Video Logging Casing Damage Image Recognition Based on GA-BP Neural Network

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Abstract. Oil casing damage detection is an important work to maintain the normal production in the oil field. Currently, the Back Propagation (BP) neural network is a frequently used method to automatically identify the casing damage. However, the BP neural network can only approach the local minimum, furthermore the learning speed is slow, and the structure selection can’t be determined accurately. Therefore, in this paper, a recognition method based on the optimization of initial threshold and initial weight of BP neural network through genetic algorithm (GA) is proposed to improve the accuracy and efficiency of neural network recognition. Based on the oil casing damage image samples, this paper firstly constructs a feature parameter table of three damage types, and then analyzes the main components of the obtained feature parameters to reduce the dimensions, and finally builds a GA-BP neural network classifier. Using the construction result of feature parameters as the network’s input parameters, the experimental results show that the accuracy rate of GA-BP neural network is 78.67%, while the accuracy rate of BP neural network is 75.22%, indicating that the recognition result based on GA-BP neural network is better.

1. Introduction

The oil casing damage will not only affect the subsequent series of exploitation, but also threaten the production safety of the whole oil field when the problem is serious, therefore, it is indispensable to find the damaged casing in time[1]. Currently using a new logging technology named visible light downhole television logging, we can get the high resolution, visual, and timely casing damage samples. However, at present, the method of identifying casing damage mainly relies on manual troubleshooting, which has many problems, such as heavy workload, low efficiency and high professional knowledge requirements. Therefore, it is an important work to study a high speed and accuracy image recognition algorithm for casing damage.

The good results of neural network in pattern recognition, classification and image processing inspire scholar to study neural network in the field of image recognition. BP neural network is widely used in image recognition because of its strong self-learning ability and nonlinear mapping ability. However, in practical application, BP neural network has limitations in setting the initial threshold and weight coefficient, which will lead to the network falling into the problem of unable to obtain the global minimum value, infinite extension of training time, etc[2]. Therefore, we build a GA-BP neural network, combined with genetic algorithm (GA) to optimize the BP neural network, in order to achieve better application effect in casing damage image recognition.
2. Genetic Algorithm to Optimize BP Neural Network
When using BP neural network for image recognition training, the basic characteristics of self-learning of BP neural network are used to compare the target output of training samples with the actual output results, then constantly changing the initial threshold and weight, making the output of neural network close to the target value. Therefore, BP neural network belongs to multilayer feedforward neural network, which is characterized by signal forward transmission and errors back propagation[3]. The state of each layer of neuron only affects the state of the next layer. The structure of BP neural network is shown in Figure 1.

![Figure 1. BP Neural Network Structure.](image1)

Genetic algorithm is a kind of intelligent optimization algorithm, which can be used to screen the initial threshold and initial weight of BP neural network, and improve the shortcomings of BP neural network algorithm. Genetic algorithm takes the encoded object to be optimized as the input of the algorithm, uses the prior knowledge method or randomly generates a group of initial population, calculates the fitness value of the initial population in turn and then sorts it, selects the individuals with high fitness value to copy directly to the next generation, and the remaining individuals carry out crossover and mutation operations[4], and calculates the probability of individual selection according to the fitness, The individuals with high probability select "genes" to cross each other to generate new individuals, complete the cross operation, and then a part of individuals randomly mutate, so as to introduce new "genes" to the existing individuals, avoiding the limitation that the number of genes can only approach the local optimal solution and cannot reach the global optimal solution.

The algorithm flow of the whole network is shown in Figure 2.

![Figure 2. GA-BP Neural Network Flowchart.](image2)

3. Extraction of Casing Damage Image Feature Parameters
3.1. Building Feature Parameters
In this experiment, clear and short casing detection video data in a basin of Sichuan Province to build a sample database[5]. In order to establish the gray, texture and shape features of the casing damage image, it is necessary to select the appropriate feature parameters. According to the damage characteristics of casing damage images, the entropy, kurtosis and mean of image gray histogram of different damage types can be obtained, so as to establish the gray characteristic parameters. Similarly, the mean value, smoothness and third-order moment of gray histogram are selected to represent the texture features of the image. In terms of shape, fracture damage is thinner and longer than perforation and deformation, so the distance from the center of mass to the center line of the fracture, the ratio of the length axis of damage, the ratio of the area of outer cut rectangle to the area of damage, and Heywood diameter are selected as the shape characteristic parameters. Using these features to build a table of all feature parameters, the calculated results are shown in the following table. Use F1 to F10 to
represent the characteristic parameter values mentioned above in turn, and the repeated results of F3 and F4 are omitted.

| Feature Parameters Table. | F1  | F2  | F3  | F5  | F6  | F7  | F8  | F9  | F10 |
|---------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Crack 1                   | 19.62 | 15.34 | 118.22 | 2.37 | 11.02 | 101.08 | 1.82 | 5.82 | 19.05 |
| Crack 2                   | 19.43 | 15.87 | 117.98 | 2.42 | 11.92 | 91.09 | 1.55 | 7.90 | 17.82 |
| Perforation 1             | 8.53 | 2.93 | 136.67 | 1.33 | 13.06 | 151.37 | 1.20 | 1.07 | 14.49 |
| Perforation 2             | 8.45 | 2.87 | 135.92 | 1.42 | 13.21 | 152.94 | 1.06 | 1.19 | 15.47 |
| Deformation 1             | 6.61 | 1.63 | 212.78 | 0.99 | 21.71 | 161.68 | 1.33 | 2.56 | 4.52 |
| Deformation 2             | 6.79 | 1.60 | 212.35 | 1.04 | 21.83 | 171.98 | 1.66 | 1.50 | 4.25 |

3.2. Preprocessing of Characteristic Parameters

Due to the large difference among the characteristic parameters, so the normalization method is used to eliminate the difference in the order of magnitude of the parameters[6]. $X_{norm}$ is used to represent the normalized data, $X$ is used to represent the original data, and $X_{max}$ and $X_{min}$ are used to represent the maximum and minimum values respectively. The normalization method is shown in formula (1):

$$X_{norm} = \frac{2 \times (X - X_{min})}{X_{max} - X_{min}} - 1 \tag{1}$$

According to the principal component analysis of characteristic parameters, the dimension is reduced to 5 dimensions, so there are 5 neurons in the input layer. According to the three damage types to be classified, the input layer is 3. Using PCA to reduce dimension effectively reduces the redundancy of feature data.

4. Experimental Results and Analysis

This experiment is reduced to five dimensions by principal component analysis, so there are five input layers of BP neurons and GA-BP neurons, and three output layers are set to represent three types of damage. Three types of casing damage images, crack, perforation and deformation, are selected. After median filtering, edge detection based on sober operator and Otsu threshold segmentation, 600 pieces of casing damage images can be obtained in two kinds of network to optimization training. Figure 4 shows three types of casing damage images.

(a) Perforation                (b) Crack               (c) Deformation

Figure 4. Three Types of Casing Damage Images.
Figure 5 shows the convergence curve of BP network and GA-BP network. From the curve, it can be seen that the convergence speed of GA-BP network is faster and the training time is shorter. The recognition rate of GA-BP network is 78.67%, the recognition rate of BP network is 75.22%, the former is 3.45% higher than the latter. Therefore, GA-BP network optimizes the shortcomings of traditional BP network, such as slow convergence speed and long training time, and improves the recognition accuracy.

5. Conclusion
In this paper, a GA-BP neural network method is proposed to optimize BP neural network in the application of damage identification. Firstly, the oil casing damage sample library is constructed, and the feature parameters of gray degree feature, texture feature and shape feature are extracted. After training the GA-BP neural network with the obtained characteristic parameters, the accuracy of the GA-BP neural network can be improved 3.45%. GA-BP neural network has the following advantages: accelerating the convergence speed of the network; shortening the training time of the network; reducing the probability of BP neural network falling into the local optimal value, and making the network more practical.

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