td>0.40</td>
<td><strong>0.12</strong></td>
<td>0.27</td>
</tr>
</tbody>
</table>

**Accuracy of Each Recognition Method under Different SNR**

Figure 3 is the curve of accuracy of each recognition method under different SNR, it can be seen that with the increase of signal to noise ratio, the recognition accuracy of each identification method...
is improved in different degree. At the same time, the recognition accuracy of SAE method is higher than that of other two recognition methods in the same SNR.

![Figure 3. Accuracy of each recognition method under different signal to noise ratio.](image)

**Conclusions**

In this paper, a signal recognition method based on SDA is proposed to solve the problem of mud pulse signal recognition. Firstly, the partial low frequency noise and random noise in mud pulse signal are removed, and then the deep neural network is trained by using the signals to realize the automatic feature extraction and recognition of the signal. In this paper, the accuracy of the methods and the main methods in the identification of mud pulse signal are analyzed and compared. The experimental results show that the accuracy of the algorithm proposed in this paper is better than others. Under the condition of different SNR of the test set, this method is more excellent and has a certain degree of robustness. Of course, the greater the SNR of the data set, the better the recognition effect. So the proposed method will be benefit to extract the symbol information from complex data in the mud pulse. However, the SNR of the test signal will directly affect the recognition effect of the proposed method, and low SNR leads to poor recognition. Therefore, in terms of future work, we need to improve the denoising method to improve the SNR as far as possible. At the same time, we also need to improve the recognition model to enhance its robustness in order to make the method have a strong engineering application value.

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**References**


