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BNNG Algorithm Modeling for Vehicle Classification Recognition under Non Line-of -sight Environment

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Abstract. At present, the automatic classification of vehicles on roads is mostly based on image recognition, and there are defects in adaptability under non-line-of-sight environments. In this paper, based on the similarity of the integration of the ecosystem model and multi-neural network model, an artificial neural network group (BNNG) algorithm was proposed. The vehicle's driving acoustic signal was taken as the research object, and it was calculated using the Artificial Neural Network (BNNG) algorithm to achieve automatic classification and recognition of vehicle models. Through experimental tests, it is shown that under non-line-of-sight environments, the accuracy of vehicle classification can be improved, and the misrecognition rate of similar models can be greatly reduced. This provided a new method for the automatic classification and identification of vehicles on roads, which was of great significance to monitor vehicle safety in non-line-of-sight environments.

1 Introduction

At present, the classification of vehicles is mainly within the line-of-sight range. Vehicles are distinguished based on the degree of road damage and occupancy in the process of driving, which is the basis for traffic statistics, road toll determination, and vehicle restrictions. Most of the traditional vehicle classification methods are based on image recognition. However, there are problems such as environmental adaptability and lack of versatility when used in practice. This article takes the acoustic signals in the vehicle driving process as research objects and uses the Artificial Neural Network (BNNG) algorithm to realize automatic classification of vehicles under non-line-of-sight environments[1].

Neural network ensemble is the use of a finite number of neural networks to learn the same problem, and the output is determined by each neural network output in accordance with certain rules. The research on neural network integration mainly focuses on two aspects: how to generate an integrated network and how to determine the output rules. Domestic and foreign scholars have proposed Boosting, Bagging, ALA, OLA, PLA [2,3] and other algorithms which have studied this aspect, but the problem of black box inside the neural network still exists. It is urgent to find a model to explore the internal learning mechanism of network integration. After previous experiments, this paper finds that there are certain similarities between the neural network integration and the evolution model of the ecosystem. For this purpose, the ecosystem model is predicted and matched with the parameters in the neural network integration. Using evolutionary rules to guide the integration of neural networks, we propose an artificial neural network group.

2 Artificial neural network group (BNNG) algorithm design

2.1. The BNNG model proposed

Ecosystem refers to the biological community and its living environment. Through the exchange of materials, energy conversion and information transmission, biological communities occupies a certain space, has a certain structure, performs certain functions, and become a dynamic equilibrium. It is a perfect dynamic in nature. Its internal evolution based on mutual assistance, competition and other rules to complete. Multi-neural networks work in a population-based manner and evolve according to the rules of ecosystem evolution. Therefore, they are called artificial neural network groups. This paper does a predictive match for the two models. Table 1 only lists some of the matching rules:

According to the basic rules in Table 1, this article proposes the following criteria: (1) If the environment variables X^M are limited, the species f_i must be limited, that is, the value of N is finite, and the best value N can be obtained based on the law of conservation of energy and distribution; (2) If environmental variables X^M different, the species needed are different, that is, the

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Table 1. BNNG model matching.

model	Match 1	Match 2	Match 3	Match 4	Match 5	Match 6	Match 7
ecosystem	environmental factor	Species	Population relations	Evolutionary rules	Interspecies difference	Survival ratio	Ecological balance
Neural network group	Input variable	Neural Networks	Network structure	Type weight change	Degree of difference	Impact factor	Expected output
BNNG	X^M	f_i	ω_i	ω_i Adjustment	A_i	Δ_i	T^n

input distribution is different and the types N needed are different. (3) There are major species and minor species in the ecosystem, so the neural network groups are divided into the main network and the incentive network, and the selection process follows the principle of similarity and difference respectively. (4) The increase of species f_i will produce impact factors Δ, which will be fed back into each species and eventually make the system one of the four states of balance/damage/re-balance/destruction.

2.2. BNNG algorithm process

It is assumed that the learning objective of the neural network group is to simulate the evolution function: $f{:}X^m \to T^n$. The neural network group is composed of N neural networks (populations) $f_1 f_2 f_3, \bullet\bullet\bullet f_N$. Each network is assigned a weight ω_i , satisfying the conditions $\omega_i \geq 0$, and $\sum_{i=1}^{N} \omega_i = 1$. The weight adjustment rule is determined by the influence factor Δ, and the specific definition is later defined. The output of the neural network group is generated by the weighted average of the participating neural networks. The output value in the group is determined by equation (1), where f_{il} is the output value of the member network within the group.

$$\overline{f}_l = \sum_{i=1}^{N} \omega_i f_{il} \tag{1}$$

Set up $x \in X^m$ to meet the distribution of $p(x)$. If the output $t(x)$ is in the input destination x , the output of f_i the first member network is $f_i(x)$, then the neural network group outputs under the input x is .

$$\overline{f}(x) = \sum_{i=1}^{N} \omega_i f_i(x) \tag{2}$$

Define the following quantities: In addition to the i member network f_i in the neural network group, the rest of the member networks are integrated in the output of the input x .

$$\overline{f}_{-i}(x) = \sum_{j=1, j\neq i}^{N} \frac{\omega_j}{1-\omega_i} f_j(x) \tag{3}$$

Global generalization error of neural network groups:

$$WE = \int p(x)[\overline{f}(x) - t(x)]^2 dx \tag{4}$$

The mero generalization error of the i member network f_i of the neural network group:

$$ME_i = \int p(x)[\overline{f}_i(x) - t(x)]^2 dx \tag{5}$$

The degree of difference between member networks f_i and neural network groups $\overline{f}$:

$$A_i = \int p(x)[f_i(x) - \overline{f}(x)]^2 dx \tag{6}$$

The degree of difference between member networks f_i and neural network groups $\overline{f}_{-i}$:

$$A_{-i} = \int p(x)[f_i(x) - \overline{f}_{-i}(x)]^2 dx \tag{7}$$

The weighted average of the globalization error of the neural network group:

$$\overline{WE} = \sum_{i=1}^{N} \omega_i ME_i \tag{8}$$

A weighted average of the degree of difference between member networks and neural network groups:

$$\overline{A} = \sum_{i=1}^{N} \omega_i A_i \tag{9}$$

Through the integrated theoretical analysis of Krogh and Vedelsby in 1995, it can be concluded that [4-7] :

$$WE = \overline{WE} - \overline{A} \tag{10}$$

Formula (3), (6), (7) can be drawn.

$$A_i = (1-\omega_i)^2 A_{-i} \tag{11}$$

Suppose $WE * A_i = \omega_i(ME_i - A_i)$, we can get from equations (8), (9), (10), (11).

$$\sum_{i=1}^{N} WE * A_i = \sum_{i=1}^{N} \omega_i [ME_i - (1-\omega_i)^2 A_{-i}] = WE \tag{12}$$

It can be seen that the smaller the local generalization error ME_i is, the greater the degree of difference A_{-i} between the network f_i and the neural network group $\overline{f}_{-i}$ is, and the smaller the global generalization error WE is. Therefore, a global generalization error threshold T needs to be set.

Set up a new incentive network: $f_K(x), K \in Z$. In the principle of biological evolution, the best type $f_K(x)$ is the basic NN network, and it is even more difficult to break the balance of the original system.

Every time it is introduced, it will have an impact factor Δ on the weight, which is defined as:

$$\Delta_i = \frac{1}{A_{-i} * ME_i} \quad (13)$$

Impact factor normalization.

$$\overline{\Delta} = \frac{\Delta}{\Delta_{\max}} \quad (14)$$

The purpose is to prevent training from falling into local minimum values and to increase the stability of the neural network group. If the network is similar, then $\overline{\Delta}$ are all equal. The output of the neural network group is similar to the average output of the neural network integration. If there are differences in the network, the evolution of impact factors will be used to promote the development of the new system to a new balance. The weights of each member network of the whole neural network group are as follows: $\omega_i = \overline{\Delta} * \omega_{i-1}$. To meet the conditions $\omega_i \geq 0$.

$$\sum_{i=1}^{N} \omega_i = 1 \quad (15)$$

The system body network and the incentive network are trained repeatedly according to the above steps. When WE is reduced to T, the training ends and the new balance is output. The neural network group algorithm completes the convergence.

3 Experimental verification of BNNG algorithm

3.1. Signal Acquisition

This experiment was conducted at night and in foggy days (non-line-of-sight environment) at the 206 National Road in Huainan for more than ten consecutive days to collect acoustic signals from passing vehicle. The data acquisition card used four-channel data acquisition card from Beijing Kerui Company. And acoustic signal sensors used the condenser microphones and matching preamplifiers of Hangzhou Aihua Company. The HV300 laser speedometer was used to measure the vehicle speed.

In order to facilitate research and improve the accuracy of data, we select the vehicle speed in the range of 40km/h-80km/h, and the speed distribution is the same as the sample. Finally, large passenger vehicles (Jinlong CCJ6100, abbreviated as CC), medium-sized passenger buses (Yutong MD6825, abbreviated as MD), small cars (Chery A5, abbreviated as A), trucks (liberation J142, abbreviated as J) were selected. Each of the four vehicle types has 40 samples, and divided into 2 groups, one group for training samples and one group for testing samples. Expected output $T(x) =$ [00, 1, 10, 11].

3.2. Determining AR Model Order

There are many methods for determining the AR model order. This article determines the final prediction error (FPE) criterion based on multiple experiments.

$$FPE(k) = \sigma_k^2 (\frac{N+k+1)}{N \quad k+1} \quad (16)$$

Among them k is the model order and σ_k^2 is the variance of the excitation source of the k-th order model, and N is the number of sample data points. As the k increases, the inaccuracy of the prediction error estimation increases, and the numerical value σ_k^2 decreases, so with the number increases, FPE will have a minimum value, and the corresponding order of the minimum value is the last determined order. By calculation, the order corresponding to the minimum value of FPE in this paper is 8[8-9].

3.3. Signal Acquisition

According to the u check value from small to large, the redundant parameters were deleted one by one to constitute a different combination of parameters. As a BNNG input vector, 1 is output when output ≥ 0.5, and 0 is output when output < 0.5. This time selected 40 training samples and 40 test samples.

$$u = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (17)$$

$$H_0 : \mu_1 = \mu_2 ; H_1 : \mu_1 \neq \mu_2$$

Table 2. Sample input training data section.

CC	*CC*	*MD*	*MD*	*A*	*A*	*J*	*J*
1	1	1	1	1	1	1	1
-2.2662	-2.1906	-3.1468	-3.1878	-2.5419	-2.6952	-1.8249	-1.8979
2.3479	2.0332	4.2635	4.5152	2.2286	2.6699	0.22601	0.32907
-2.094	-1.6246	-3.149	-3.6852	-0.37192	-0.78451	0.67266	0.70654
1.6637	1.2135	1.3727	2.0307	-0.34879	-0.35569	0.47977	0.44619
-1.0867	-0.72649	-0.56508	-1.0761	-0.42777	-0.13064	-0.47657	-0.5362

0.62375	0.45733	0.36962	0.60269	0.78063	0.57171	-0.28681	-0.27251
-0.18669	-0.1609	-0.14385	-0.19833	-0.30428	-0.25719	0.20991	0.22486

3.4. Determining the BNNG Classifier Body and Incentive Network

According to the distribution of the input signal and the principle of similarity defined in the algorithm, this article determines the main network as bp, ebp, tbp, cbp four kinds of networks. According to the number of the main network, structure and the principles of the differences specified in the algorithm, we determine that the incentive network are Perceptron, Radial basis (exact fit), Radial basis (fewer neurons), Generalized regression, Linear layer (design).

3.5. Experimental Results and Analysis

This article programmed to implement BNNG algorithm in matlab7.0 environment, a total of 24 kinds of network types were introduced. After many simulations straining, the specific vehicle recognition rate results are shown in Table 3, and the training error curve is shown in Figure 1, 2.

Table 3. Vehicle recognition rate results.

Network number	*Network name*	*Instructions*	*Hidden layer nodes*	*Network type*	*Correct recognition rate (%)*			
					CC	*MD*	*A*	*J*
1	Bp1-3	Error back propagation network	3，5，8	3	100	75	100	70
2	Cbp1-4	Cascaded Back Propagation Network	3，5，8，10	4	100	95	100	100
3	Ebp1-4	Elman neural network	2，3，4，5	5	100	75	100	75
4	Tbp1-7	Time delay back propagation network	2，3，4，6，7，10，14	7	100	60	100	75
5	Main network	Four main body network convergence		19	100	80	100	75
6	Incentive network	GR, etc.		5	95	75	100	90
7	Overall network	After introducing the incentive network			100	95	100	100

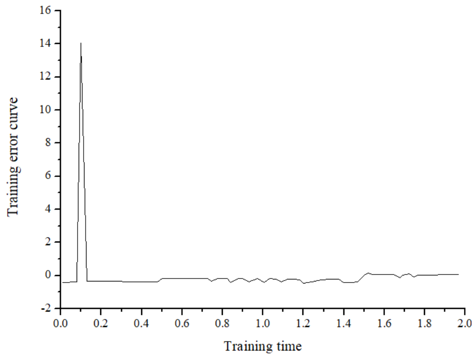

Fig. 1. Single Network Training Error Curve.

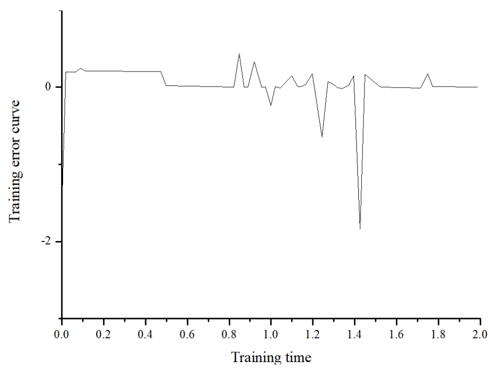

Fig. 2. Neural network group training error curve.

According to the data in Table 3, large passenger cars (CCs) and small cars (A) have obvious characteristic acoustic signals and the lowest misidentification rate of models, while the medium-sized passenger cars (MD) and freight cars (J) have the highest. However, as a whole, it is shown that acoustic signals of different models are used as research objects, and neural network group algorithms can identify vehicle types. Especially under non-line-of-sight environments, the recognition rate of approximate vehicle models can be improved, the generalization error can be reduced, and the overall training time can be increased. The classification recognition improves the verification method. From Fig. 1 and 2, we can see that: (1) There is ambiguity in the constraint relationship between the number of the main network and the input space; (2)The turbulence is caused by the error caused by the incentive network. It is necessary to study the stationary algorithm to improve the robustness.

4 Conclusion

In the non-line-of sight environment, taking the acoustic signal of vehicle driving as the research object, and using the bionic neural network group (BNNG) algorithm proposed in this paper, the experimental test shows that the vehicle classification and recognition can be achieved. The accuracy of vehicle classification is improved, and the misidentification rate of similar models is greatly reduced. This provides a new method for the automatic classification and identification of vehicles on roads and is of great significance for the monitoring of vehicle safety under non-line-of-sight environments. At the same time, the BNNG algorithm is a new neural network integration model, which establishes and evolves the network according to the rules of ecological evolution. The analysis of experimental data shows that there is a certain similarity between the simulated ecological neural network group and the natural ecological balance model, which provides a theoretical and experimental reference value for the unified framework of neural network integration theory, and also provides a new method and basis for pattern recognition under complex conditions.

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