Research on identification algorithm of railway freight train number based on GSO-BP algorithm

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Abstract. In the stage of character recognition, it is necessary to select the algorithm that matches the character features of train number. The train number characters of railway freight trains are all printed in straight style. Compared with handwritten characters, each character has relatively fixed features. However, due to the complex operation environment of railway freight trains, the character regions are cracked, tilted and partially missing. Therefore, it is very important to select an algorithm with good robustness. In view of the above analysis, this paper proposes a research on railway freight car number recognition algorithm based on GSO-BP algorithm, the experimental results show that the proposed method is effective in character recognition.

1. Introduction

Compared with handwritten, each character has relatively fixed characteristics. However, due to the complex operation environment of railway freight trains, the character region appears fracture, tilt, partial missing and other situations. Therefore, it is very important to choose a robust algorithm. At present, for image recognition tasks, the more common recognition methods are template matching recognition[1], classifier recognition[2], neural network recognition[3]. The template matching method is to measure the similarity distance between the characters in the template library and the characters to be recognized by using the similarity principle. Classifier recognition methods usually need the help of discriminant function, such as support vector machine. This kind of method can separate objects by establishing a hyper plane with the maximum interval. Neural network recognition method is to simulate the human brain organization. The algorithm calculation process simulates the process of biological neural system reflecting things. It has the basic characteristics of biological neural system. The application of neural network solves the problems that other pattern recognition methods are difficult to solve. Its classification function is especially suitable for the application of pattern recognition and classification. Feed forward BP network is the most widely used form of neural network, which has strong generalization ability and fault tolerance ability. During the training process of neural network, there may be problems of local optimization and slow convergence speed. Therefore, reference [4-6] proposes to use intelligent algorithms such as genetic algorithm, particle swarm optimization and dragonfly search to optimize the parameters of neural network. Compared with other optimization algorithms, group search algorithm also known as GSO, it is more effective Optimizer algorithm and has stronger global search ability [8]. In view of the above analysis, this paper proposes a research on railway freight train number recognition algorithm based on GSO-BP algorithm, which
takes the output cumulative error of BP neural network as the fitness function of GSO algorithm, speeds up the convergence speed of BP neural network, and improves the problem of local optimization.

2. A brief introduction to basic algorithm of character recognition

2.1 BP Neural Network

BP neural network is composed of input layer, hidden layer and output layer. The calculation process of its output value is shown in equation 1. The process of network consists of forward computation and back propagation. In the process of forward propagation, the data is imported from the input layer, and the output is obtained in the output layer after weighted summation and nonlinear mapping. In the process of back propagation, the network weight \( W \) and threshold \( B \) are adjusted according to the deviation between the network output and the expected output, so that the error decreases along the gradient direction until the actual output and the expected output are within the predetermined range.

The loss function calculation formula is shown in equation 2.

\[
y = \text{purelin} \left( W_{i2} \times \text{tansig} \left( W_{i1} \times x_i + \theta_1 \right) + \theta_2 \right)
\]

\[
\text{Loss} = \sum_{j=1}^{M} \left( y_j - y'_j \right)^2
\]

Where \( y_j \) is the actual output value of the \( j \)-th sample and \( y'_j \) is the expected output. \( \text{tansig}(\cdot) \) and \( \text{purelin}(\cdot) \) are nonlinear mapping functions from input layer to hidden layer and hidden layer to output layer respectively.

In order to simplify the structure of BP neural network and improve the operation efficiency, the separated character area of train number is divided into 8 areas, and the proportion of foreground pixels in each area to the foreground pixels in the whole character area is calculated as the input of BP neural network. Therefore, the input number of BP neural network is determined to be 8. The input diagram of BP neural network is shown in Figure 1, and the input calculation is shown in Formula 3. According to the conclusion of reference [4], when the input node is \( n \) and the number of hidden layer nodes is \( 2^n + 1 \), the network model recognition ability is better, so the number of hidden layer nodes is 17. The network structure is shown in Figure 2.

The output of the network is \( y \in (3,100) \), the specific value is 100bin2dec \((y_1y_2y_3y_4y_5y_6)/33\), where \( y_1y_2y_3y_4y_5y_6 \) is a 6-bit binary number. According to TB/T1.1 standard, in addition to 10 digits from 0 to 9 participating in the coding of railway freight car number, there are 23 English letters, a total of 33 characters to be recognized. Therefore, 6-bit binary is used to encode these 33 characters, and the encoding results are shown in Table 1. The output of the network will change between \( \{3,100\} \), and the output error will be output according to the rounding principle.
Table 1. Character coding table

| number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | ⋮ | 27 | 28 | 29 | 30 | 31 | 32 | 33 |
|--------|---|---|---|---|---|---|---|---|---|----|----|----|----|---|---|---|---|---|---|---|---|
| character | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | A | B | C | ⋮ | S | T | U | W | X | Y | Z |
| y1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ⋮ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| y2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ⋮ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| y3 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | ⋮ | 0 | 0 | 0 | 0 | 1 | 1 | 1 |
| y4 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | ⋮ | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| y5 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | ⋮ | 0 | 0 | 1 | 1 | 0 | 0 | 1 |
| y6 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | ⋮ | 0 | 1 | 0 | 1 | 0 | 1 | 0 |

2.2. Introduction of GSO

GSO includes three kinds of members: discoverer, wanderer and wanderer. Discoverer and searcher are the main body to find the best, and the addition of wanderer is to avoid the algorithm falling into local optimum. The discoverer is the individual with the current optimal fitness, and the rest are randomly allocated with wanderers and wanderers according to the ratio of 4:1. When the optimization process is stagnant, it means that the algorithm may fall into local optimization, increasing the number of wanderers from one fifth to two fifths. In an n-dimensional search space, the i-th individual has four attributes in the k-th iteration: position $X_i^k$, search angle $\phi_i^k=(\phi_{i1}^k, \phi_{i2}^k, \cdots, \phi_{in}^k)$, search direction $D_i^k(\phi_i^k)=(d_{i1}^k, d_{i2}^k, \cdots, d_{in}^k)$ and fitness $f_{value}=f(X_i^k)$. The search direction $D_i^k$ is obtained by transforming the search angle $\phi_i^k$ according to formula 3, 4 and 5. In each iteration, the search steps of discoverer, wanderer and wanderer are as follows:

$$d_{i1}^k = \prod_{\rho=1}^{n-1} \cos(\phi_{i\rho}^k)$$  \hspace{1cm} (3)

$$d_{i2}^k = \sin(\phi_{i(n-1)}^k) \prod_{\rho=1}^{n-1} \cos(\phi_{i\rho}^k)$$  \hspace{1cm} (4)

$$d_{in}^k = \sin(\phi_{in}^k)$$  \hspace{1cm} (5)

1) Discoverer location update

The location updates of discoverers are searched from the front, left and right sides respectively, and the fitness function values of discoverers are calculated in each direction. The three locations are updated according to formulas 6, 7 and 8.

Front position update:

$$X_i = X_i + r_1 l_{max} D_1^k(\phi_i^k)$$  \hspace{1cm} (6)

Right position update:

$$X_i = X_i + r_1 l_{max} D_2^k(\phi_i^k + r_2 \theta_{max}/2)$$  \hspace{1cm} (7)

Left position update:

$$X_i = X_i + r_1 l_{max} D_3^k(\phi_i^k - r_2 \theta_{max}/2)$$  \hspace{1cm} (8)

Where, $r1$ is a random number that obeys the standard normal distribution, and $r2$ is a random number uniformly distributed in $\{0,1\}$. $l_{max}$ is the maximum transfer distance in the search process, calculated by formula 9, $\theta$ max is the maximum search angle, and the value setting is calculated by formula 10.
Where $U_i$ and $L_i$ are the upper and lower boundaries of the $i$-th vector, and $n$ is the spatial dimension of the search algorithm. Figure 3 shows a three-dimensional schematic of the algorithm search.

\[
l_{\text{max}} = \sqrt{\left\| U - L \right\|^2 + \sum_{i=1}^{n} (U_i - L_i)^2}
\]
\[\theta_{\text{max}} = \frac{\pi}{\text{round}(\sqrt{n+1})}\]

(9) (10)

The fitness values of the above three directions are calculated respectively. If there is a position whose fitness is better than the current position, the position with the best fitness is set as the position of the next discoverer, and the position is updated according to formula 6, 7 or 8. Otherwise, the search direction is updated as shown in formula 11.

\[
\varphi^{k+1} = \varphi^k + r_2 \alpha_{\text{max}}
\]

(11)

If the discoverer position is not updated after $w$ consecutive iterations, the search angle is updated as shown in formula 12.

\[
\varphi^{k+w} = \varphi^k
\]

(12)

2) Follow location update
Note that the current position of the follower is $X_{ik}$ and the search angle is $\psi_{ik}$. Unlike the discoverer update rule, the follower will move towards the discoverer in each iteration process. The position update rule is shown in formula 13.

\[
X_{i}^{k+1} = X_{i}^{k} + r_3(X_{\psi}^k - X_{i}^k)
\]

(13)

Where $r_3$ is a random number satisfying uniform distribution.

3) Rogue location update
If the current individual belongs to the vagrant, the current position is recorded as $X_{ik}$. The search angle is updated according to formula 14, and the moving distance is randomly selected for position update.

\[
X_{i}^{k+1} = X_{i}^{k} + c_1l_{\text{max}}(\varphi^{k+1})
\]

(14)

The principle of random movement of the wanderer can effectively solve the problem of local optimization, and it is also the problem of selecting the group search algorithm for local optimization.

3. Application of BP neural network model optimized by two group search in train number recognition
The GSO is used to optimize the parameters of BP neural network. After a certain number of iterations, the current position of the discoverer is output as the optimization result and assigned to BP neural network to realize character recognition. The flow chart of BP neural network optimized by GSO algorithm is shown in Figure 4.
According to the above figure, character recognition in this chapter is divided into the following steps:

step1: according to the structure of BP neural network, the number of parameters and the upper and lower boundaries of parameters are determined, and the individual position of group search algorithm is determined, which is composed of \((W_1, W_2, B)\);

step2: take the network error as the fitness function of the algorithm, and the definition of the function is shown in equation 15.

\[
f_{\text{value}} = \sum_{i=1}^{n} \text{abs}(y_i - o_i)
\]  \hspace{1cm} (15)

Where \(n\) is the number of training samples, \(o_i\) is the ideal state value of the \(i\)-th sample, and \(y_i\) is the corresponding actual state value.

step3: calculate the fitness function. The principle that the smaller the better should be followed when the cumulative error is used as the fitness function value. Taking the minimum fitness value of all positions as the optimal position, the discoverer's position will be updated to the current position, and the remaining individuals will be randomly assigned as followers and vagrants according to the ratio of 4:1 to update the position.

step4: determine whether the maximum number of iterations has been reached. If the number of iterations is satisfied, the iteration is stopped, and the location information of the current discoverer is assigned to BP neural network for initialization; otherwise, the search optimization is continued.

step5: prepare the data set to train the BP neural network. When the accuracy is satisfied, the training is completed. The trained BP neural network is used for recognition.

As can be seen from Figure5, after nearly 60 iterations, the fitness function of the algorithm tends to be stable. After 100 iterations, the location information of the current discoverer is obtained.
4. Conclusion
This paper presents a method of train number recognition based on GSO-BP. The algorithm is mainly based on GSO algorithm and BP neural network. Through the analysis and comparison of common recognition methods, the BP neural network with good robustness is selected for single character recognition, and the global optimization algorithm GSO is used for optimization to improve the positioning accuracy of the network.

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References
[1] Yang Dazhi. Recognition and application of railway freight car number based on image processing[D]. Chengdu: Southwest Jiaotong University, 2010.
[2] Xin Mingyuan. Research on Locomotive Number Recognition Based on image processing [D]. Chengdu: Southwest Jiaotong University, 2018.
[3] Meng Zhaoping, Tian Yongdong, Lei min. BP neural network model and application for prediction of coal seam gas content[J]. Journal of China University of mining and technology, 2008,37 (4): 456-461.
[4] Xu Qingfeng, Yu Ruyue, Gou Yuxuan, Zhao Yunze, Li Yong, Huang Yuanfang. Prediction accuracy analysis of soil organic matter in Huang Huai Hai dry farming area based on cloud genetic BP neural network [J]. Journal of China Agricultural University, 2021,26 (04): 167-173.
[5] Huang Baozhou, Yang Junhua, Lu Siling, Chen Haifeng, Xie Dongshen. Prediction of wave capture power based on improved particle swarm optimization neural network algorithm[J]. Acta solar energy Sinica, 2021,42 (02): 302-308.
[6] Zhang Xiao, Qian Yuliang, Qiu Zheng, Zhang Yun. Gas turbine fault diagnosis based on BP neural network optimized by dragonfly algorithm [J]. Thermal power engineering, 2019,34 (03): 26-32.