J. Cent. South Univ. (2017) 24: 1476−1482
DOI: 10.1007/s11771-017-3551-4

Springer

Driving decision-making analysis of car-following for autonomous vehicle under complex urban environment

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Abstract: The decision-making under complex urban environment become one of the key issues that restricts the rapid development of the autonomous vehicles. The difficulty in making timely and accurate decisions like human beings under highly dynamic traffic environment is a major challenge for autonomous driving. Car-following has been regarded as the simplest but essential driving behavior among driving tasks and has received extensive attention from researchers around the world. This work addresses this problem and proposes a novel method RSAN (rough-set artificial neural network) to learn the decisions from excellent human drivers. A virtual urban traffic environment was built by PreScan and driving simulation was conducted to obtain a broad set of relevant data such as experienced drivers' behavior data and surrounding vehicles' motion data. Then, rough set was used to preprocess these data to extract the key influential factors on decision and reduce the impact of uncertain data and noise data. And the car-following decision was learned by neural network in which key factor was the input and acceleration was the output. The result shows the better convergence speed and the better decision accuracy of RSAN than ANN. Findings of this work contributes to the empirical understanding of driver's decision-making process and it provides a theoretical basis for the study of car-following decision-making under complex and dynamic environment.

Key words: autonomous vehicle; car-following; decision-making; rough set (RS); artificial neural network (ANN); PreScan

1 Introduction

The autonomous vehicles have received comprehensive attention recently in the fields of transportation, road safety, etc [1]. Many research institutions, such as the Carnegie Mellon University (CMU), Stanford University, Mercedes Benz Company, Google, etc., have done a lot of research work and greatly promoted the development of autonomous vehicles.

As one of the significant factors affecting traffic performance and safety, car-following behaviors have become one of the major concerns in study on decision-making of autonomous vehicles [2]. General Motors (GM) laboratory focused on the car-following behavior and proposed a new method for microscopic driving behavior research, which greatly promoted basic research on the car-following model [3]. Study enlightened many researchers that car-following decision of autonomous vehicle is not a mechanical process, MICHAELS [4] studied the car-following behavior based on Psychology Theory and driver's characteristic, which proved that the driver factors should also be considered when making car-following decisions. With the development of intelligent transport systems (ITS) and self-driving vehicles, the studies on key factors affecting decision-making process of autonomous vehicles under complex urban environment attracted the researchers [5].

Study mentioned above employed the analytical approach of the car-following behaviors, but they may had some limitations because of the unpredicted, highly dynamic and incomplete traffic data. Often, there may be relevant factors that are uncertain and variables that are only partially observable. Under these situations, there are difficulties in extracting car-following decision rules, and the car-following decision-making of autonomous vehicles still remains a great challenge [6, 7].

Combining the advantages of rough set (RS) and artificial neural network (ANN), this work proposed a novel approach RSAN for car-following behavior of autonomous vehicle to extract and learn driver's decision rules from human's driving process [8]. RS has been demonstrated to be very effective in artificial intelligence field [9]. The deterministic mechanism for the description of error in RS theory is always simple [10]. In addition, the rules generated by RS are often unstable

Foundation item: Project(9142020013) support by the National Natural Science Foundation of China
Received date: 2016−12−15; **Accepted date:** 2017−04−01
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and have low classification accuracies. Therefore, RS cannot make car-following decisions with high accuracy. ANN is accepted as the most powerful classifier with low classification-error rates and strong robustness to noise [11]. However, ANN show a less favorable when facing large data problems, for example, surrounding state data of autonomous vehicles under urban traffic environment. The knowledge of ANN is hidden in their structures and weights [12]. It is often difficult to extract rules from a well-trained Artificial Neural Network. The combination of RS and ANN can not only reduce the impact of weak interdependency data, but also find key influential factors that are used as the inputs of an artificial neural network for training and learning the car-following decision [13].

2 Methodology

2.1 Rough set and artificial neural network

Rough set (RS) theory introduced by Pawlak is a mathematical tool in analyzing and processing the imprecise, inconsistent and incomplete information. It can effectively analyze and deal with complex and dynamic information of urban environment and even find the implicit knowledge and reveal the law of potential [14]. The basic concepts of rough set theory are summarized as follows.

An information system can be described as a 4-tuple: $S=\langle U, A, V, f\rangle$, U is a finite set of objects and it is defined as domain, in which elements are known as the object. A is a finite set of attributes; $V=U_{a\in A}$, V_a is a domain of attribute a, and f: $U\times A\rightarrow V$ is called information function, which assigns information value for each attribute of each object, and for $\forall a\in A$, $\forall x\in U. f(x,a)\in V_a$.

In classification problems, an information system is also seen as a decision table assuming that $A=C\bigcup D$ and $C\bigcap D=\phi$, where C is a set of condition attributes and D is a set of decision attributes. Let S={U, Q, V, f} be an information system: every $P\subseteq A$ generates an indiscernibility relation IND(P) on U, which is defined as follows:

$$IND(P)=\{x,y\in U\times U \mid \forall p\in P, f(x,a)=f(y,a)\} \tag{1}$$

Let $P\subseteq A$, $X\subseteq U$. The P-lower approximation of X (denoted by $\underline{P}X$) and the P-upper approximation of X (denoted by $\overline{P}X$) are defined in the following expressions:

$$\underline{P}X=\{Y\in U/P: Y\subseteq X\} \tag{2}$$

$$\overline{P}X=\{Y\in U/P: Y\bigcap X\neq\phi\} \tag{3}$$

$\underline{P}X$ is the set of all objects from U that can be certainly classified as elements of X employing the set of attributes P. $\overline{P}X$ is the set of objects of U that can possibly be elements of X using the set of attributes P. The P-boundary (doubtful region) of set X is defined through Eq. (3).

$$Bnd_p(X)=\overline{P}X-\underline{P}X \tag{4}$$

The set $Bnd_p(X)$ is the set of objects, which cannot be certainly classified according to X using only the set of attributes P. Decision rules derived from a decision table can be used for recommendations concerning new objects. Specifically, matching its description to one of the decision rules can support the classification of a new object.

Artificial neural network (ANN) is an effective method, which can mimic the process of knowledge acquisition and organization skills of the human brain. The individual computational units that make up artificial neural network are referred to as nodes, units, or processing elements (PEs).

BP neural network is based on the gradient descent method, which minimizes the sum of the squared errors between the actual and the desired output values. The basic formula of BP algorithm is:

$$W(n)=W(n-1)+\Delta W(n) \tag{5}$$

While

$$\Delta W(n)=\eta\frac{\partial E}{\partial W}(n-1)+\alpha\Delta W(n-1) \tag{6}$$

where W means weight; η means learning rate; E means gradient of error function; $\alpha\Delta W(n-1)$ means weight incremental quantity. According to Kolmogorov theorem and BP fix quantify, three layers BP network with sigmoid function as excitation function can approach any continual function in any precision.

2.2 Model RSAN based on RS and ANN

The common advantage of RS and ANN is that they do not need any additional information about data like probability in statistics or grade of membership in fuzzy-set theory [15]. RS approach is employed to preprocess the data and provides useful techniques to reduce irrelevant and redundant attributes in a large database [16]. ANN has the ability to approach complex functions and the results are robust to noises [17]. In practice, there are often vast amounts of sensor data updated every few minutes.

The flow diagram of extracting the driver's car-following behavior is shown in Fig. 1. Firstly, redundancies in the raw data can be deleted and key influential factors on decision can be extracted automatically by RS theory. Then, ANN model is well trained to learn the drivers' decision experience in order to make car-following decision for autonomous vehicles.

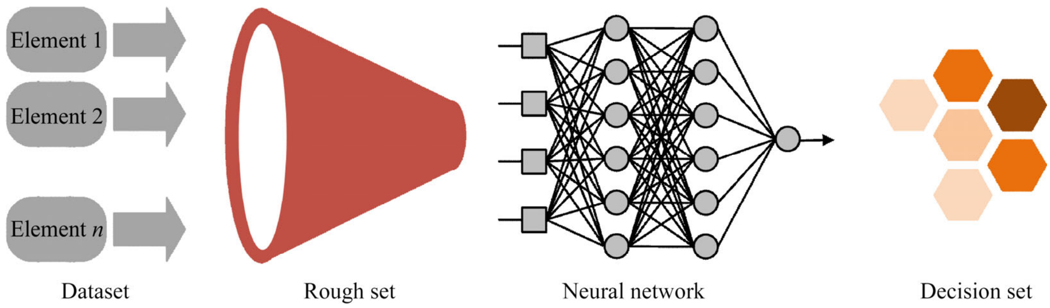

Fig. 1 Process of combination of rough set and neural network

3 Simulation experiment design

This work focuses on decision-making of the autonomous vehicle in urban traffic environment. We study the car-following behavior, which is the most common, simplest but essential driving task. To build microscopic driving behavior models, we set up a virtual traffic environment based on PreScan where simulation of car-following driving can be conducted and massive driving data from experienced drivers can be obtained easily. And then, the car-following decision can be learned by the proposed method RSAN.

PreScan is a software tool designed as a development environment for advanced driver assistance systems (ADAS) and intelligent vehicle (IV) systems [18]. PreScan comes with a powerful graphics preprocessor, a high-end 3D visualization viewer, and an associated interface with standard MATLAB/Simulink. It can build 3D traffic virtual scene, generate vehicles, pedestrians, traffic lights and other control modules. Moreover, it also provides an interface for Simulink and allows users to effectively control and operate the simulation process. It can be seen as a simulation and verification environment for intelligent vehicle systems. For instance, these are systems with sensors that monitor the vehicle's surroundings and that use the acquired information to take action. Such actions may range from warning the driver of a potentially dangerous situation to actively evading hazards by means of automatic braking or automatic steering.

3.1 Virtual traffic simulation environment

Urban road environment surrounding Beijing Institute of Technology is the designated study site to simulate in PreScan, which includes expressway, main road and secondary road making it significantly representative. In this work, the experimental vehicle for car following equipped with external driving simulator hardware was under the control of human driver. Other vehicles were governed by a predefined driving behavior model to control their paths and velocities. It should be noted that the speed of surrounding vehicles almost mirrored the traffic flow characteristics of real world. The external driving simulator was Logitech G27 with steering wheel and pedal. The virtual urban traffic environment and the driving simulation experiment is shown in Fig. 2.

3.2 Participants in simulation experiment

Before experiments, the drivers were arranged to drive at least 4 km to get familiar with the virtual environment and the driving simulator. In the absence of any guidance, the drivers drive freely to finish the whole journey. Finally, we conducted the experiments and drivers take appropriate action to avoid collisions according to the road traffic situation. During the experiments, the drivers were arranged properly in a quiet experiment room. The data set collected included position, velocity, and acceleration both in lateral and longitudinal directions. In addition, the driving process was recorded by video, which provided convenience for the data analysis.

In these experiments, 90 drivers include 60 males (66.7%) and 30 females (33.3%) were involved which is shown in Table 1. Table 2 describes the age of participants. Sample age ranges from 20 to 60 years old, with drivers of 20−30 years old accounted for the proportion of 53.33%, 31−40 accounted for 35.56%, 41−50 accounted for 7.78%, 51−60 accounted for 3.33%. Driving experience distribution ranges from 3 to 20 years, with an average of 8.56 years.

3.3 Data acquisition and preprocessing

One of the effective approach to study the car-following driving behavior under the complex and dynamic urban environment is that learning experience from human driver. RS and ANN are effective mathematical tools to discover knowledge and learn the reasoning process of the human brain. The driving data collected in simulation experiments included: ① vehicle movement parameters, such as position, velocity, acceleration and steering wheel angle, etc.; ② basic information about the drivers, such as driving age, driving mileages, etc. The vehicle motion parameters were obtained by "to file" and "to work-space" module

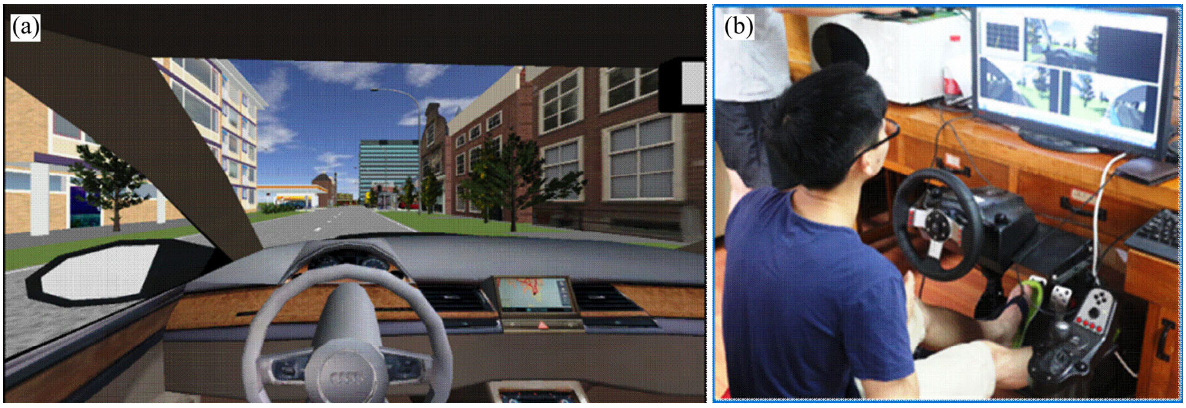

Fig. 2 Virtual urban traffic environment (a) and driving simulation experiment (b)

Table 1 Gender of participants

Gender	Number of people
Male	60
Female	30

Table 2 Age of participants

Age/year	Number of people
20−30	48
31−40	32
41−50	7
51−60	3

Table 3 Samples of car-following behavior data

Time	V_{lead}	D	V_{sub}	a
13.40	6.00	6.57	5.64	−0.11
13.60	6.00	6.64	6.12	−0.11
13.80	6.05	6.72	6.02	−0.11
14.00	6.85	6.80	6.66	−0.11
16.70	7.18	8.36	7.19	−0.05
16.90	7.07	8.51	7.31	0.44
17.10	8.01	8.63	7.64	0.76
17.30	9.23	8.73	8.60	0.90

in PreScan and driver's basic data were obtained by questionnaire survey.

In the pre-processing of data, we found the lateral acceleration of car-following behavior satisfied the condition: $|a|<2$ m/s^2. Thus, combining with the experiment video and lateral acceleration, car-following process from the whole driving trip can be picked up and the distorted data can be eliminated. The frequency of raw data obtained was 100 Hz. To reduce the difficulty of calculation, data was selected with the frequency reduced to 20 Hz. During the process of car-following, the decision rules were extracted by structuring driving decision table based on RS theory. Taking into account the impact of relative distance and velocity on decision-making, the decision table was built in which acceleration was selected as decision attribute and other else were condition attribute. Table 3 shows part data of car-following behavior.

4 Decision of car-following behavior based on RSAN

4.1 Preprocessing of driver's car-following behavior based on RS

RS theory studies the knowledge discovered and reasoning process in the form of rules. In this work, RS was used to extract the car-following decision rules from drivers in order to find the key influential factors on decision and reduce the impact of uncertain data and noise data on decision process. Equidistant discretization was employed to simplify the information table and then information table was discretized by semi-naive-scaler algorithm [19]. Table 4 shows the breakpoints of each condition attribute. The key condition attributes, which have a critical influence on decision-making, were extracted by attribute reduction. The decision rules and its physical meaning are shown in Table 5. Taking rule (2) as an example, when the relative distance D satisfies the condition: 7.7 m<D<10.2 m, and the velocity of the subject car V_{sub} is less than 5.6 m/s, the driver's acceleration decision incline to choose from −1.5 m/s^2 to 0.4 m/s^2.

Table 4 Breakpoints of each condition attribute

Condition attribute	A	A1	A3
D/m	7.7	10.2	12.7
V_{sub}/(m·s^{-1})	5.6	7.7	9.9
V_{lead}/(m·s^{-1})	6.52	7.27	8.02
a/(m·s^{-2})	−1.5	0.4	2.3

Table 5 Decision rules of driver extracted by attribute reduction

Rule	Condition	Decision	Physical meaning of rules
(1)	$D(A)$ V_{sub} $(ABCD)$	$a(A)$	D<7.7 m => a<−1.5 m/s^2
(2)	$D(B)$ V_{sub} (A)	$A(B)$	7.7 m<D<10.2 m, V_{sub}<5.6 m/s =>−1.5<a<0.4 m/s^2
(3)	$D(B)$ V_{sub} (BCD)	$a(A)$	7.7 m<D<10.2 m, V_{sub}>5.6 m/s =>a<−1.5 m/s^2
(4)	$D(C)$ V_{sub} (C)	$A(C)$	10.2 m<D<12.7 m, 7.7<V_{sub}< 9.9 m/s =>0.4<a<2.3 m/s^2
(5)	$D(C)$ V_{sub} (D)	$a(B)$	10.2 m<D<12.7 m, V_{sub}>9.9 m/s =>−1.5<a<0.4 m/s^2
(6)	$D(D)$ V_{sub} $(ABCD)$	$a(D)$	D>12.7 m=>a>2.3 m/s^2

4.2 Learning driver's car-following behavior based on RSAN

ANN can mimic the information processing process of human brain. Combining with RS theory, this work proposed a novel method RSAN to learn the decisions experience from excellent human drivers in which the key condition attributes extracted above were the input and the acceleration decision was the output. We trained these sample data and adjusted relevant parameters. The training results from RSAN can be the same or even better than ANN after simplifying its input parameters seen in Table 6.

Table 6 Reduction and parameters of artificial neural network model

Name	Parameter	Model
Reduction 1	D, V_{lead}, V_{sub}, a	ANN
Reduction 2	D, V_{sub}, a	RSAN

The basic ANN is too slow for applications especially in road traffic environment which has the high demand for real-time and accuracy. Thus, the Levenberg–Marquardt algorithm was used. This algorithm is a variation of Newton's method designed for minimizing functions that are sums of squares of other non-linear functions. It is well suited to neural-net-work training, where the performance index is the mean squared error. The key step in the Levenberg–Marquardt algorithm is the computation of the Jacobian matrix. The back propagation process computed the sensitivities through a recurrence relationship from the last layer backward to the first layer. The forecasted value of reduction is shown in Fig. 3.

5 Results and discussion

In this work, RSAN improved ANN by the RS theory is employed for learning the driving decision-making knowledge under complex and dynamic urban

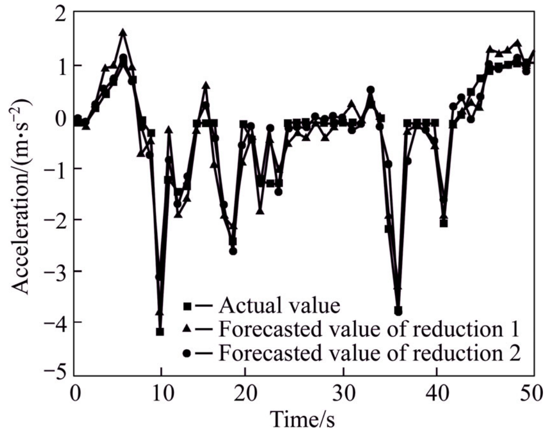

Fig. 3 Comparisons of forecasted value for ANN model and RSAN model

environment. The key influential factors on decision have been obtained in previous section. This section discusses the training results and compares the performance of RSAN and ANN.

Figure 4 shows the comparison of absolute error between forecasted value of the ANN and RSAN models. Moreover, the comparison of relative error is shown in Fig. 5. Overall, the RSAN model is more precise than the ANN model. Table 7 shows the comparison of main performance index. Maximum absolute error and relative

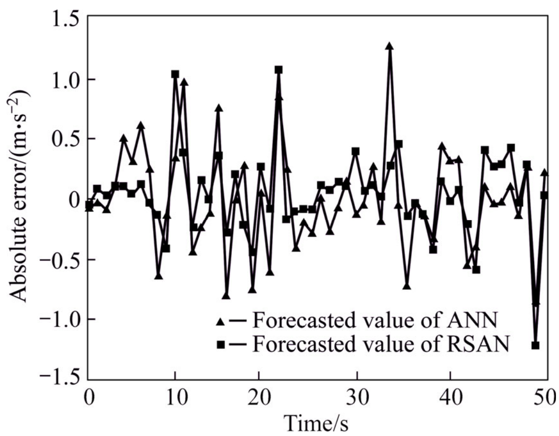

Fig. 4 Comparison of absolute error

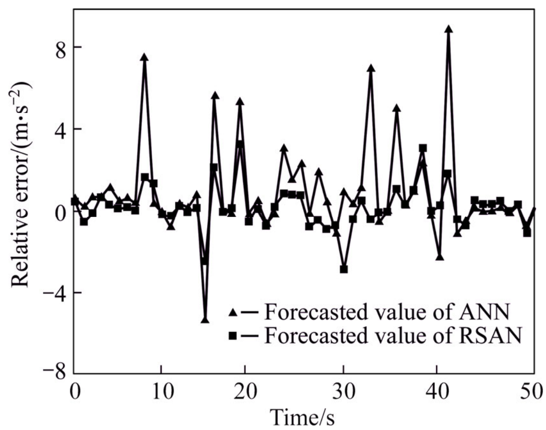

Fig. 5 Comparison of relative error

Table 7 Comparison of main performance index

Model	Maximum absolute error/ $(m \cdot s^{-2})$	Average absolute error/ $(m \cdot s^{-2})$	Maximum relative error/%	Average relative error/%	Training time/s
ANN	1.275	0.326	8.843	1.415	486
RSAN	1.065	0.237	3.208	0.687	96

error of RSAN model is 1.065 m/s^2 and 0.687% while ANN is 1.275 m/s^2 and 1.415%. Average absolute error and relative error of RSAN model is 0.326 m/s^2 and 1.416% while ANN model is 0.237 m/s^2 and 0.688%. The training time of RSAN is 486 s and is less than 486 s of ANN. In addition, the result shows that RSAN model can provide the better accuracy of forecasts and the better convergence speed when learning driver's car-following decision.

Making car-following decision is challenging because of not only the uncertainty of environment perception by an autonomous vehicle, but also the difficulties introduced by complex and dynamic traffic state. This paper improved ANN by RS theory to learning the excellent drivers' decision experience for autonomous vehicles. RS theory is used to deal with large amount of raw data and reduce information table, with the number of evaluation criteria reducing and no information loss. This work contributed to the effectiveness of RS theory as a data preprocessor of ANN. RS theory help the ANN to avoid the influence of noise data and distorted data. The experimental results showed that the driver would keep the constant velocity when the relative distance between subject vehicle and lead vehicle maintains between 8.3 m to10.8 m, and the driver's decision is acceleration when the relative distance is larger than 12 m. The performance of RSAN showed that the decision-making system was capable of completing the car-following maneuver stably and quickly.

6 Conclusions

Making intelligent decisions autonomously at a level similar to that of human beings is necessary in the development of autonomous driving for urban traffic environments. A virtual urban traffic environment was built and driving simulation was conducted to obtained the relevant data. In order to learn the excellent drivers' decision experience, a novel approach RSAN was proposed based on ANN and RS theory. The findings from this study enhance the empirical understanding of driver's decision-making process and can contribute to the development of decision-making of autonomous vehicles in urban traffic.

The most significant contribution of the present work is that we considered the drivers' experience when making stable and quick car-following decisions. However, some limitations of the methodology applied cannot be ignored in this work. The reaction time of different drivers, which have significant influences on the car-following decision, were not investigated in this paper. The robustness and reliability of the RSAN model benefited from the simulator and the uncertainty of sensors in real environment were not considered. These remain topics of future study. In addition, other more complex driving behavior have not fully explored e.g. the merging behavior in congested weaving sections and the crossing behavior at intersections. These driving scenarios remain considerable challenges for autonomous driving in urban environment.

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(Edited by DENG Lü-xiang)

Cite this article as: CHEN Xue-mei, JIN Min, MIAO Yi-song, ZHANG Qiang. Driving decision-making analysis of car-following for autonomous vehicle under complex urban environment [J]. Journal of Central South University, 2017, 24(6): 1476−1482. DOI: 10.1007/s11771-017-3551-4.