Acoustic target recognition algorithm based on particle swarm neural network

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Abstract. In order to improve the automatic recognition rate of acoustic targets, this paper conducts research on acoustic target recognition algorithms based on particle swarm neural network. Firstly, the mathematical description of the particle swarm optimization algorithm is described, and the initial parameters and algorithm flow of the particle swarm optimization algorithm in the experiments in this paper are given. Second, the design includes the central processor, power supply, signal conditioner, filter, trigger circuit, and state. Acoustic target recognition prototypes of display circuit, memory, target type indication circuit, serial port, crystal circuit, microphone and hardware interface circuit, etc. Finally, using the collected acoustic signals of tanks and helicopters, a semi-physical simulation experiment was designed to carry out target recognition. Experimental research and experimental results verify the effectiveness and stability of the acoustic target recognition system in this paper.

1. Introduction

Acoustic target recognition is an important task of intelligent transportation systems, which has important academic value, and will also generate huge social and economic benefits [1]. In the military field, how to classify and identify various wheeled vehicles and tracked vehicles is of great value for ground reconnaissance, battlefield situation awareness, threat assessment, command decision-making, and precise strike in modern warfare [2, 3]. At present, for the detection and identification of civilian acoustic targets, optical methods are mainly used [4], and the detection and identification technologies for military acoustic targets include acoustic detection [5, 6], seismic wave detection [7, 8], and electromagnetic wave detection [9, 10]. Three. Among them, sound detection technology has the advantages of good concealment, all-weather work, no radar and other working blind spots, simple system structure, low cost and small size, and is widely used. For the automatic recognition of acoustic targets under complex background conditions, Shanghai Jiaotong University designed an acoustic target recognition system based on fuzzy comprehensive evaluation [11]. Based on the characteristics of the acoustic signals of typical targets on the battlefield, Nanjing University of Science and Technology designed DSP-based and wavelet Fast battlefield sound target recognition system [12]. With the development of electronic technology, the acoustic target recognition system tends to be miniaturized and fast. In this paper, an acoustic target recognition system based on particle swarm neural network is designed.
algorithm and a prototype are designed, and the prototype is analyzed for tank and helicopter targets through experiments the validity and stability of identification.

2. Swarm Neural Network Optimization Algorithm

Particle swarm neural network is a neural network model in which particle swarm optimization algorithm and neural network are mixed with each other [13]. This paper introduces the mathematical description of the particle swarm optimization algorithm, and gives the initial parameters and algorithm flow of the particle swarm optimization algorithm in the experiments in this paper. At the same time, in the experiment, it is compared with the traditional neural network algorithm.

2.1. Mathematical description

In the basic particle swarm optimization algorithm, a particle swarm consists of \( m \) particles, and the position of each particle represents the potential solution of the optimization problem in the \( n \) dimensional search space. The mathematical description of the particle swarm optimization algorithm is as follow. Assume that in a one-dimensional search space, a population of particles is \( x = (x_1, x_2, \cdots, x_m)^T \), where the position of the first particle is \( x_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,n})^T \), and its speed is \( v_i = (v_{i,1}, v_{i,2}, \cdots, v_{i,d})^T \). Its individual extremum is \( p_i = (p_{i,1}, p_{i,2}, \cdots, p_{i,n})^T \), the global extremum of the population is \( p_g = (p_{g,1}, p_{g,2}, \cdots, p_{g,n})^T \). After the particle finds the above two extreme values, it updates its speed and position according to the following two formulas:

\[
 v_{i,d}^{k+1} = v_{i,d}^k + c_1 \text{rand}(p_{i,d}^k - x_{i,d}^k) + c_2 \text{rand}(p_{g,d}^k - x_{i,d}^k) \tag{1}
\]
\[
 x_{i,d}^{k+1} = x_{i,d}^k + v_{i,d}^{k+1} \tag{2}
\]

Where, \( c_1, c_2 \) called the learning factor, \( \text{rand()} \) is a random number between \((0, 1)\); and the velocity \( v_{i,d}^k \) and position \( x_{i,d}^k \) of the particle in the \( d \) dimension in the \( k \) iteration; and the position \( p_{i,d}^k \) of the individual extreme value of the particle in the \( d \) dimension; \( p_{g,d}^k \) is the position of the global extremum of the population in the \( d \) dimension. In order to reduce the possibility of particles leaving the search space during the evolution process, it is usually limited to a certain range, that is \( v_{i,d} \in [-v_{\text{max}}, v_{\text{max}}] \), if the search space of the problem is limited at \([-x_{\text{max}}, x_{\text{max}}]\), it can be set as \( v_{\text{max}} = kx_{\text{max}}, 0 \leq k \leq 1 \).

2.2. Initial parameter settings

One of the biggest advantages of the original particle swarm optimization algorithm is that it does not need to adjust too many parameters, but a few parameters in the algorithm directly affect the performance and convergence of the algorithm. The parameter settings of the particle swarm optimization algorithm involved in this article are as follows:

1) Number of particles. The larger the number of particles, the larger the spatial range of the algorithm search, and it is easier to search for the global optimal solution. However, the increase in the calculation amount increases the search time, which is not conducive to the timeliness of the system. Based on the analysis of previous experiments, the number of particles is 30.

2) Particle length. The particle length is the length of the problem, which is determined by the specific optimization problem.

3) Particle range. The particle range is determined by the specific optimization problem. The particle range in the experiments in this paper is the value range of the problem parameters.
4) Maximum particle velocity. The maximum particle velocity determines the maximum distance a particle can move in a flight. In this paper's experimental analysis, the maximum particle velocity is set to \( v_{\text{max}} = kx_{\text{max}}, k = 0.5 \).

5) Learning factors. \( c_1, c_2 \) indicates the degree to which particles are affected by social knowledge and individual cognition, so it set to the same value to give both the same weight, \( c_1 = c_2 = 2 \).

6) Algorithm termination conditions. Similar to the genetic algorithm, the termination condition of the particle swarm optimization algorithm can generally be set to reach the maximum number of iterations or meet a certain error criterion.

7) Fitness function. In this paper's experimental analysis, the objective function is directly used as the fitness function.

2.3. Particle Swarm Optimization Algorithm Flow
The algorithm flow of the particle swarm optimization algorithm is as follows:

1) Initialize the random position and velocity of the particle swarm according to the initialization process;
2) Calculate the fitness value of each particle;
3) For each particle, compare its fitness value with the fitness value of the best position it has experienced. If it is better, use it as the current best position;
4) For each particle, compared its fitness value with the fitness value of the best position experienced globally, and if it is the best, used it as the current global best position;
5) Evolve the speed and position of the particles according to the iterative equations (1) and (2);
6) If the end condition is not reached (usually a good enough adaptation value or a preset maximum number of generations is reached), then return to step (2).

3. Experimental analysis

3.1. Prototype of acoustic recognition system
As shown in Figure 1, it is a sound identification system test prototype, which includes the above-mentioned peripheral hardware circuits, where 1 is a central processing unit, 2 is a power source, 3 is a signal conditioner, 4 is a filter, and 5 is a trigger circuit. 6 is a status display circuit, 7 is a memory, 8 is a target type indicating circuit, 9 is a serial port, 10 is a crystal oscillator circuit, and 11 is an interface between a microphone and a hardware circuit.

(a) The front side of the acoustic recognition hardware system test prototype
(b) The back side of the acoustic recognition hardware system test prototype

Figure 1. Prototype of acoustic target recognition hardware system
3.2. Acoustic target recognition signal acquisition test

This test uses a quaternary acoustic sensor to form a circular array with a diameter of 1m. During the test, the sampling frequency of the signal is 62.5kHz and the range is 10V. The acoustic signals of tanks and helicopters were collected in the early stage of this research group. This experiment uses acoustic playback to simulate acoustic targets. The location of the test device is shown in Figure 2. The specific test steps are as follows:

1) The microphone array is placed in a non-same wave-front, and the relative position of the microphone and the sound source is shown in Figure 3;
2) Acquire the signal at a fixed position of the sound source 1 # ~ 11 # opposite the static sound array;
3) Move the sound source at a uniform speed at positions 1 # ~ 11 # opposite to the static sound array to collect signals;
4) Randomly move the sound source at positions 1 # ~ 11 # opposite to the static sound array, with different speeds, and collect signals.

![Figure 2. Location of the device](image1)

![Figure 3. Relative position of the test](image2)

3.3. Analysis of acoustic target recognition results

Based on the particle swarm neural network optimization algorithm, the total number of acoustic signal samples selected in the stationary state, uniform motion state, and maneuvering state were: 20, 25, 30, 35, 40, 45, 50, and the tank and helicopter targets were identified respectively. Test. The test results are counted based on the target type indicator signal in the prototype. At the same time, in order to verify the effectiveness of the particle swarm neural network optimization algorithm, it is compared with the traditional neural network algorithm. Table 1 shows the recognition results of helicopter and tank target test prototypes.

(1) Analysis of the effectiveness of the test prototype of the acoustic recognition system. It can be seen from Table 1 that whether the traditional neural network algorithm or the particle swarm neural network optimization algorithm is applied in this test prototype, the recognition rate of the tank remains above 66.7%, and the recognition rate of the helicopter target remains at 73.3% Above, especially in combination with the particle swarm neural network optimization algorithm of this article, the recognition rate of the tank has remained above 75%, and the recognition rate of the helicopter target has remained above 84%, thus confirming whether it is based on traditional theoretical algorithms or based on In the improved algorithm, the experimental prototype of the acoustic recognition system designed in this paper can effectively complete the recognition of acoustic targets, and can ensure the effectiveness of the recognition results.

(2) Stability analysis of test prototype of acoustic recognition system. As can be seen from Table 1, based on the traditional neural network algorithm, for tank targets, as the total number of samples increases, the recognition rate remains at 66.7% ~ 72%, the average recognition rate is 68.8%, and the recognition rate variance is 1.75%. As the total number of samples increases, the recognition rate stays at 73.3% ~ 80%, the average recognition rate is 75.3%, and the variance of the recognition rate is 2.2%; it can be seen that the prototype of the acoustic target recognition test is based on a traditional neural
network algorithm, the degree of fluctuation of the recognition rate is less, and the system is stable. In the particle swarm neural network optimization algorithm, for tank targets, as the total number of samples increases, the recognition rate remains at 75% to 88.6%, the average recognition rate is 83.5%, and the variance of the recognition rate is 4.12%; for helicopter targets, with the increase of the total number of samples, the recognition rate remained between 84% and 91.1%, the average recognition rate was 87.3%, and the variance of the recognition rate was 2.35%. By the same token, the recognition rate of the test prototype has less fluctuation and the system is stable. However, from the analysis of the degree of fluctuation of the recognition rate, the optimization algorithm based on the particle swarm neural network is more complicated and computationally intensive than the traditional neural network algorithm. Therefore, the degree of fluctuation of the recognition rate of the corresponding experimental prototype also increases.

(3) Analysis of recognition rate of different targets. From Table 1, it can be seen that, whether based on the traditional neural network algorithm or the particle swarm neural network optimization algorithm, the recognition rate of the acoustic target recognition test prototype for the helicopter target is higher than that for the tank target. Related. From the analysis of the sound signal propagation, compared with the helicopter target, the distance from the tank target to the sound array is much lower than the distance from the helicopter to the sound array. Therefore, the helicopter sound source is more satisfied with the point sound source. From the collection and analysis of acoustic signals, the reflection of the tank acoustic signals through the ground and the interference of environmental noise are strong, and the signal-to-noise ratio of the collected sound source signals is low. Therefore, the recognition rate of the tank target is low. Analyze from another angle to improve the sound source signal. The signal-to-noise ratio can improve the recognition rate of acoustic targets.

| sample | Neural network algorithm | Particle Swarm Neural Network Optimization Algorithm |
|--------|--------------------------|---------------------------------------------------|
|        | Tank target | Helicopter target | Tank target | Helicopter target |
|        | Identify correctly | Recognition rate% | Identify correctly | Recognition rate% | Identify correctly | Recognition rate% | Identify correctly | Recognition rate% |
| 20     | 14          | 70.0            | 15          | 75.0            | 15          | 75.0            | 17          | 85.0            |
| 25     | 18          | 72.0            | 20          | 80.0            | 21          | 84.0            | 21          | 84.0            |
| 30     | 20          | 66.7            | 22          | 73.3            | 25          | 83.3            | 26          | 86.7            |
| 35     | 24          | 68.6            | 26          | 74.3            | 31          | 88.6            | 31          | 88.6            |
| 40     | 27          | 67.5            | 30          | 75.0            | 34          | 85.0            | 35          | 87.5            |
| 45     | 31          | 68.9            | 34          | 75.6            | 38          | 84.4            | 41          | 91.1            |
| 50     | 34          | 68.0            | 37          | 74.0            | 42          | 84.0            | 44          | 88.0            |

4. Conclusion
All manuscripts must be in English, also the table and figure texts, otherwise we cannot publish your Based on the software and hardware design, this paper completes the assembly and commissioning of the prototype of the acoustic target recognition system based on the particle swarm neural network algorithm. The effectiveness and stability of the test prototype are verified by taking tank and helicopter targets as the target. Based on the test results, it is known that the recognition rate of the tank target remains at 75% to 88.6%, the average recognition rate is 83.5%, and the variance of the recognition rate is 4.12%; for the helicopter target, the recognition rate is maintained at 84% to 91.1%, and the average recognition is 87.3%, and the variance of the recognition rate is 2.35%. The experimental results verify the effectiveness and stability of the acoustic target recognition system designed in this paper.
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