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A Novel Active Safety Algorithm using Improved Neural Network

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Abstract: In recent years, with the beginning of the close integration of the Intelligent Transportation System (ITS) and vehicle *ad hoc* networks, the active safety of vehicle *ad hoc* network, just as collision warning, has become an important direction. This study puts forward a novel active safety algorithm that is suitable for the traffic road on the basis of improved neural network. This algorithm contains three parts, including target selection, risk level classification and forecast and active collision avoidance and realizes the whole process of vehicle active collision avoidance. The simulation result verifies the rationality of this algorithm and also provides a feasible method for unmanned driving technology.

Key words: Collision avoidance algorithm, neural network, vehicular *ad hoc*, networks, risk level

INTRODUCTION

Vehicular *ad hoc* Networks (VANET) is a new kind of multi-hop mobile and wireless communication network, which has become the hot spot in the wireless network research field. VANET can help the driver to timely acquire information about the running state of the vehicles around the driver's and the road condition, such as speed, direction, state, signal indication and road incidents. It can help the driver to acquire in advance the time to respond to and deal with the accidents so as to better ensure traffic safety. The vehicle collision avoidance system is an important part of the security application of VANET (Garcia-Costa *et al*., 2013; Barrachina *et al*., 2012). Through their equipped wireless transceivers, vehicles can communicate with other vehicles or road facilities, exchange vehicle running state and geographic position information. The above information can be used to predict collision probability (Sotelo *et al*., 2012; ElBatt *et al*., 2006). Huang *et al*. (2011) studied the real-time location method to locate each vehicle through vehicle-mounted radio. Chang *et al*. (2010) use the data fusion system together with the Global Positioning System coordinate to predict vehicle collision. However, there is certain difficulty in acquiring the vehicle's dynamics information by using data fusion alone. Chen *et al*. (2011) proposed a communication protocol for the most frequent rear-end collision. The above model does not take the driver's characteristic into account. The research objective of the vehicle collision avoidance algorithm is to give the alarm to alert the driver and control the vehicle to avoid collision if the driver does not give feedback when an accident is about to happen. In consideration of the driver's habits, collision avoidance algorithm not only should give the alarm correctly when a danger is about to happen but also should not give false alarm when there is no danger. Otherwise, the driver will be numb to the early warning system, neglect the alarm and even turn off the early warning system (Zhang *et al*., 2006; Wang *et al*., 2009). Therefore, a good early warming algorithm should be suitable for the driver's characteristics and it should take most of the situation into account so that the driver can respond to and deal with various dangerous situations in order to avoid collision.

This study enables the system to learn about the driver's characteristics by adopting the neural network method. In this way, the system will be suitable for the driver's characteristics and make the alarm similar to the driver's driving habits in order to better improve the effect of early warming. The mathematical model that is suitable for the collision avoidance algorithm is established on the basis of improved adaptive resonance theory 2 (IART2) neuron. Integrate the physical parameters which can reflect road conditions into the IART2 neuron. The IART2-based neural network can classify road conditions well, give corresponding alarm by combining with driver's habits that it has memorized and put forward the active collision avoidance algorithm in an emergency on the basis of vehicle turning movement rule analysis.

This study is dedicated to designing an active safety algorithm in accordance with the practical situation. For

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this purpose, firstly, the active collision avoidance system select dangerous object by adopting minimum safety distance model. Secondly, in the section of risk level classification and prediction, we propose an adaptive neural network. Thirdly, active collision avoidance phase, if the system does not detect the driver's action, it will be forced braking. Lastly, shown by simulation test, the system will be suitable for the driver's characteristics and make the alarm similar to the driver's driving habits in order to better improve the effect of early warning.

ACTIVE COLLISION AVOIDANCE ALGORITHM

The active collision avoidance system learns about the driver's characteristics by adopting the neural network method. The mathematical model that is suitable for the collision avoidance algorithm is established on the basis of IART2 neuron and realizes the whole process of vehicle active collision avoidance. The system flow chart is shown in Fig. 1. The whole life cycle of vehicle active collision avoidance system includes processes such as target selection, risk level classification and prediction, active collision avoidance. Target selection process starts to run after the system start-up. It will detect the potential danger object in a certain angle and calculate physical quantities such as collision time and minimum distance for each object, so as to choose the most possible collision node and provide related information for risk level classification and prediction in time. The target selection algorithm is an IART2 neural network based reasoning and classification system with self-learning ability. It should be trained by samples in advance. It will generate a classification result corresponding to an input mode after the sample training. And decide whether to start active collision avoidance or not according to the given classification result and the driver's feedback.

There are many potential danger objects when you are driving on the road. All of these objects have a certain probability to collide with your vehicle. As a result, how to detect danger objects is the first thing to be considered in active collision avoidance algorithm (Yan *et al*., 2010). When the vehicle scans through microwave radar, there is a problem about the scanning angle. Determine the angle size in advance can make the scanning more accurate and effective.

Target selection: Make the microwave radar to scan in the range of the scanning angle, calculate each scanned node and give prediction of future distance. Here, suppose the relative displacement at time t is $\overrightarrow{l_{rel}(t)} = (l_x, l_y)$, t, the relative velocity is $\overrightarrow{v_{rel}(t)} = (v_x, v_y) = \overrightarrow{l_{rel}(t)} - \overrightarrow{l_{rel}(t-1)}$. Predict the relative displacement vector and the relative velocity vector at time τ and calculate the distance at a future time τ.

$$\begin{aligned}\text{Dist}(\tau) &= \| \overrightarrow{l_{rel}} + \tau\cdot\overrightarrow{v_{rel}} \| = \sqrt{(l_x+\tau\cdot v_x)^2 + (l_y+\tau\cdot v_x)^2} \\ &= \sqrt{(v_x{}^2+v_y{}^2)\cdot\tau^2 + 2(l_x\cdot v_x + l_y\cdot v_x)\cdot\tau + l_x{}^2 + l_y{}^2}\end{aligned} \qquad (1)$$

According to Eq. 1, the minimum value of dist (τ) is denoted as:

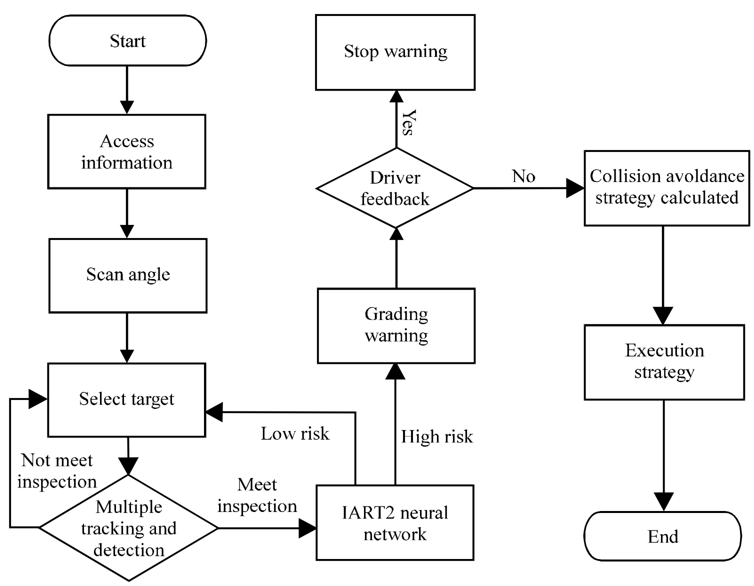

Fig. 1: System flow chart of active collision avoidance

$$\mathrm{dist}(\tau)_{\min} = \sqrt{\frac{4ac-b^2}{4a}}$$

In this equation, $a = v_x^2+v_y^2$, $b = 2\,(l_x.v_x+l_y.v_y)$, $c = l_x^2+l_y^2$ Here, dist $(\tau)_{\min}$ is the minimum safety distance.

The algorithm chooses the minimum node of dist $(\tau)_{\min}$ in all nodes to be the most dangerous object. Conduct analysis and reasoning in the neural network of risk level classification and prediction so as to get further results.

RISK LEVEL CLASSIFICATION AND PREDICTION

Selection of neural network characteristic quantities: The early warning algorithm should conform to the driver's characteristics. Considering that different drivers usually have different responses under the same condition, which mainly manifests as different time lengths of the braking action when danger is about to happen, the parameters should be structured to reflect the driver's characteristics.

Considering that the a driver may have the same vigilance parameter under single working condition and that the working condition characteristics are mainly determined by factors such as the relative velocity, relative distance and relative direction of the vehicle, let:

$$\overrightarrow{I(t)} = (dl_x, dl_y, dv_x, dv_y)$$

In this equation, dl_x, dl_y is the relative displacement on the corresponding coordinate component, dv_x, dv_y is the relative velocity on the corresponding coordinate component and the included angle of vector quantity I and vector quantity I' can be considered as the measurement of the two vector quantities' level of similarity. The smaller the angle is, the higher the level of similarity.

The driver's sensitivity coefficient under some working condition could be determined by the braking distance and the minimum safe distance. Therefore, let the sensitivity coefficient of the characteristic quantity ξ be:

$$\xi = \begin{cases} \frac{s_{abs}}{s}\,(s \geq s_{abs}) \\ 1(s \leq s_{abs}) \end{cases} \tag{2}$$

In Eq. 2:

$$s_{abs} = v_c \cdot t_{resp} + \frac{v_c^{\,2}}{2acc}$$

IART2 neural network: The adaptive resonance theory 2 (ART2) neuron is shown in Fig. 2a. The ART2-type neural network can make specific classification for the continuous input samples and it has self-learning function. Therefore, classification reasoning can be made for the vehicle running working condition by constructing the ART2 neural network and the danger level can be directly decided by the results.

The hierarchical structure of ART2 network is mainly divided into the input layer and the output layer. Each node of the input layer is connected with that of the output layer. Figure 2a shows us the connection of some node of the input layer and that of the output layer, which is recorded as a neuron (Lu *et al*., 2010). The ART2 neuron can also be divided into two layers, including the attention subsystem F_1 and orientation subsystem F_2. The function of F_1 is to memorize the input vector quantities

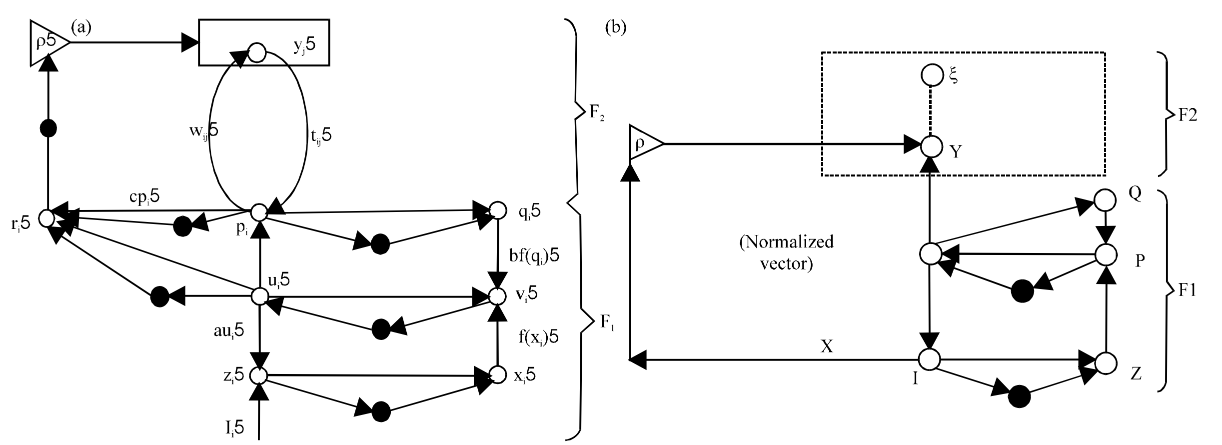

Fig. 2(a-b): (a) Adaptive resonance theory 2 (ART2) neuron and (b) improved adaptive resonance theory 2 (IART2) neuron for short-term and long-term and the function of F_2 is to classify the vector quantities and give feedback to F_1 layer.

In consideration of the need of the collision avoidance algorithm, the layer feedback function of ART2 is abandoned and the subsystem for physical characteristic quantity measurement gain is added. The improved ART2 neural network (IART2) is shown in Fig. 2b. In the IART2, the input mode is n-dimensional vector $\vec{I} = (I_1, I_2, \cdots, I_n)$. The vector components can take continuous variable and its output mode is:

$$\vec{\xi} = (\xi_1, \xi_2, \cdots, \xi_n)$$

in which $\xi_i \in [0, 1]$. Figure 2b shows the connection of some input component node with some node of the competitive layer. I, U, Z, P, Q of F1 layer completes functions such as the weakening and strengthening and the normalization of the input vector quantity, which has an effect of enhancing the signal. F2 layer contains parameter Y that reflects the physical characteristic quantity and coefficient ξ that represents the sensitivity of this working condition. Parameter ρ is the alert degree parameter and its value controls the classification result, which refers to the similarity level of some F2 layer node's input mode on the respect of the physical characteristic quantity.

Figure 2 Adaptive Resonance Theory 2 (ART2) and Improved Adaptive Resonance Theory 2 (IART2) neuron structure.

Build a model for the intelligent early warning algorithm according to the IART2 neural network structure. In order to reflect the vehicle's running condition, $\overrightarrow{l_{rel}(t)}$ and $\overrightarrow{v_{rel}(t)}$ should be taken as the input of the neural network, that is to set:

$$\overrightarrow{I(t)} = (l_x, l_y, v_x, v_y)$$

as the input mode of the neural network at time t and the output value is $\vec{\xi}$. The IART2 network structure is shown in Fig. 3. When the neural network has finished its learning, it can give the classification result ξ_t of any input mode:

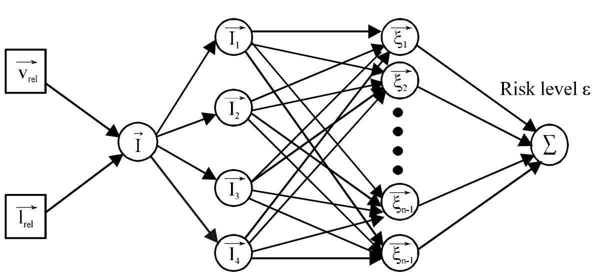

Fig. 3: Improved adaptive resonance theory 2 (IART2) neural network structure

$$\overrightarrow{I(t)} = (l_x, l_y, v_x, v_y)$$

The risk level is recorded as ε.

Erly warning process and the training algorithm

Early warning process: Each successful execution of the target selection algorithm can provide a input for this early warning algorithm. Put vector quantity $\overrightarrow{l_{rel}(t)}$ and $\overrightarrow{v_{rel}(t)}$ into the neural network to calculate the sensitivity coefficient ξ_t. Continue to track the corresponding vehicle of this vector quantity to monitor in real time that whether the $\frac{s_{abs}}{s}$ in running condition is greater than ξ_t.

Training algorithm: The specific steps of the training algorithm are as follows:

Step 1: Select learning samples $\overrightarrow{I(t)} = (l_x, l_y, v_x, v_y)$

Step 2: Initialize the parameter of F1 layer to 0. Start the short-term memory learning and execute over and over again:

$$X_i = I_i + aU_i,\ Z_i = \frac{X_i}{\|X\|},\ P_i = f(Z_i) + bf(Q_i),\ U_i = \frac{P_i}{\|P\|}$$

until U_t converge to ε

Step 3: Input $\sum_{i=1}^{n} U_i W_{ij}$ into F2 layer, compare the input accepted by all of the active nodes in F2 layer and select j that maximize $\sum_{i=1}^{n} U_i W_{ij}$ as the winning neuron

Step 4: If node j is selected for the first time, then let Y (j) = residue (I). Turn back to step 1, or calculate the physical characteristic quantity measurement residue (I). If:

$$\frac{|\text{residue}(I) - Y(j)|}{Y(j)} < 1 - \rho$$

modify ξ_t and W_{ij} according to Eq. 3:

$$\xi_j = \frac{\xi_j + \text{residue (I)}}{2}$$
$$W_{ij} = d\,(1-d)\left(\frac{U_i}{1-d} - W_{ij}\right) \tag{3}$$

Otherwise, disable this node and turn back to step 3 to select the winning node for another time. If none of the node conforms to the requirement, then create new nodes in F2 layer and modify the corresponding parameters according to Eq. 3.

Step 5: Release all of the disabled nodes in F2 layer and turn back to Step1 to learn the next sample

Active collision avoidance: The active collision avoidance algorithm is applied under the circumstance that the driver doesn't give any feedback action after the early warning was given by the early warning algorithm. Before the collision, if the early warning had already been given by the early warning algorithm but the driver still didn't give any feedback, then the active collision avoidance measures should be started, which include turning, slowing down, etc. Assume that the vehicle's running condition at this time is: The relative displacement is $\overrightarrow{l_{rel}(t)}$, the velocity vector of this vehicle is $\overrightarrow{v_c(t)}$, the velocity vector of the object vehicle is $\overrightarrow{v_t(t)}$, the maximum turning angle of this vehicle is $\hat{\theta}$ and the turning radius of the maximum turning angle of this vehicle is r.

Among the above variables, the relative displacement $\overrightarrow{l_{rel}(t)}$ is acquired through microwave radar measurement; $\overrightarrow{v_c(t)}$ is acquired through the angle and the infrared sensor in the vehicle:

$$\overrightarrow{v_t(t)} = \overrightarrow{l_{rel}(t)} - \overrightarrow{l_{rel}(t-1)} + \overrightarrow{v_c(t)}$$

$\hat{\theta}$ and r are determined by the property of this vehicle, whose parameters can be input into the system during the installation.

In order to improve fuel economy, priority should be given to the "turning" operation, which is also called "changing lane", between "slowing down" and "turning". Therefore, judging the vehicle's steering is the key to the feasibility of this decision.

When the vehicle speed is $\left\|\overrightarrow{v_c(t)}\right\|$, it is obvious that the turning angle θ should not be set as $\hat{\theta}$ for the safety. Assume that turning is not permitted under the maximum vehicle speed and that the turning angle at rest is the vehicle's maximum turning angle $\hat{\theta}$, then the linear relation between θ and $\hat{\theta}$ is:

$$\theta = \hat{\theta} - \frac{\left\|\overrightarrow{v_c(t)}\right\| \cdot \hat{\theta}}{V_{max}} \tag{4}$$

When analyzing the turning operation of the vehicle, assume that the turning operation can be simplified as that shown in Fig. 4.

It can be seen from Fig. 4 that after the angle θ is given, function R (θ) of the turning radius with the turning angle need to be further calculated, which is:

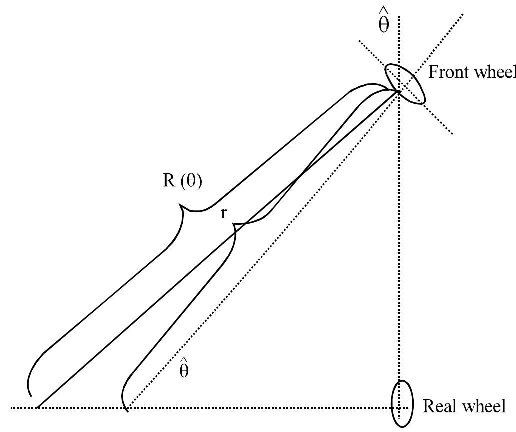

Fig. 4: Schematic diagram of the vehicle's turning radius

$$R(\theta) = \frac{r \cdot \sin(\hat{\theta})}{\sin(\theta)} \tag{5}$$

Assuming that the linear velocity $\left\|\overrightarrow{v_c(t)}\right\|$ and the turning radius R (θ) are known, the turning angle per unit time α is:

$$\alpha = \frac{\left\|\overrightarrow{v_c(t)}\right\|}{R(\theta)} \tag{6}$$

In order to predict the vehicle's running state, need to predict the velocity vector at time τ for the velocity vector $\overrightarrow{v_c(t)}$ at time τ.

Forms of the polar coordinates $\overrightarrow{v_c(t)}$ are:

$$\begin{cases} v_c(x) = \left\|\overrightarrow{v_c(t)}\right\| \cdot \cos(\varphi) \\ v_c(y) = \left\|\overrightarrow{v_c(t)}\right\| \cdot \sin(\varphi) \end{cases} \tag{7}$$

In order to facilitate discussion, record the velocity vector value $\overrightarrow{v_c(t)(\tau)}$ after time τ asc $\overrightarrow{v_c(t)}$. According to Eq. 7, there is:

$$\begin{cases} v_c(\tau)(x) = \left\|\overrightarrow{v_c(t)}\right\| \cdot \cos(\varphi + \tau \cdot \alpha) \\ v_c(\tau)(y) = \left\|\overrightarrow{v_c(t)}\right\| \cdot \sin(\varphi + \tau \cdot \alpha) \end{cases} \tag{8}$$

And then:

$$\begin{cases} v_c(\tau)(x) = \left\|\overrightarrow{v_c(t)}\right\| \cdot [\cos(\varphi) \cdot \cos(\tau \cdot \alpha) - \sin(\varphi) \cdot \sin(\tau \cdot \alpha)] \\ v_c(\tau)(y) = \left\|\overrightarrow{v_c(t)}\right\| \cdot [\sin(\varphi) \cdot \cos(\tau \cdot \alpha) + \cos(\varphi) \cdot \sin(\tau \cdot \alpha)] \end{cases} \tag{9}$$

According to the exact value of $\overrightarrow{v_c(t)}$, $\overrightarrow{v_t(t)}$, $\overrightarrow{l_{rel}(t)}$ the relative distance at the future time T is:

$$\text{dist}_t(T) = \left\| \overrightarrow{l_{rel}(t)} - \int_0^T \overrightarrow{v_c(\tau)} d\tau \right\| \tag{10}$$

According to Eq. 9 and 10:

$$\begin{aligned}\text{dist}_t^2(T) &= \left\| \overrightarrow{l_{rel}(t)} - \int_0^T \overrightarrow{v_c(\tau)} d\tau \right\|^2 \\ &= l_x^2 + l_y^2 + P^2 - 2P\left[(l_x\cos(\varphi) + l_y\sin(\varphi))\cdot\sin(\alpha T) + (l_x\sin(\varphi) - l_y\cos(\varphi))\cdot\cos(\alpha T)\right]\end{aligned}$$

Let:

$$\begin{aligned}&(l_x\cos(\varphi) + l_y\sin(\varphi))\cdot\sin(\alpha T) + (l_x\sin(\varphi) - l_y\cos(\varphi))\cdot\cos(\alpha T) \\ &= \sqrt{(l_x\cos(\varphi) + l_y\sin(\varphi))^2 + (l_x\sin(\varphi) - l_y\cos(\varphi))^2}\cdot\sin(\alpha T + \gamma)\end{aligned} \tag{11}$$

There is:

$$\begin{aligned}&\text{dist}_t^2(T)_{min} \\ &= l_x^2 + l_y^2 + P^2 - 2P\cdot\sqrt{(l_x\cos(\varphi) + l_y\sin(\varphi))^2 + (l_x\sin(\varphi) - l_y\cos(\varphi))^2}\end{aligned} \tag{12}$$

Thus it can be seen that when the turning direction is set, then $\text{dist}_t(T)_{min}$ can be calculated out. Therefore, it can be judged directly that whether this turning operation will avoid collision or not through whether the value of $\text{dist}_t(T)_{min}$ is in the danger range or not. If both of the turning operations on both sides cannot avoid collision, then the forced braking should be executed.

SYSTEM SIMULATION

Establishment and selection of samples: In the target selection algorithm, establish the learning samples by the method of parametric equation division, screen the samples and input the screened samples into the neural network for learning. The parametric equation of velocity and displacement can be represented as:

$$\begin{cases} dvx = \rho_1\cdot\cos(\theta_1) \\ dvy = \rho_1\cdot\sin(\theta_1) \end{cases} \quad \begin{cases} dsx = \rho_2\cdot\cos(\theta_2) \\ dsy = \rho_2\cdot\sin(\theta_2) \end{cases} \tag{13}$$

According to Eq. 13, maximize the value of ρ and θ, divide ρ and θ according to the fixed particle size in order to get the learning samples:

$$\begin{cases} dvx = (\frac{i}{n})\rho_1\cdot\cos(\frac{j}{n}\theta_1) \\ dvy = (\frac{i}{n})\rho_1\cdot\sin(\frac{j}{n}\theta_1) \end{cases} (i, j = 1, 2, ..., n) \quad \begin{cases} dsx = (\frac{k}{n})\rho_2\cdot\cos(\frac{l}{n}\theta_2) \\ dsy = (\frac{k}{n})\rho_2\cdot\sin(\frac{l}{n}\theta_2) \end{cases} (k, l = 1, 2, ..., n) \tag{14}$$

The simulation of the model in this study is carried out in MATLAB. Suppose ρ_1 = 30 m sec^{-1}, ρ_2 = 100 m, $\theta_1 = \theta_2 = \pi$, n = 15. Screen the acquired learning samples according to the target selection algorithm, the value of X component displacement, Y component displacement, X component relative velocity and Y component relative velocity is shown in Table 1.

Classification result: After taking the above samples for training, the classification result of the samples in the neural network is shown in Fig. 5. Pei *et al.* (2012) define the Inverse of Time-to-collision (TTC^{-1}) as the evaluation index with the grading warning and braking safe distance model adopted based on hazardous level ε, establish a model which can be suitable for the driver's characteristics. But due to lack of systematic theoretical guidance, the model is difficult to accurately achieve. It can be seen from the Fig. 5 that the distribution is relatively equalized and presents a law of local concentration, which is relatively consistent with the actual situation. From the classification, the algorithm divides all of the learning samples into 23 working conditions, of which each condition has similar physical parameters and matching degree of its own (which can be seen as the value of the included angle of the sample

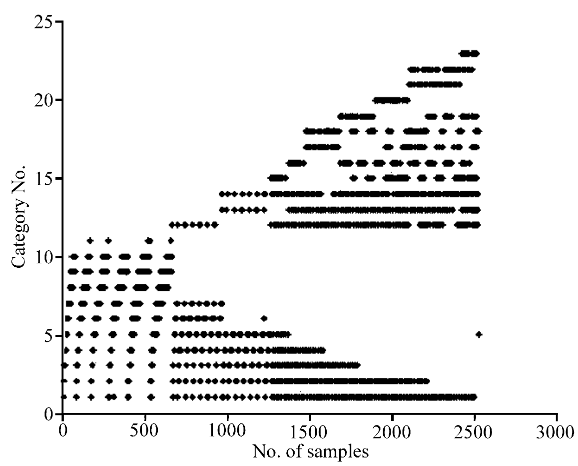

Fig. 5: Distribution of the sample types

Table 1: Value of learning samples

Sample No.	X Displacement (m)	Y Displacement (m)	X Relative velocity (m sec)	Y Relative velocity (m sec)
1	6.5210	1.3861	-1.9663	-0.4158
2	6.5210	1.3861	-1.8271	-0.8135
3	6.5210	1.3861	-1.6180	-1.1756
4	6.5210	1.3861	-1.3383	-1.4863
……	……	……	……	……
2519	10.4528	99.4522	-2.9268	-27.8466
2520	2.0601	6.3432	-3.7082	-11.4235

Table 2: Corresponding sensitivity coefficient of each node in F2 layer of the neural network

Node No.	Sensitivity	Node No.	Sensitivity	Node No.	Sensitivity	Node No.	Sensitivity
1	0.7807	7	1.0000	13	0.2239	19	0.0667
2	1.0000	8	1.0000	14	0.4695	20	0.0432
3	1.0000	9	1.0000	15	0.1466	21	0.0339
4	1.0000	10	1.0000	16	0.1055	22	0.2895
5	1.0000	11	0.9844	17	0.1009	23	0.0353
6	1.0000	12	0.3672	18	0.6235		

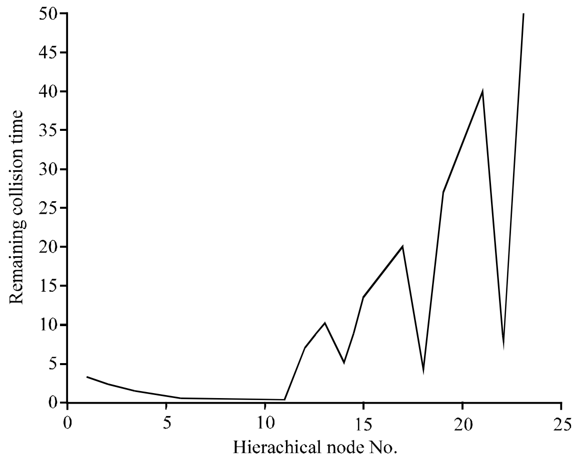

Fig. 6: Physical characteristic quantity of the node in F2 layer

vector quantity). The automatic increase of the classification number can also reflect the "self-adaption" characteristic of the IART2.

According to the characteristic quantity of each node in F2 layer, the physical characteristic quantity of the classification node can be obtained as shown in Fig. 6.

It can be seen from Fig. 6 that the difference between the corresponding physical characteristic quantities of some of the layer nodes is large, whereas the difference between that of some other layer nodes is small. This is because the road condition is not fully determined by the physical characteristic quantity but determined by both the physical characteristic quantity and the goodness fit of the input vector together. In addition, the variation of the physical characteristic quantity is not too big, which reflects that the selection of the samples is relatively reasonable. The sensitivity coefficient of each node in F2 layer is shown in Table 2.

The sensitivity coefficient reflects the driver's sensitivity to this working condition, which is the key parameter for the neural network to learn the driver's driving behavior. It can be seen from the simulation result that the difference between the sensitivities of each node is relatively big due to the randomness of sample selection. But when the real driver's behaviors are input as samples, the sensitivities of each node should have some similarity. However, the final sensitivity coefficients of the neural network are quite different between different drivers.

CONCLUSION AND FUTURE WORK

This study models and simulates the process of the vehicle collision avoidance systematically and establishes the neural network collision avoidance algorithm that is suitable for driver characteristics, which has a certain practicability and can be regarded as a reference solution for the researchers in this field. The simulation result shows that IART2 neural network has a preferable function of working condition classification. The final classification result also successfully presents the driver's sensitivity coefficients of each node, which fully proves the feasibility of the scheme. The future work is focused on the intelligent control of neural network on vehicles and the further improvement of the robustness and instantaneity of this algorithm.

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