Research on control system of small intelligent drilling rig based on lithology identification

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Abstract. Intelligent oil drilling rig can automatically complete the whole drilling process without human intervention, and can integrate big data with drilling, geology, logging and other disciplines. Aiming at the problem of insufficient rock breaking capacity and complex and changeable drilling process, a small intelligent drilling rig control system is designed. The structural drilling parameter samples such as WOB and rotating speed obtained by the sensor are used for lithology identification in the software MATLAB by using the neural network pattern recognition toolbox and GRNN generalized regression neural network respectively, and the control block diagram of the automatic drilling system is designed in Matlab / Simulink. The neural network control algorithm is used to compare with the classical PID control, The results show that the overshoot and rise time are significantly reduced, and the effect is good. When applied to the oil rig to realize constant WOB drilling, it is conducive to reasonably select the bit type, timely adjust the drilling parameters and improve the drilling efficiency, so as to realize the real intelligence of the oil rig.

1. Introduction

In order to reduce oil production cost and improve logging and drilling technology, it is very important to study new oil rigs in oil exploration and development [1-4]. With the development of intelligent technology, information technologies such as big data [5-7] and cloud computing are more and more widely used in the oil industry. Intelligent oil drilling rig has become an inevitable trend in the field of oil drilling equipment.

Petroleum exploration and development is complex [8] and changeable. Rock drilling is a nonlinear and time-varying process, so it is difficult to establish an accurate mathematical model. In order to realize real-time drilling control under complex geological conditions, a small intelligent drilling rig control system is designed. According to the drilling parameters such as WOB, rotating speed and torque obtained in real time, BP neural network algorithm is used to identify lithology through MATLAB neural network pattern recognition toolbox and GRNN generalized regression neural network, and the control block diagram of automatic drilling system is designed in Simulink. Neural network control is applied to oil drilling rig to realize constant WOB drilling, which provides technical support and reference for intelligent drilling design.
2. Design of small intelligent drilling system

2.1. One basic composition of small drilling rig
The composition of small intelligent drilling rig is determined according to the drilling process requirements, including WOB sensor, top drive motor, speed detection mechanism, etc. the drilling parameters such as WOB, speed and torque are obtained in real time through the sensor.

![Fig 1. basic composition of small intelligent drilling rig](image)

2.2. Automatic drilling control system
The main purpose of the automatic drilling control system is to ensure that the bit WOB is a constant WOB value, as shown in Figure 2. In order to simplify the control algorithm, the automatic drilling control system mainly includes inner hydraulic ring, middle speed ring and outer WOB ring. The transfer functions of the three control links are designed and calculated respectively, and the three loop transfer functions are built in Simulink.

![Figure 2. structure diagram of automatic drilling system](image)

PID controller is a basic control mode to improve industrial control, and the control mode is simple. Figure 3 is the classical PID control simulation control block diagram.
2.3. Application of neural network control in automatic drilling

As a controller, neural network can effectively control uncertain, uncertain systems and disturbances, so that the control system can achieve the required dynamic and static characteristics.

Take the input of the original PI controller, i.e. error E, as the input X of the neural network controller and the output y of the PI controller as the output of the neural network. Run the simulation program to obtain a section of training data:

BP algorithm for neural network training. The training procedure is:

cle
p=x.signals.values';  % Neural network training samples
T=y.signals.values'; % Neural network training target value net = newff (minmax (P), [20 10 1],
{ 'Tansig', 'Tansig', 'purelin' }, 'trainlm');
net.trainparam.epochs=1000;  % The number of iterations is set to 1000
net.trainparam.goal=0.0001; % The error is set to 0.1
net.trainParam.lr = 0.01;  % The error is set to 0.1
net.trainParam.showWindow = 1;
net=train(net,p,T);  % Training neural network
o=sim(net,p);
figure;
plot(p,T,'*',p,o); % Draw the result and error curve after training
gensim(net,-1);

BP algorithm is used for neural network training, the training error curve and the fitting curve after training are:
2.4. Operation results of neural network control

According to the drilling field data, when the bit weight on bit is about 20t, the drilling speed is directly proportional to the square of the weight on bit. Therefore, the step signal with amplitude of 20 is selected as the input of the controller. The automatic drilling control system model is built in Matlab / Simulink system. The obtained neural network controller (below the figure) is used for simulation and compared with the PID control model (above the figure). As shown in the figure 7 below, and the system inputs the same step response signal in PID control and neural network control. The simulation comparison diagram of control system is shown in Figure 8.

Figure 5. training error curve

Figure 6. training fitting curve

Figure 7. control model block diagram
It can be seen from the figure that the rise time of the system under PID control is 2.5s, while the rise time of the system under neural network control is 0.2S and the overshoot is 0. Therefore, in terms of overshoot and rise time, the effect of neural network control is obviously better than PID control, and each performance index is good.

3. Formation lithology identification
Facing the complex formation environment, lithology identification [9] is one of the important research contents in formation evaluation, reservoir description and real-time drilling monitoring. Identifying the lithology information of the current position of the bit during drilling can optimize the drilling parameters according to the characteristics of formation lithology [10], improve the rock breaking efficiency and reduce the drilling cost.

3.1. BP neural network algorithm modelling
Using the nonlinear characteristics of neural network [11-14], the static, dynamic, inverse dynamic and prediction models of nonlinear system can be established to realize system modeling and identification. The algorithm modeling process is shown in Figure 9.

Figure 8. control response curve

Figure 9. algorithm flow
3.1.1. BP neural network lithology identification model

The sensor \cite{15} can collect the actual WOB, ROP, torque, mechanical vibration, etc. of drilling, and fully use the parameters collected by the sensor \cite{16} to realize pattern recognition.

The neural network has the ability of pattern recognition. In this paper, a three-layer BP neural network structure \cite{17} is adopted. As shown in Figure 10, the input layer contains four neurons corresponding to the input average WOB, the average bit speed, average torque and average ROP. The output layer contains two neurons, corresponding to the two types of lithology to be identified.

![Figure 10. lithology identification neural network](image)

3.1.2. Selection of learning samples

The neural network learning algorithm is used to train the learning samples in the standard input-output model \cite{18}. 26 of the 36 rock sample groups obtained are selected and sent to the lithology recognition model of BP network shown in Figure 3-2 for training. The connection weight of neural network is adjusted through learning. When the training meets the requirements, the remaining 5 are used as verification set and test set respectively. The required input mode can be recognized by using neural network parallel reasoning algorithm.

| Bit pressure /KN | Speed /rpm | Torsion /N*m | Mechanical drilling /m/h | Output | Lithology   |
|------------------|------------|-------------|--------------------------|--------|-------------|
| 98.878           | 10.906     | 1949.084    | 10.906                   | 0      | sandy rock  |
| 100.548          | 10.603     | 1864.769    | 10.603                   | 0      | sandy rock  |
| 101.294          | 9.811      | 1942.814    | 9.811                    | 0      | sandy rock  |
| …                | …          | …           | …                        | …      | …           |
| 98.578           | 10.663     | 1869.247    | 10.663                   | 0      | sandy rock  |
| 150.938          | 61.239     | 2985.361    | 19.652                   | 0      | sandy rock  |
| 150.211          | 62.394     | 2967.878    | 18.28                    | 0      | sandy rock  |
| …                | …          | …           | …                        | …      | …           |
| 153.697          | 62.956     | 3016.565    | 15.403                   | 0      | sandy rock  |
| 154.508          | 62.864     | 3016.271    | 16.203                   | 0      | sandy rock  |
| 148.255          | 62.700     | 1958.939    | 8.398                    | 1      | granite     |
| …                | …          | …           | …                        | …      | …           |
| 148.267          | 62.36      | 1985.789    | 8.774                    | 1      | granite     |
| 148.178          | 62.296     | 2312.775    | 8.556                    | 1      | granite     |
| 147.850          | 62.771     | 2233.958    | 8.505                    | 1      | granite     |
3.1.3. Neural network output results
When neural network solves the problem of pattern recognition, it usually creates a network to learn and train the classified target data, and finally uses the trained network for the classification process. Neural network pattern recognition toolbox mainly uses confusion matrix and mean square error to evaluate the effect of network.

Figure 11. confusion matrix

Figure 12. mean square error diagram

Fusion matrix is called confusion matrix or matching matrix. It is a matrix indicating the effectiveness of classification.

Figure 11 shows the confusion matrix for training set, verification set, test set and three kinds of data after combination. The numbers in the box represent the number of samples in each data set, and the percentage represents the proportion of each sample in this data set. The value in the green box is
the correct response value, the value in the red box is the wrong response value, the lower and right light gray boxes represent the accuracy of the corresponding sample attribute prediction, and the value in the blue box is the accuracy of the overall response. It can be seen from the figure that the correct response value is very high, the error response value is very low, and the accuracy of the overall response is very high. Therefore, the lithology recognition accuracy of the neural network model is very high.

As shown in Figure 12, the mean square error diagram shows that the three colored solid lines are: MSE performance of each generation of BP training process. With the iterative process, the error decreases gradually. The best dotted line indicates that the BP network is trained on the first generation of the 17th generation, and the error is very small until the 17th generation converges.

Input parameters of neural network: \{WOB, rotating speed, torque, ROP\}
Output parameters of neural network: \[[0 \ 1]\] - sandstone
\[[1 \ 0]\] - granite

When predicting lithology by neural network, two samples 1 and 2 correspond to each other in the output layer.

The outputs Y1 and Y2 of the neural network meet the following conditions at the same time:
1) \(y_1 = \max (y_1, y_2)\);
2) \(y_1 \geq 0.9\);

It is considered that the measured lithology is 1, otherwise it is considered that the measured lithology cannot be identified.

Five groups of rock samples are sent to the BP network lithology recognition model trained for prediction. The identification results are shown in Table 2. It can be seen from the table that the actual results of the training network on the prediction samples are consistent with the actual situation.

| catalogue number | actual rock nature | BP algorithm network output | BP algorithm provides the identification results |
|------------------|-------------------|----------------------------|----------------------------------|
| 1                | Sandy Rock        | [4.4258e-08 \ 1]          | Sandy Rock                       |
| 2                | Sandy Rock        | [4.1174e-08 \ 1]          | Sandy Rock                       |
| 3                | granite           | [1 \ 1.3130e-11]          | granite                          |
| 4                | granite           | [1 \ 1.5079e-09]          | granite                          |
| 5                | granite           | [1 \ 1.4418e-11]          | granite                          |

3.2. GRNN generalized regression neural network
Generalized regression neural network is a radial basis function network based on mathematical statistics\(^{[21]}\). Its theoretical basis is nonlinear regression analysis. GRNN has strong nonlinear mapping ability and learning speed. When there are few sample data, the prediction effect is very good, and the network can also deal with unstable data.

3.2.1. Algorithm modeling
GRNN consists of four layers in structure, namely input layer, mode layer, summation layer and output layer\(^{[22]}\). The number of neurons in the input layer is equal to the dimension of the input vector in the learning sample. Each neuron is a simple distribution unit, which directly transmits the input variables to the mode layer.
3.2.2. Program simulation

The data matrix is established according to the drilling parameters, the program is written, and the GRNN generalized regression neural network algorithm is used for lithology identification. The recognition rate is 86.111%, and the simulation diagram is as follows:

![Figure 13. diagram of mean square error](image1)

![Figure 14. diagram of sample partial autocorrelation function](image2)

4. Formation lithology identification

Figure 15 shows the whole process of small intelligent drilling rig system control. Specific steps:

Step 1: the sensor group collects drilling parameters, the computer processes the data and identifies the formation lithology, and queries the experience database to obtain the required feed force;

Step 2: the feed force is input to the neural network controller, which changes the size of the electrical signal and adjusts the pressure of the electro-hydraulic proportional valve;

Step 3: the pressure of the inlet and outlet of the actuator cylinder is adjusted, and the feed force is adjusted awesome.

Step 4: pressure sensor collects the pressure value of the inlet and outlet of the pressurized oil cylinder, and gets the same size of the actual feed force and the feed force required for rock breaking. If it is not equal, it will jump to Step 2 until awesome.

![Figure 15. Intelligent control flow chart](image3)
5. Conclusion
(1) Using pattern recognition toolbox and GRNN generalized regression neural network for data analysis, the output accuracy is very high and the recognition rate is high;
(2) The automatic drilling control system of the drilling rig uses neural network for intelligent control, which improves the response time and drilling efficiency and reduces the error;
(3) The realization of intelligent of small drilling rigs will have a positive impact on the more comprehensive, refined and reliable use of new drilling rigs in the future, and improve the oil exploitation level and drilling technology.

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