# Driverless Planning and Decision-Making based on GRU

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**Abstract.** In the wake of the swift advancement of artificial intelligence, driverless technology has progressively emerged as a revolutionary technology. The existing driverless technology primarily relies on advanced sensors, artificial intelligence and machine learning algorithms, with a view to perceiving and analyzing the surrounding environment in real time, and making driving decisions accordingly. At the present time, despite the fact that driverless technology has introduced a lot of convenience to human travel, it still encompasses a significant number of challenges, such as safety, perception technology, vehicle control, road planning, cost and other issues. In a similar vein, the safety issue is an unavoidable part of the discussion on the driverless. Driverless vehicles require robust system safety and protection mechanisms. This paper is designed to establish a data model by analyzing the NGSIM dataset, and to probe the driverless perception capability and decision-making on intelligence in behavior-aware motion perspective with GRU approach. Eventually, it was concluded that neither too many nor too few neighboring vehicles should be taken into account when forecasting the trajectory of each vehicle in the coming years, while the appropriate neighboring vehicles should be selected to achieve the best prediction results.

**Keywords:** Driverless technology, behavior-aware, GRU.

## 1. Introduction

Driverless technology represents a revolutionary technology that seeks to enable vehicles to drive on their own in the absence of a human driver. The available driverless technology primarily counts on advanced sensors, artificial intelligence, in addition to machine learning algorithms, thereby sensing and analyzing the surrounding environment on a real-time basis, while making driving decisions accordingly. In the current self-driving vehicle, there exist three major categories of perceptual decision control methods: sequential planning, behavior-aware motion planning, as well as end-to-end planning. The sequential planning falls into the most traditional approach, where perception, decision-making and control are three non-interfering parts. The highlight of behavior-aware planning, the phase of this approach, lies in the introduction of unmanned vehicles to predict and comprehend the behaviors of other participants in the traffic environment, with a view to making safe and intelligent driving decisions. As one of the hottest methods nowadays, end-to-end planning falls into the category of one of the most sought-after methods, which is designed to obtain the relationship between vehicles and control signals from the image level through data training based on DL and DRL techniques. This paper seeks to establish a data model by analyzing the NGSIM dataset, and to probe the driverless perception capability and the intellectual decision-making in behavior-aware motion perspective with GRU approach.

Given the fact that unmanned vehicles have been developed earlier in foreign countries, the research is comparatively perfect. Over recent years, the research on unmanned vehicles has primarily focused on the realization of the fifth level, namely complete autonomous driving, which does not require human intervention without any restriction on the driving environment. It can automatically cope with a variety of complex traffic conditions and road environments. In the case of driving to the destination from the starting place without assistance from human beings, it requires only the information of the starting place and the ending place, for which the automobile will be responsible for the entire safety of the vehicle, without any interference of the driver and without any limitation of the specific roads. Driverless refers to the utilization of computers, sensors, controllers and other technologies to actualize automatic driving of vehicles without human intervention or supervision. Driverless features the advantages of improving traffic safety, efficiency, and comfort. However, it also confronts the complex issue of driving decision-making, and the ways to make reasonable behavioral choices in various road environments and traffic situations are one of the key technologies of driverless.

Foreign research on optimization and decision-making for driverless has achieved relatively more results, which primarily involves rule-based methods, model-based methods, in addition to data-based methods and others. Among them, data-based methods leverage machine learning and other technologies to learn driving strategies from a massive amount of data, featuring superior generalization ability and adaptability, which is a more sought-after research direction at present. For instance, Zhang et al. presented a driverless decision-making mechanism based on Optimized Support Vector Regression (OSVR), which is capable of predicting the optimal acceleration and steering angle in accordance with the state of the vehicle and environmental information, in addition to achieving the control of the vehicle through a fuzzy controller. This mechanism is capable of improving the stability and safety of driverless vehicles in an effective manner [1]. In the meantime, Zhang proposed an adaptive decision-making method based on optimized embedded reinforcement learning, which is capable of realizing the automatic entry and exit and lane changing of driverless vehicles in roundabout scenarios. This method exploits a deep neural network as a value function approximator, and adjusts the network parameters through an optimization algorithm to boost the learning efficiency and performance [2]. In addition, this method is also an effective way to tackle uncertainty and multi-intelligent body interaction issues in roundabout scenarios.

When it comes to decision-making and optimization of driverless, domestic scholars have primarily adopted different methods based on models and learning to perform optimization and decision-making for various scenarios and tasks in terms of behavioral selection, path planning, and speed control of driverless. For instance, Qu presented a driverless intelligent decision-making and control method based on deep reinforcement learning under hierarchical architecture, which decomposed the decision-making and control issues of driverless into two sub-issues of high-level planning and low-level control, which were optimized and learned respectively by adopting reinforcement learning algorithms based on deep neural networks [3]. This method is effective in processing the complex and changing traffic environment, so as to improve the safety and stability of the driverless. On the other hand, Liang et al. studied the driverless behavioral decision-making method based on Bayesian network, which utilized the Bayesian network to conduct modeling and reasoning regarding the traffic environment around the driverless vehicle. In accordance with the different contexts, the appropriate behavioral modes were selected and the behavioral parameters were adjusted by combining with fuzzy logic, which could cope with the uncertainty and randomness in an effective manner, thereby improving the flexibility and adaptability of the driverless vehicle [4]. Lastly, Zhang et al. examined the optimal scheduling method of driverless water trucks in airport flight area. In response to the issues of path conflict and operation delay that existed during the operation of water trucks in the airport flight area, they established an optimal scheduling model of water trucks based on mixed integer programming, and employed heuristic algorithms to perform the solving, which effectively improved the operation efficiency of the water trucks, and cut down on the operation cost and risk [5].

For the current time, despite the fact that driverless technology has brought a wealth of convenience to human travel, it still involves a significant number of challenges, such as the issues of safety, perception technology, vehicle control, road planning, and cost. There are two aspects that need to be taken into account when driverless carries out the decision-making process, namely sensor technology and real-time localization and mapping technology. In a similar way, safety is an unavoidable session in the discussion of the driverless. In conclusion, driverless vehicles are required to be equipped with robust system security and protection mechanisms.

## 2. Methods

### 2.1. Data

This paper uses the NGSIM data set, which is a collection of vehicle travel over time by researchers through the "Next Generation Simulation" project. This data set covers the intersection of structured roads, high-speed up and down gates. The data collection system senses and tracks the vehicle in the video and generates the vehicle movement trajectory points.

### 2.2. Behavior-Aware Motion Planning

As the top-level decision module of unmanned driving, Behavior-Aware Motion Planning obtains the information of all parties and makes a behavior decision for path planning and execution, and finally passes it to the underlying control module to drive the vehicle. This approach enables to upgrade the decision planning process to an interactive process involving the driver-driving vehicle and of the driving vehicle-external environment. The purpose of this method is to include the uncertainty of the external environment in the decision planning, so as to improve the safety of autonomous vehicles. Among them, cooperation and interaction, probalistic approach, partially observable Markov decision process and learning based approaches.

### 2.3. Research on Behavior-Aware Motion Planning

Driverless vehicles require intelligent decision-making capabilities and the ability to make safe and reasonable driving decisions based on perceived environmental information. Artificial intelligence and machine learning techniques can help vehicles learn and adapt to different traffic situations, and predict and optimize them based on historical data. Deep Imitation Learning (DIL) is perceived as one of the most prospective solutions, since compared to manually designed driving strategies, it automatically learns complex human driving maps to drive system data, thereby improving autonomy. Human brain learning has been proposed as one of the ways to improve machine learning. In the research, attempts were made to design dual neural circuit policy (NCP) architectures in deep neural networks on the basis of the asymmetry of human neural networks, so as to promote the analysis of the data [6]. This is a new line of thinking, and although the results are not proved to be effective in the whole situation, they still provide a starting point for subsequent studies. They also develop multimodal architectures that include modeling the environment around themselves and training the deep reinforcement learning (DRL) agent [7]. It has been demonstrated that partitioning the autonomous driving issue into a multi-layered control architecture and leveraging the power of artificial intelligence to tackle each layer separately provides a higher degree of stability. Or some scholars apply Deep Q-network, DQN to decide whether to maneuver [8]. By designing two similar deep learning frameworks, a secondary approximator is used to determine the ways in which a comfortable gap can be chosen and follow the vehicle in front of it. With the generation of polynomial lane change trajectories, pure tracing control is achieved for path tracking. This is equally a highly robust validation approach.

### 2.4. Advantages and Principles of GRU

Gate Recurrent Unit (GRU) is one kind of Recurrent Neural Network (RNN). In the same way as Long-Short Term Memory (LSTM), it is also proposed to tackle the issues of long-term memory and gradient in back propagation. In comparison to LSTM, the utilization of GRU can reach comparable results, which is also easier to train by comparison, thereby improving the training efficiency to a great extent, making it more preferable to use GRU in many cases.

On the basis of RNN, Donsuk Lee et al. processed state graphs by employing a variant of the graphical network (GN) layer, which in turn modeled the interactions between agents [9]. A graph-based multi-intelligent trajectory and interaction prediction model was introduced. The merit of this approach lies in the fact that the model can capture the multi-modal behavioral interaction patterns of the interacting agents in an efficient manner while learning the semantic meaning. However, RNNS are difficult to train and capture long-term dependencies because the long-term dependencies effect is hidden by short-term dependencies. The most important feature that LSTM and GRU share is the update from time t to time $t+1$, which is absent from traditional loop units, which always replace the excitation or the contents of a cell with a new value calculated from the input and the previously hidden state.

The input rules of GRU are illustrated in Figure 1, with a current input $x^t$. The hidden state $h^{t-1}$ is passed down from the previous node, which holds the relevant information of the previous node. In conjunction with $x^t$ and $h^{t-1}$, the GRU derives the output $y^t$ of the current hidden node, as well as the hidden state $h^t$ passed on to the next node.

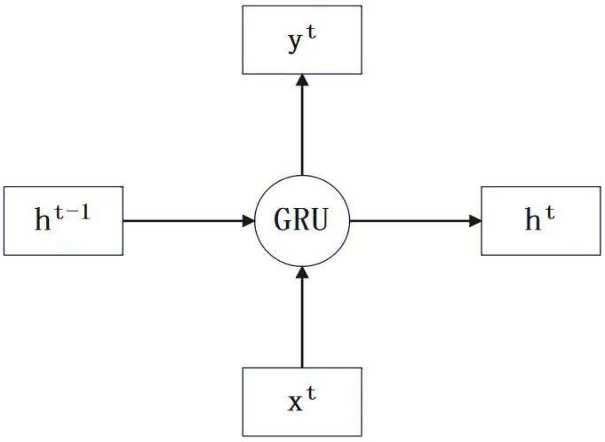


**Fig. 1** The GRU input process

GRU is a variant of LSTM that also tackles the long dependency issue in RNN networks. In LSTM, three gate functions were introduced, namely input gate, forget gate and output gate. In GRU, there are only two gates, namely update gate and reset gate. Figure 2 illustrates the forward propagation process of GRU.

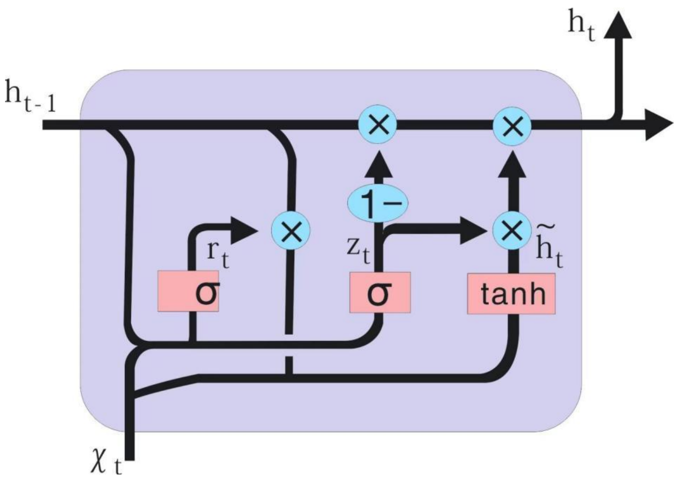


**Fig. 2** Forward propagation of GRU

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (1)$$

$$z_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (2)$$

$$h'_t = tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + h) \quad (3)$$

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h'_t \quad (4)$$

### 2.5. Experimental Method

In order to predict the vehicle trajectory problem, the historical trajectory of all objects in the observation scene is used as a reference for the future trajectory prediction of objects. Because it's easier to predict an object's velocity than its position. The historical position and speed of the object are input into the model, and the model predicts the speed of the object at the next moment through the function. The predicted location is then weighted by the predicted velocity and the historical location. The model consists of input preprocessing module, spatial interactive sensing Transformer layer and location prediction model.

With a given traffic scenario, it is assumed that n objects are observed within a certain time period, where the raw data is pre-processed into a three-dimensional tensor. $c = 4$ is set to label the coordinates $(x, y)$ and velocities $(u, v)$ of the objects at a time step, with all coordinates and velocities normalized to the range $(-1,1)$. With the input data $X \in R^{n*t_h*c}$ obtained from the pre-processing module, this essay accomplishes the following tasks: embedding and labeling $x_t^i = X[i, t]$, as well as mapping it with an embedded network $\varphi$ representing the state of object $i$ at a length of time $t$, which is employed to speedily unfold the following modeling process, where the velocity and coordinates are unified.

$$e_t^i = \varphi(x_t^i . W_e) \tag{5}$$

In this context, $W_e$ is the embedding weight. Multi-Layer Perceptron (MLP) is employed as the embedding layer. In contrast to the standard Transformer encoder layer, which is merely applicable to time-dependent modeling, the MLP utilized in this paper allows for capturing and integrating the time dependence of vehicle trajectories, as well as the spatial interactions between vehicles.

In accordance with the derived $X \in R^{n*t_h*d_{model}}$ and the adjacency matrix A, a Spatial Graph Multi-Head Attention Network is employed for detecting the interaction of vehicles over the spatial dimensions. For time length $t$, the characteristic values of $n$ vehicles in the time period $t$ can be selected, and the observed values are expressed by mathematical formulas. The use of fully connected graphs to represent vehicle interactions is inefficient. In this paper, the adjacency matrix $A$ is used to replace the fully connected graph, requiring that two vehicles cannot be located outside the adjacent lanes, and ensuring that only when the real-time distance between two vehicles is less than the threshold $T_{\text{dist}}$, the message will be delivered over time step $t$ from vehicle $j$ to $i$.

$$attention(i) = \frac{softmax([m^{j \to i}] j \in N(i))}{\sqrt{d_k}} [v_t^j] j \in N(i) \tag{6}$$

In this paper, a GRU-based encoder-decoder is employed to forecast the position of the vehicle at the next moment. In the first step of decoding, the decoder receives and processes the eigenvalue in the encoder and the speed of the object in the last time length to estimate the speed of the vehicle. During the next decoding step, the decoder performs a prediction by utilizing its own hidden characteristics and the velocities of all the predicted objects from the previous time step as inputs. However, if the trajectories of multiple vehicles affect each other at some point in the future, this method cannot handle this situation. To combat this potential problem, the decoder used in this article accesses the hidden features of the vehicles in the previous step, in addition to employing multi-head self-focusing modules, thereby directing the messaging between these vehicles.

A two-layer GRU is used in a GRU based codec module. In this paper, the number of hidden units of the GRU is fixed to 60, with the $\tanh$ activation function applied to re-scale the output of the decoder to be in the range $(-1,1)$.

In this experiment, PyTorch library is used to achieve regression, and the total loss can be calculated as follows [10]:

$$loss = \frac{1}{t} \sum_{t=1}^{t_f} ||Y_t^{pred} - Y_t^{gold}||^2 \tag{7}$$

# 3. Results and Discussion

## 3.1. Adjacent Threshold Value Selection

This experiment needs to use the adjacent distance threshold $T_{dist}$ and the adjacent lane threshold $T_{lane}$ to construct the adjacent map of each vehicle, that is, this essay considers the trajectory information of other vehicles within $T_{dist}$ and within $T_{lane}$, to predict the future action trajectory of this vehicle. Therefore, this experiment needs to solve the optimal choice of these two neighboring thresholds, even if the error between the prediction of the future trajectory and the actual trajectory is minimal. The experiment controls the adjacent distance threshold $T_{dist}$ and the adjacent lane threshold $T_{lane}$ as a fixed value, and the size of another threshold value is changed to obtain the experimental error RMSE. The experimental results are shown in Figure 3 below. As can be seen in Figure 3 (a), the RMSE is minimum when $T_{dist}$ value is 40; in Figure 3 (b), when $T_{dist}$ is fixed, the $T_{lane}$ value is 1. Therefore, in subsequent experiments, the adjacency plots for each vehicle will be determined as the adjacent distance threshold $T_{dist} = 40$ and the adjacent lane threshold $T_{lane} = 1$.

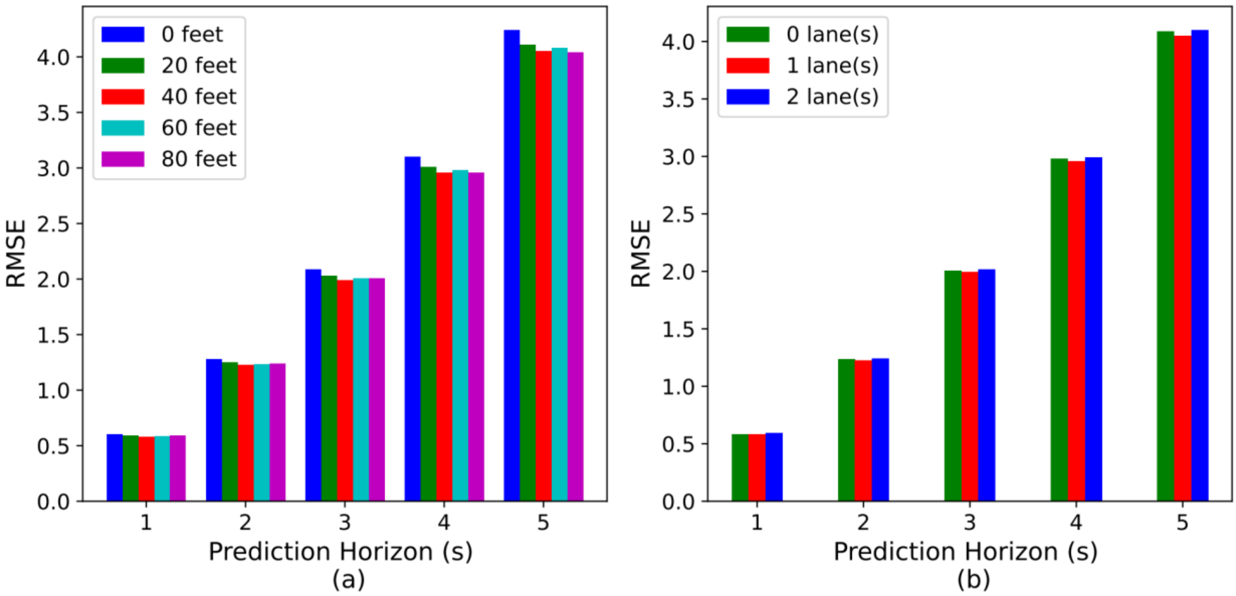


**Fig. 3** Relative error RMSE

## 3.2. Time Attention Distribution

As shown in Figure 4 of the time attention distribution chart, when predicting the future travel trajectory of attached vehicles, the closer the state is to the current time, the higher the correlation degree, and the lighter the color in the figure. Thus, when predicting a driving trajectory, the model focuses more on the states of several neighboring time step rather than on long previous states, similar to the situation in real life.

TMHA and SGMA are based on attentional mechanisms. The attentional mechanism in deep learning is fundamentally analogous to the selective visual attention mechanism of human beings. Its core objective is also to select the information that is more critical to the current task goal from a multitude of information resources. It mirrors the degree of association between an element and other elements. As a consequence, with a view to further analyzing the mechanism of the model, this experiment was performed to visualize the distribution of attention generated by TMHA and SGMA in the last layer of the model.

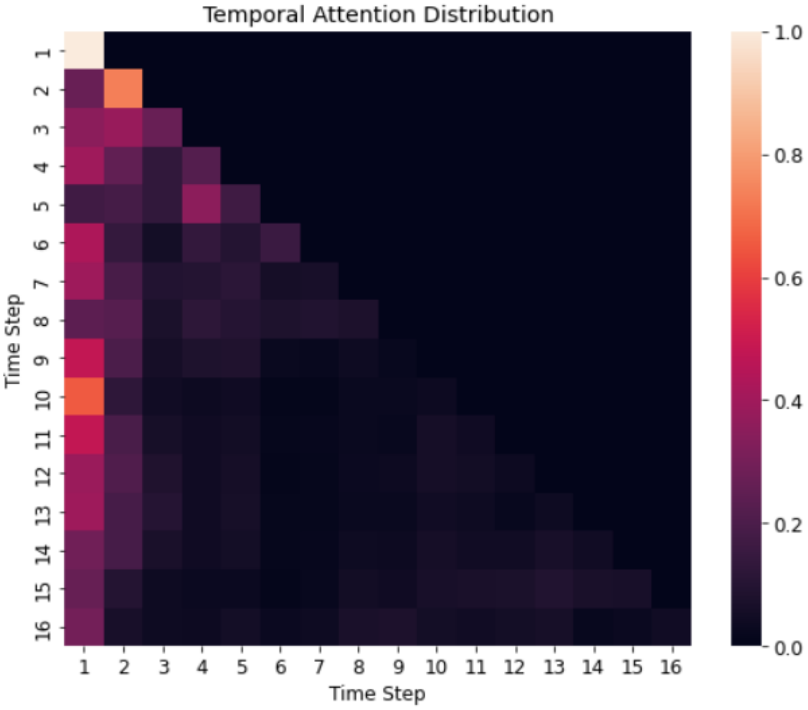


**Fig. 4** Distribution of time attention

### 3.3. Spatial Attention Distribution

As shown in the spatial attention distribution chart of Figure 5, the closer the vehicle is to the current vehicle, the higher the correlation is when it comes to forecasting the prospective trajectory of the attached vehicle. In the figure, the lighter the color. Therefore, when predicting the driving trajectory, the model focuses more on the driving trajectory of other vehicles close to the driverless car, so these vehicles are more likely to interact with the driverless car, rather than the vehicles far away from the driverless car, which is similar to the situation in real life.


**Fig. 5** Distribution of spatial attention

## 4. Conclusion

When making the decision of unmanned vehicles, decision system should not consider neither too many adjacent vehicles nor too few adjacent vehicles. Only the appropriate adjacent vehicles should be selected to achieve the best prediction effect. When predicting the trajectory of driverless vehicles, decision system will always pay more attention to other vehicles with a small time and space distance from the driverless car, and make decisions based on this evidence.

The main advantage of the model this essay used is that the SIT-based model predicts trajectories more accurately compared to other baselines, especially in the case of long-term predicted and highly interactive scenarios. Because it considers vehicle interactions during the encoding and decoding stages.

Although the GRU structure is simple, so the training speed is fast. However, the LSTM model has more parameters, more powerful functions, and more expressive ability. Introduction Minimal Gate unit (MGU) contains only one gate, which is a variant of GRU, combining the reset gate into the update gate. Through the design of only one gate structure, MGU is greatly simplified in parameters, only 2 / 3 of GRU, so the training speed is greatly improved in all problems, especially as the length of the sequence increases, GRU and LSTM cannot get results in acceptable time, while MGU will be very fast. Therefore, in order to get more accurate prediction results, researchers need to use different models to test in different situations.

Despite some challenges, driverless technology is still considered an important direction in the future of transportation. Through continuous research and innovation, this paper can expect greater breakthroughs and applications in driverless technology in the future.

## Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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