Driving Decision-making Analysis of Lane-changing for Autonomous Vehicle under Complex Urban Environment

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Abstract: Lane-changing decision-making is critical to complete driving mission for autonomous vehicles under complex urban environment. The complex information (such as the running conditions of interfering vehicles, signal lamp, and road facilities) have a great influence on autonomous vehicle's lane-changing decision. This paper proposes to use the Rough Set theory to abstract the lane-changing rules to support the decision-making of autonomous vehicles under the complex urban environment. Firstly, a virtual urban traffic environment is built by Prescan (a simulation environment for developing advanced driver assistant system). Secondly, the Rough Set theory is proposed to reduce the influence of weak interdependency data, and extract the driver's decision rules. Finally, the result is that: 1) During the intention generation process of lane-changing, the decision-making a is associated only with the relative distance between the subject Car and the interfering $Car2$ (D_2) and the relative velocity between the subject Car and the leading $Car1$ (V_1). 2) Both of the decision-making rules during intention generation and implementation phase process are extracted based on Rough Set method, which provide a theoretical basis for the lane-changing decision-making under complex urban environment.

Key Words: autonomous vehicle; lane-changing; decision-making; rough set; Prescan

1 INSTRUCTION

The autonomous vehicles have received comprehensive attention recently [1], and are applied in the transportation and military widely. Many universities, research institutions, and automobile enterprises have launched the corresponding research on autonomous vehicle decision-making (car-following, lane-changing, overtaking, etc.), such as the Carnegie Mellon University (CMU), the Munich University of German Federal Armed Forces, Mercedes Benz Company, Google, etc.

To date, lane-changing behavior has significantly influenced traffic performance and safety, and has become one of the main research contents on the autonomous vehicle decision-making [2]. GM (General Motors, GM) laboratory had firstly done a lot of work, which greatly promoted basic research on the lane-changing model, it initiated a new microscopic driving behavior research method [3]. Junior had proposed multiple driving states decision system, which could transform one driving state to another, and achieved lane-changing based on perceived characteristics of traffic environment [4]. Ford Motor and TORC used the Hierarchical Finite State Machine(HFSM), which was a driving control module based on arbitration theory to control their vehicle Odin to make lane-changing [5]. These lane-changing decision systems are designed based on the mechanical formula or the road types, but they do not fully realize the influence of human drivers driving experience, which can be very useful to guide and give more appropriate decision if driving rules can be extensively extracted. Some researchers presented algorithms for strategic decision making regarding lane-changing maneuvers, considering the influence of human drivers driving experience. Nilsson, J proposed to select the desired lane and velocity profile of human drivers by reducing the complexity of the model and introducing a binary decision variable [6]. Furda, A proposed a decision model based on driver multi criteria decision-making method, the results were in accordance with traffic regulations and the safety requirements could be ensured [7].

The above studies about lane-changing behaviors are focusing on the analytical and numerical perspectives, but the environment (highway and City main road) was always closed relatively and the variables were always immutable. It is also difficult to extract relevant factors and driver decision rules in the environment of urban general roads, for the urban general roads are always complex, and full of noise data, weak interdependency data, and domain-independent data [8,9]. In this paper, the Rough Set theory is proposed to reduce the influence of weak interdependency data, and extract the lane-changing behavior rules from the simulation data of human driving.

2 METHODOLOGY

Rough Set theory introduced by Pawlak is a mathematical tool that can describe imperfection and uncertainty, can effectively analyze and deal with complex and dynamic information of urban environment,

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and find the implicit knowledge, reveal the law of potential[10], The basic concepts of Rough Set theory are introduced 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 $f: U \times A \to V$ 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 $A = C \cup D$ and $C \cap D = \emptyset$, 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:

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

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 $\overline{PX}$) are defined in the following expressions:

$$\underline{P}X = \{Y \in U/P: Y \subseteq X\} \quad (2)$$

$$\bar{P}X = \{Y \in U/P: Y \cap X \neq \emptyset\} \quad (3)$$

$\underline{P}X$ is the set of all objects from *U* which can be certainly classified as elements of *X* employing the set of attributes *P*. $\bar{P}X$ is the set of objects of *U* which can possibly be elements of *X* using the set of attributes *P*. The *P*-boundary (doubtful region) of set *X* is defined through (4)

$$Bnd_p(X) = \bar{P}X - \underline{P}X \quad (4)$$

The set $B_{np}(X)$ 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.

In practice, there are often vast amounts of sensor data, which updated typically every few minutes. RS theory provides useful techniques to reduce irrelevant and redundant attributes rom a large database with many attributes. The flow diagram of extracting the driver's car-following behavior is shown in Fig. 1.

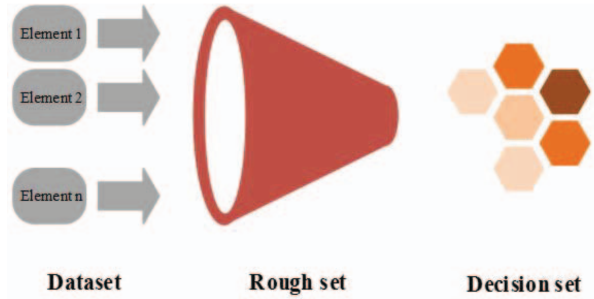

Fig.1 Full process of the Rough Set

3 EXPERIMENTAL DESIGN

This paper focuses on the autonomous vehicle tactical level decision-making in the urban general roads environment. Prescan is a simulation software for developing advanced driver assistant systems (ADAS) and intelligent vehicle (IV) systems. It can be used to build 3D traffic. virtual scene, generate vehicles, pedestrians, traffic lights and other control modules. It also provides an interface for Simulink and allows users to control and operate the simulation process conveniently.

Prescan comes with a powerful graphics preprocessor, a high-end 3D visualization viewer, and a connection to standard MATLAB /Simulink. It is composed of various main modules. Some of these main modules represent a specific world. The Sensor World in which multiple sensor readings are simulated and captured; The Visualization World in which multiple viewpoints on a scene can be visualized such as the bird eye view, a human view or a moving camera view, and the combined Dynamics & Controller World in which dynamics models and controllers are simulated.

3.1 Building the Virtual Traffic Scenario based on Prescan and Google SketchUp

In the simulation experiment, the virtual traffic scene is a straight road around Beijing Institute of Technology. Google SketchUp imported the scene of Open-street-map to the Prescan, and the landmark buildings surrounding the roads are built, as shown in Fig.2.

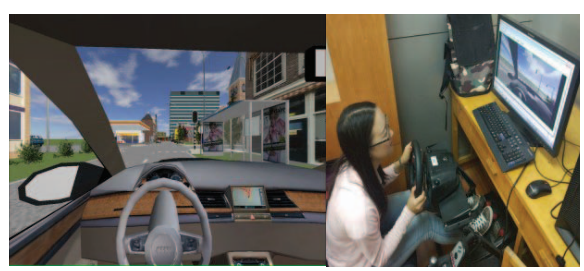

Fig.2 Part of the simulation

3.2 Establishing Vehicle Model

The experimental vehicle was set as a 3D dynamical model from the selection of vehicle models, and driver input model was Man-in-the-loop, and control gear was Logitech G27, gear and pedal. Other vehicles were set by a predefined driving behavior model to control their paths and velocities.

3.3 Participants in Simulation

The drivers are arranged to drive a certain mileage to get familiar with the experiment conditions. In these experiments, 46 non-professional participants were involved which was shown in Table 1 and Table 2. The participants include 30 males (65.2%) and 16 females (34.8%).

Table 1 Gender of participants

Gender	*Males*	*Females*
Number of people	30	16

Their ages range from 20 to 60 years, with drivers of 20-30 years old accounted for the proportion of 56.53%, 31-40 years old accounted for the proportion of 34.78%, 41-50 years old accounted for the proportion of 6.52%, 51-60 years old accounted for the proportion of 2.17%. Driving experience distribution range of 3-20 years, an average of 10.21 years of driving experience (standard deviation SD = 8. 29).

Table 2 Age of participants

Age (year)	*20-30*	*31-40*	*41-50*	*51-60*
Number	26	16	3	1
Percent	56.53%	34.78%	6.52%	2.1%

Finally, the experiments are conducted and different decision-making strategies of drivers are compared. During the experiment, the drivers are arranged properly in a quiet experiment room. Drivers should take appropriate to avoid collisions.

3.4 Acquisition of Data

In order to research lane-changing behavior under the complex and dynamic urban environment, which includes the noise, function of around vehicles, ride facilities, etc. Different categories of data sets were collected in this experiment: 1) vehicle movement parameters, such as vehicle position, velocity, acceleration and steering wheel angle, etc. 2) basic information about the driver, such as driver's age, driving mileages, etc. The extraction and storage of vehicle motion parameters were obtained mainly through "to file" and "to Work-space" module in the Simulink and driver's basic data were obtained through questionnaire survey. Data frequency in the Simulink was 100Hz. During data-preprocessing, partial data distortion was removed according to the vehicle kinematic principles with the frequency reduced to 20Hz.

4 EXTRACTING THE DRIVER'S LANE-CHANGING BEHAVIOR RULES BASED ON ROUGH SET

The process of lane-changing decision-making is affected by the driver's own characteristics, the performance of the vehicle, and the surrounding road traffic environment. The lane-changing decision-making is a typical hierarchical decision process, and the intention generation and the implementation phase of lane-changing are analyzed in this article.

4.1 Data of lane-changing behavior

The Fig 3 shows the process of lane-changing behavior. The red Car is subject car. V_1, V_2 and D_1, D_2 are the relative velocity and relative distance between the subject car and the interfering $Car1$ and $Car2$. Considering the safe and speed limit factors of general urban environment, the initial velocity of $Car1$ and $Car2$ is 5m/s.

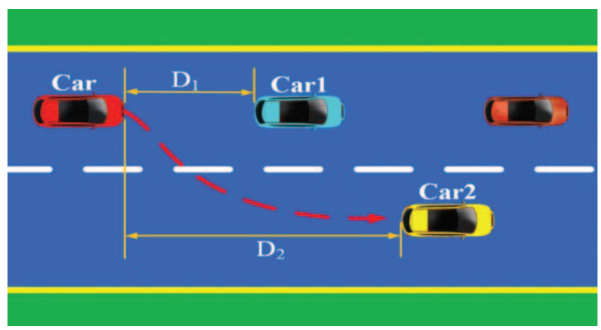

Fig 3 lane-changing process

Car-following and lane-changing behavior together constitute the micro driving behavior. They are both contact and difference, and cannot be analyzed separately. It is necessary to analyze the driving behavior in the urban environment to obtain the start time of lane-changing behavior. Through the acquisition and analysis of the lateral acceleration of the vehicle (shown in Fig 4), the lateral acceleration is maintained at -2m/s^2 to 2m/s^2 during the car-following behavior.

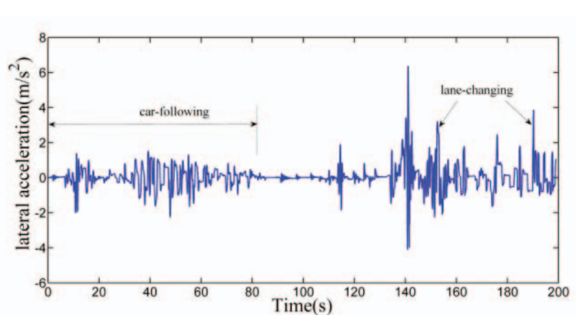

Fig 4 The change of lateral acceleration

At one time of lane-changing behavior shown in Fig 5, the lane-changing behavior is between the time of 13.7s to 14.2s through the above rules. Thus, the data of time 13s to 14.25s is selected to analyze the lane-changing decision-making.

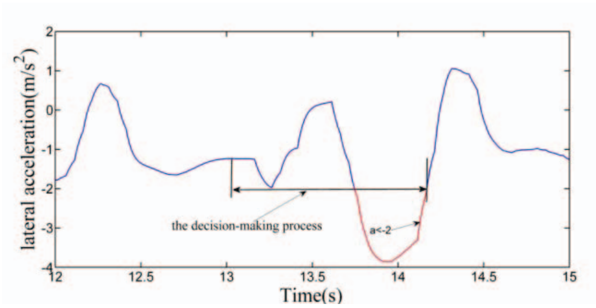

Fig 5 The change of lateral acceleration of lane- changing

4.2 Extracting the decision-making rules during the intention generation process of lane-changing

4.2.1 Constructing an information table

Since the factors that influence decision-making of the lane-changing decision-making are the relative velocity and distance between the subject car and the interfering cars.

V_1, V_2 and D_1, D_2, which are the relative velocity and relative distance between the subject car and the interfering $Car1$ and $Car2$, are adopted as the condition attributes of the lane-changing decision-making systems. The lateral acceleration a is considered as the decision attribute. The data in Table 3 are part of lane-changing information table.

Table 3 Part of lane-changing information table

Time/s	*D₁/m*	*D₂/m*	*V₁/m·s⁻¹*	*V₂/m·s⁻¹*	*a/m·s⁻²*
13.00	22.13	27.62	6.68	5.83	-1.24
13.05	21.80	27.33	6.67	5.82	-1.24
13.10	21.47	27.04	6.66	5.81	-1.24
…	…	…	…	…	…
14.10	14.88	21.34	6.54	5.63	-3.36
14.15	14.56	21.06	6.54	5.62	-2.36
14.20	14.23	20.78	6.53	5.61	-1.25

4.2.2 Data discretization

Equidistant discretization was used to simplify the information table, in order to construct a decision table. Data of lane-changing information table was discretized by breakpoints. The table 4 is the breakpoints of each condition attribute and the table 5 is the decision table after the discretization.

Table 4 The breakpoints of each condition attribute

	A	*A₁*
D₁/m	18.89	21.52
D₂/m	23.06	25.34
V₁/*m·s⁻¹*	6.58	6.63
V₂/*m·s⁻¹*	5.68	5.75
a/*m·s⁻²*	-2.51	-1.16

Table 5 part of lane-changing decision table

Time/s	*D₁/m*	*D₂/m*	*V₁/m·s⁻¹*	*V₂/m·s⁻¹*	*a/m·s⁻²*
13.00	C	C	C	C	B
13.05	C	C	C	C	B
13.10	C	C	C	C	B
…	…	…	…	…	…
14.10	A	A	A	A	A
14.15	A	A	A	A	B
14.20	A	A	A	A	B

4.2.3 Simplicity and extraction

To obtain the key condition attributes, which have more influence on the decision, the decision rules of the drivers were extracted by attribute reduction .The result was shown in Table 6.

Table 6 The decision rules during the intention generation process of lane-changing

Condition attribute		**Decision**	**Physical meaning of rules**
D₂(C)	V₁(C)	a(B)	D₂>5.34m，V₁>6.63m/s => -2.51<a<-1.16m/s²
D₂(B)	V₁(B)	a(B)	23.06m<D₂<25.34m, 6.58m/s<V₁<6.63m/s => a>-1.16m/s²
D₂(B)	V₁(A)	a(A)	23.06m<D₂<25.34m, V₁<6.58m/s => -2.51<a<1.16m/s²
D₂(A)	V₁(A)	a(A)	D₂<23.06m, V₁<6.58m/s => a<-2.51m/s²

The result during the intention generation process of lane-changing shows that: 1) The decision-making a is associated only with D_2 (the relative distance between the subject Car and the interfering $Car2$) and V_1 (the relative velocity between the subject Car and the leading $Car1$). 2) When the relative velocity V_1 and the distance of the adjacent lane D_2 satisfy certain conditions, the driver will generate the lane changing intention.

4.3 Extracting the decision-making rules during the implementation phase process of lane-changing

During the implementation phase process of lane-changing, the lateral acceleration a changed a lot as shown in Fig 6. Thus, the lateral acceleration a can be considered as the decision attribute.

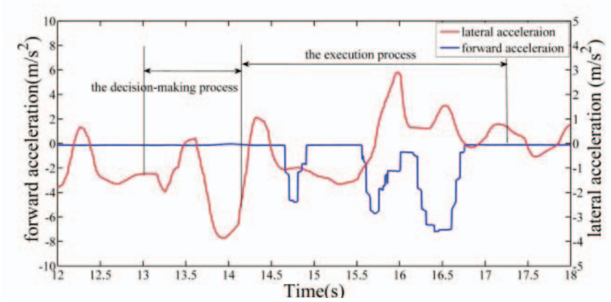

Fig 6 The change of lateral acceleration during the implementation phase process of lane-changing

The Rough Set method, which is used to extract the decision-making rules during implementation phase process, is same with the intention generation process of lane-changing. The decision-making rules extracted is shown as table 7.

Table 7 The decision rules during the implementation phase process of lane-changing

Condition attribute			**Decision**	**Physical meaning of rules**
D_1(BCD)	D_2(BCD)	V_1 (D)	a(D)	D_1>4.9m, D_2>13.58m, V_1>5.10m/s => a>-1.88m/s^2
D_1(BCD)	D_2(BCD)	V_2 (D)	a(D)	D_1>4.9m, D_2>13.58m, V_2>4.16m/s => a>-1.88m/s^2
D_1(A)	D_2(A)	V_1 (A)	a(D)	D_1<4.90m, D_2<13.58m, V_1<2.31m/s => a>-1.88m/s^2
D_1(A)	D_2(A)	V_2 (A)	a(D)	D_1<4.90m, D_2<13.58m, V_2<1.26m/s => a>-1.88m/s^2
D_1(A)	D_2(A)	V_1 (C)	a(C)	D_1<4.90m, D_2<13.58m, 5.10m/s>V_1>3.70m/s =>-1.88>a>-3.65m/s^2
D_1(A)	D_2(A)	V_2 (C)	a(C)	D_1<4.90m, D_2<13.58m, 4.16m/s>V_2>2.71m/s =>-1.88>a>-3.65m/s^2
D_1(A)	D_2(A)	V_1 (B)	a(A)	D_1<4.90m, D_2<13.58m, V_1<2.31m/s => a<-5.42m/s^2
D_1(A)	D_2(A)	V_2 (B)	a(A)	D_1<4.90m, D_2<13.58m, V_1<2.31m/s => a<-5.42m/s^2
D_1(B)	D_2(A)	V_1 (C)	a(A)	7.9>D_1>4.9m, D_2<13.58m, 10m/s>V_1>3.70m/s => a<-5.42m/s^2
D_1(B)	D_2(A)	V_2 (C)	a(A)	7.9>D_1>4.9m, D_2<13.58m, 4.16m/s>V_2>2.71m/s => a<-5.42m/s^2

The result during the implementation phase process of lane-changing shows that: 1) While the relative velocity of the car (V_1 or V_2) is large, the change of the relative distance of the current lane D_1 and the adjacent lane D_2 has little effect on the behavior decision. 2) While the relative distance of the current lane D_1 and the adjacent lane D_2 is small, the relative velocity of the car (V_1 or V_2) has a great influence on the decision-making of lane-changing.

5. CONCLUSION

In this paper, we present the application of Rough Set approach for extracting the lane-changing decision-making under urban environment. The driving simulation environment is built by PreScan, the driver's lane-changing decision was extracted through the Rough Set Theory.

The method of Rough Set is used to deal with large amount of data and fast operation. By using the method of Rough Set, we can get reduced information table, which implies that the number of evaluation criteria is reduced with no information loss. The results show that 1) During the intention generation process of lane-changing, the decision-making a is associated only with the relative distance between the subject Car and the interfering $Car2$ (D_2) and the relative velocity between the subject Car and the leading $Car1$ (V_1). 2) Both of the decision-making rules during intention generation and implementation phase process are extracted based on Rough Set method, and the specific numerical rules are given shown as Table 6 and Table 7, which can provide a theoretical basis for the lane-changing decision-making under complex urban environment.

While the results are Inspiring, there are also some limitations of the methodology need further study. Although the equidistant discretization method is used to reduce the influence of the data discretization, there are some information loosed inevitably, a better discretization method is needed to be further exploration. Also, The impact of characteristic under different drivers during lane-changing needs to be further consideration.

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