Assessment of the RSS Model Suitability using Graph Neural Network based on a Naturalistic Driving Dataset

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Abstract: We propose a method to evaluate the RSS model using data obtained from real roads. Recently, the Responsibility-Sensitive Safety (RSS) model representing the minimum safety distance has been proposed. After that, there were studies to evaluate the RSS model using simulators. Most virtual simulation studies showed that the RSS model guarantees safety but adversely affects traffic flow by estimating the distance too long than necessary. We evaluated the RSS model using data obtained in natural situational environments, unlike previous studies. First, we found correlations representing distances between vehicles from the data using Graph Neural Networks. Using the obtained correlations, we expressed it as a mathematical model through symbolic regression. As a result of comparing the model we found with the RSS model, we verified that the RSS model has a significant trade-off between safety and traffic flow.

1 INTRODUCTION

Although many research efforts on autonomous driving have not yet been perfect for fully autonomous driving, advanced driving assistant systems (ADAS), which require lower technologies than fully autonomous driving, have already been commercialized (Chai et al., 2020; Mishra et al., 2021; Mishra et al., 2022). Among ADAS, adaptive cruise control (ACC) is a typical longitudinal control system and is a technology that maintains a safe distance between the subject vehicle and the leading vehicle. The ACC system might not work correctly if the front vehicle suddenly decelerates or another vehicle abruptly cuts in front of the subject vehicle (Magdici and Althoff, 2017; Bae et al., 2020).

There have been many studies to set the safety distance standard between a leading vehicle and a subject vehicle to improve the safety of ACC against these worst conditions. Intel Mobileye proposed the Responsibility Sensitive Safety (RSS) model associated with NHTSA and IEEE SA (Shashua et al., 2018). RSS model suggests a safety distance model through mathematical methodologies using the subject vehicle's response time, velocity, and acceleration and the velocity and deceleration of the leading vehicle.

In particular, since it is a safe distance calculated based on the worst-case, it is a model that emphasizes that a collision does not occur if this distance is maintained within the RSS model (Shalev-Shwartz et al., 2017).

A simple mathematical model can express the correlation between the leading vehicle and the subject vehicle. Most safety-distance studies have proposed slightly modified models of the RSS model based on theoretical analysis or evaluated the suitability of the RSS model through simulations.

In this work, we propose a new method to evaluate the safety distance margin of the RSS model through artificial intelligence (AI) approach based on actual road data. First, we identified the correlations between vehicles with Neural Networks using accident-free vehicle data obtained from the natural road environments. Second, the correlations found through Neural Networks were expressed in a formula using symbolic regression. We propose a new model representing the safety distance between the leading vehicle and the subject vehicle through this process. This study aims to demonstrate that the proposed model could reduce the trade-off between safety distance and improving traffic flow compared to the RSS model. We also verified that the RSS model could affect the traffic flow by estimating more space than the required minimum distance for safety.

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2 RELATED WORK

2.1 Car-Following Model

The Car-Following Model refers to an analysis technique developed to define the correlation through changes in acceleration, velocity, and headway distance between two consecutively driving vehicles. The purpose is to predict the response of the subject vehicle according to the movement of the leading vehicle. We can divide the car-following model into three main domains: Gazis-Herman-Rothery (GHR), safety distance or collision avoidance (CA), and psychophysical or behavioral points (AP) (Brackstone and McDonald, 1999). This paper utilizes the CA field approach. There have been many studies in the field of CA. Lefevre et al. proposed a model that creates a model from the driver's actual driving trajectory and mixes a controller that restricts driving for safety (Lefevre et al., 2015). Wen-Xing and Li-Dong proposed a safety distance model using the expected average velocity (Wen-Xing and Li-Dong, 2018). It is similar to our methodology because it uses the predicted velocity. Still, the difference is that we propose the formula through correlations predicted through GNNs based on data obtained from the actual environments rather than using mathematical approaches. And there is the RSS model that has been evaluated and used a lot recently. The RSS model is divided into five cases as follows;

- Safe longitudinal distance — same directions
- Safe longitudinal distance — opposite directions
- Safe Lateral Distance
- Longitudinal Safe Distance for Two Routes of Different Geometry
- Lateral Safe Distance for Two Routes of Different Geometry

Since our purpose is to evaluate using data obtained from the natural environment, only the safety distance model for the same direction can be obtained from the referred database. Equation (1) shows the Safe longitudinal distance formula of the RSS model (Shashua et al., 2018).

$$d_{min} = \left[v_r\,\rho + \frac{1}{2}\,a_{max,accel}\,\rho^2 + \frac{(v_r + \rho a_{max,accel})^2}{2a_{min,brake}} - \frac{v_f^2}{2a_{max,brake}}\right]_+ \quad (1)$$

where $[x]_+ = max\{x, 0\}$.

v_r indicates the subject vehicle and v_f indicates the leading vehicle. This is a formula considering the worst-case scenario in which the subject vehicle accelerates to $\alpha_{max,accel}$ for ρ time when the leading vehicle rapidly decelerates to $\alpha_{max,brake}$. It may not always be proper to consider the worst-case scenario. For this reason, numerous studies evaluating the adequacy of RSS have been conducted. Among them, there were studies that RSS improves the safety performance of ACC, but it can reduce traffic flow efficiency in terms of the traffic flow by maintaining a distance longer than necessary (Mattas et al., 2019). There were several studies to solve this problem. Li et al. proposed a modified model that can reduce the safety gap and make traffic flow more efficient at the same time based on the RSS through a theoretical analysis method (Li et al., 2018). Chai et al. proposed an efficient model that can reduce the trade-off between safety and traffic flow by dividing the interval between the leading vehicle and the subject vehicle into three sections and slightly modifying the RSS depending on the situation (Chai et al., 2020). Naumann et al. proposed a methodology to find reasonable parameters of RSS based on physical limitations (Naumann et al., 2021). Kim et al. extracted and verified the safety distance for each velocity by applying the actual vehicle spec to the RSS model (Kim et al., 2021).

Previous papers have proposed methodologies that verify the RSS through simulation or slightly modify the existing model through mathematical analysis. The RSS model was created by combining widely known physical and mathematical theories. Cranmer et al. showed that the formula derived through artificial intelligence (AI) expresses the actual motion of atoms better than the formula used in the existing atomic motion theories (Cranmer et al., 2020). Based on the results of Cranmer et al., the purpose of this paper is not to slightly modify the existing model or verify it through simulations but to find a new formula using the results of extracting correlations between vehicles through AI based on data obtained from natural road environments (Cranmer et al., 2020).

2.2 Graph Neural Networks

First, we need to figure out the correlations representing the distance between vehicles. The vehicle data obtained from the natural road environments we want to use is not structured data such as images. Graph Neural Networks (GNN) are Neural Networks structures suitable for analyzing unstructured data. The advantage of GNN is that GNN can work with unstructured data such as images without preprocessing. Therefore, compared to other types of Neural Networks, GNNs are relatively more robust to inductive bias compared with Convolution Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) (Battaglia et al., 2018). An additional advantage of GNN is that the correlations between nodes can be found via the edges between each node. For these reasons, we used GNNs to find the safety distance between vehicles in this work. In this paper, the nodes of GNNs will be each vehicle, and the edges represent the distance between the vehicles, which are the correlations between the nodes we want to find.

GNNs started by applying Neural Networks to acyclic graphs proposed in Sperdui and Starita, and many studies were conducted until the late 2000s (Sperduti and Starita, 1997). They aimed to learn the target node's representation by iteratively propagating neighbor information. However, these methodologies required too much computation. Since then, ConvGNNs studies have applied many CNN's methods that can compute in parallel to solve various problems (Wu et al., 2020).

We can classify ConvGNNs into two spectral-based and spatial-based architectures. Spectral-based ConvGNNs are trained to learn filter parameters using the concept of Graph Fourier Transform throughout the graph signal processing.

However, in spectral-based, the eigenbasis problem changes when graph perturbation occurs. The issue is that the learned filters are domain-dependent and cannot apply to other structures, and the eigendecomposition $O(n^3)$ computational complexity (Wu et al., 2020). In particular, to solve the computational complexity problem, ChebNet (Defferrard et al., 2016) and GCN (Kipf and Welling, 2016) reduced the amount of computation through several approximations and simplifications. Nevertheless, there are still issues such as per- forming eigendecomposition on a spectral basis or processing the entire graph at once (Wu et al., 2020). Many other studies have been done to solve hard problems based on GCN (Chen et al., 2018; Chen et al., 2017; Chiang et al., 2019).

There are also spatial-based ConvGNNs studies to solve the aforementioned spectral-based problems. Spatial-based ConvGNNs are derived from the concept of existing CNNs that set the representation of a specific node and the representation of adjacent nodes as one patch and update it through convolution. It is the same concept as the initial GNNs but differs in performing a convolution operation.

Compared to spectral-based ConvGNNs, it does not require expensive operations such as eigendecomposition and is easy to generalize to new graphs because it does not rely on Fourier-based. And it has the advantage of solving the problem that can only be computed on the undirected graph, which is a disadvantage of spectral-based. Many studies have used performance development using these advantages (Micheli, 2009; Li et al., 2017; Masci et al., 2015).

In particular, the performance of inductive data has been greatly improved due to Graph Attention Networks (GAT) (Veličković et al., 2017). They applied a self-attentional layer that applies attention mechanisms to learning the relative weights of two connected nodes, allowing us to generalize the unseen graph. In general, the adjacency matrix, which means Graph Structure, is used as an input for GNNs. The adjacency matrix refers to a matrix indicating the correlations between each node. In particular, GCN is fixed with the given Adjacency Matrix values as the features of edges, which mean the connections between nodes. However, GAT does not fix these values but applies attention mechanisms to learn the correlation between nodes. Therefore, it can adapt to a new graph more efficiently with a bit of training. Since the data used in this paper is realtime vehicle data at a fixed location, it is necessary to repeatedly train the unseen graph in which vehicle information changes continuously. Therefore, attention mechanisms, which are the core of GAT, are essential for finding the correlations between two vehicles, which is the most important part of this paper. More details on data are described in the *Method*.

In addition to finding correlations between the current data of each vehicle, we can find more sophisticated correlations if historical data can be used together.

We used Spatio-Temporal Graph Neural Networks (STGNNs) to get more accurate correlations, which added the concept of time to the spatial-based ConvGNNs. Based on STGNNs, many studies have improved the performance in various fields such as recommendation system and traffic prediction (Li et al., 2017; Guo et al., 2019; Wu et al., 2019; Roy et al., 2021; Tian and Chan, 2021).

We found that the structure of STAWNet (Tian and Chan, 2021) is most suitable for our purposes. The first reason is that most GNNs required an Adjacency Matrix, which is graph structure information, as input. However, it is difficult to understand the connection structures between all vehicles with the data obtained from the real environments we want to use.

To solve this problem, STAWNet did not use an adjacency matrix but applied the self-attentional layer used in GAT to obtain the adjacency edge weights. As a result, we can find that the self-learned relationship showed a similar relationship found in the actual data. At the same time, it was possible to find a hidden relationship between the remaining nodes that did not appear. We thought it was appropriate for the part where we wanted to see the correlations between the leading vehicle and the subject vehicle. And since it is the architecture that includes the concept of temporal, a more sophisticated correlation can be inferred by using past data simultaneously as the present.

We utilized STAWNet, which uses a Spatio-Temporal architecture without requiring an adjacency matrix as input, to find the correlations between the two vehicles by training it after modifying it for our data set and purpose.

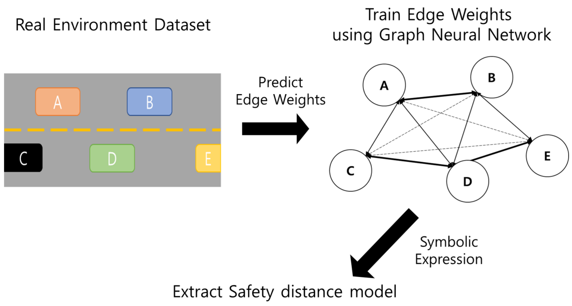
2.3 Symbolic Regression

Symbolic regression is an analysis method that directly creates a function that can explain the re-relationship between dependent and independent variables for given data. A lot of studies have been done based on (Sampson, 1976), which is one of the techniques to solve the optimization problem. Symbolic regression has been generally studied based on genetic algorithms (GA), genetic programming (GP), and Neural Networks (NN) (Mundhenk et al., 2021). We used GA based Eureq (Schmidt and Lipson, 2009). Eureqa stochastically combines algebraic expressions to create an optimized closed-form equation. The criteria for optimization are computational complexity and accuracy. In the problem of finding the safety distance in realtime, if the realtime is not guaranteed through complex calculations, it may cause a collision, so we used only simple +,-,/,* among many operators. For example, suppose a complex operation such as power appears in an expression obtained through symbolic regression. In that case, realtime performance may not be guaranteed as the time complexity is $O(n)$ or more.

3 METHOD

Our process can be summarized as follows.

- First, the Graph Neural Network is trained using vehicle data obtained from the real road environments to find the edge embedding features and correlations between each vehicle.
- Second, we apply symbolic regression using the found correlations (edge embedding features) to find the optimal formula to describe the relationships.
- Finally, the optimal formula found is applied to the dataset to calculate the error from the real values and validate the formula.



$$d_{min} = \frac{Velocity_{ego}^{2} + Velocity_{preceding} + Acceleration_{ego} + Velocity_{ego}}{\alpha \times Velocity_{preceding}}$$

Figure 1: Proposed process for extracting the safety distance model using Graph Neural Network based on the naturalistic driving dataset.

Our overall process is shown in Figure 1.

3.1 Dataset

We used the highD dataset as data obtained from natural real road environments. The highD dataset is the data captured using a drone on German Highways (Krajewski et al., 2018). Other naturalistic datasets (Geiger et al., 2013; Yu et al., 2020; Caesar et al., 2020; Lee et al., 2014; Houston et al., 2020) are those typically obtained via vehicles. We needed data that could get information about multiple vehicles simultaneously. Using a drone's data observed with a bird-eye view was suitable for our purpose. The highD dataset has data on the current velocity and acceleration of the subject vehicle, the ID of the sur- rounding vehicle, the velocity and acceleration of the leading vehicle, the distance to the vehicle in front, headway distance, time-to-collision.

We can see that this dataset contains information that can be utilized to compare the RSS model. This allowed us to select only the data from the highD dataset and use it to input the GNNs. The information we used is as below.

- Subject vehicle Velocity & Acceleration
- Leading vehicle Velocity & Acceleration
- The initial distance between two vehicles

Since our purpose is to compare the natural driving pattern with the RSS, only the information used in the RSS was extracted from the dataset and used. Next, we trained the GNN using the data.

3.2 Graph Neural Network Training

We used a modified structure of STAWNet. First, we defined each input feature as a temporal data frame. Second, the final input features were characterized by concatenating all input information. While the training phase, the output is trained to predict the velocity of each vehicle. GNNs have the advantage of being able to derive the results of all nodes at once. This setting of GNN helps find the correlations between vehicles by predicting the velocity, which is the movement of all vehicles. The feature maps of the self-attentional layers indicating the correlations of each node were extracted by the training. Based on the feature maps, the embedding space with significant variance mentioned in Cranmer et al. can generalize well and have high performance (Cranmer et al., 2020). Only the feature map with the largest variance was extracted among many self-attention feature maps. The results are shown in Figure 2. Figure 2.(a) shows the 2-hops adjacency matrix from the highD dataset. It is the result of normalization with the following equation in order to represent it on the same scale as Figure 2.(b).

$$W_{ij}^d = exp(-\frac{dist(v_i, v_j^2}{\sigma^2}) \quad if \quad dist(v_i, v_j) \leq \kappa_d \tag{2}$$

W_{ij}^d represents the correlation between each node calculated by $dist(v_i, v_j)$, which denotes the euclidean distance between node v_i and v_j, σ is the standard deviation of the distances and κ_d means distance threshold (Li et al., 2017).

Next, Figure 2.(b) shows the test result with the largest variance among self-attentional feature maps. The result of the corresponding feature map was extracted through the equation shown below.

$$W_{ij}^s = \frac{e_i e_j}{\|e_i\| \|e_j\|} \qquad if \quad W_{ij} \geq \kappa_s \tag{3}$$

W_{ij}^s can determine the correlation between node embeddings based on cosine similarity. That is, it is possible to know the edge weights between each node (Tian and Chan, 2021).

Looking at the thick red line, we can see the correlation similarity between the real adjacency matrix and the edge weights of the prediction results is similarly well expressed. Therefore, we can extract the self-learned adjacency matrix, which is the distance between vehicles obtained through training, In addition, the relationship between vehicles with unknown correlations in the dataset was able to find hidden relationships through self-learned to some extent. So, we used the correlations extracted through GNNs as the y value of symbolic regression.

3.3 Symbolic Expression

The extracted edge correlations were set to y, and the information used as input to the GNN was set to x,

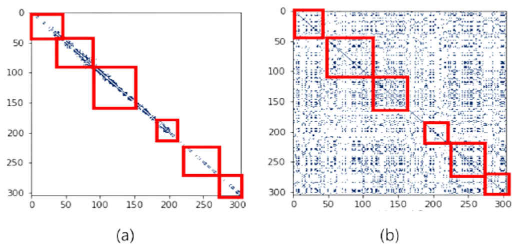


Figure 2: The comparison between (a) the real adjacency relationship from dataset and (b) the self-learned relationship on the training.

and applied to Eureqa, a symbolic regression package. The advantage of Eureqa is that it provides various information, such as accuracy and computational complexity, and at the same time finds the optimal formula through ranking. Since our goal is to find the required safety distance formula for vehicles in real-time, we chose an equation that exhibits relatively low computational complexity and high accuracy.

4 RESULTS & DISCUSSION

Using the learned results, the optimal formula was derived through symbolic regression. We obtained safety distance from the naturalistic driving dataset, which shows that the safety distance was relatively small compared to the RSS model. And as a result of applying the formula to accident-free data used for learning and checking the error with the real value, it was confirmed that there was almost no error.

It can be a formula that can reduce the trade-off between the safety distance and the traffic flow. The best matching formula found through symbolic regression is as follows;

$$d_{min} = \frac{v_r^2 + v_f + a_{v_r} + v_r}{\alpha \quad \times \quad v_f} \tag{4}$$

where v_r indicates the subject vehicle, v_f indicates the leading vehicle and a_{v_r} means acceleration of the subject vehicle. α is hyper-parameter.

Correlations extracted from GNN appear as values between 0 and 1 due to soft-max knowing the importance of each other. So, after performing symbolic regression, we additionally proceeded to find α that can reduce the error with the data. As a result, α becomes approximately 2.0.

Comparing the number of parameters required for the RSS model with the number of necessary parameters for our model, we can see that few are required. Table 1 shows the parameter comparison. In Table 1, *SV* means the subject vehicle and *LV* means the leading vehicle.

Table 1: Comparison of the number of parameters in our model and RSS model.

	Our Model	RSS Model
SV Velocity	Yes	Yes
SV Accel	Yes	Yes
LV Accel	No	Yes
LV Velocity	Yes	Yes
Response Time	No	Yes

Table 2: Comparison of our model and RSS model for various situations.

RSS Model		Subject Vehicle(km/h) 120	110	100	90	80	70	60
Leading Vehicle (km/h)	120	70.9	47.7	26.1	6.1	-	-	-
	110	89.0	65.8	44.3	24.2	5.8	-	-
	100	105.5	82.4	60.8	40.8	22.4	5.5	-
	90	120.5	97.3	75.7	55.7	37.3	20.5	5.2
	80	133.9	110.7	89.1	69.1	50.7	33.8	18.6
	70	145.7	122.5	100.9	80.9	62.5	45.7	30.4
	60	155.9	132.8	111.2	91.2	72.7	55.9	40.6

Our Model		Subject Vehicle(km/h) 120	110	100	90	80	70	60
Leading Vehicle (km/h)	120	61.0	51.4	42.6	34.6	27.5	21.2	15.8
	110	66.5	56.0	46.4	37.7	30.0	23.1	17.2
	100	73.1	61.6	51.0	41.5	32.9	25.4	18.8
	90	81.2	68.4	56.6	46.0	36.5	28.1	20.9
	80	91.3	76.8	63.7	51.7	41.0	31.6	23.4
	70	104.2	87.7	72.7	59.0	46.8	36.0	26.7
	60	121.5	102.3	84.7	68.8	54.5	41.9	31.0

Using parameters such as the RSS model can be more conservative due to unnecessary parameter combinations. The model with more considerable margins for the necessary distance may impede the traffic flow while autonomous vehicles drive in the actual road environment (Chai et al., 2019). So we can see that our model with fewer parameters is more efficient. Finally, we compared the number of various cases according to the velocity change between the leading vehicle and the subject vehicle. The results are shown in Table 2. At this time, the RSS model needs a response time of ρ. Since we trained the GNNs assuming the data period is 1 second, we set ρ to compare it to the same environments. In addition, For the maximum acceleration/deceleration of the vehicle, we put a value of $4m/s^2$ for maximum acceleration and of -4.9m/s^2 for maximum deceleration, respectively, as defined by the FSRA (Full Speed Range Adaptive Cruise Control) system of the international standard ISO-22179 (Park et al., 2018). The results can be divided into three cases. First, assuming that the subject vehicle is driving faster than the leading vehicle by more than 20km/h, the RSS model results show that the distance should maintain a distance from 1.2 to 1.4 times greater than our model. Second, assuming that the subject vehicle and the leading vehicle drive at the same velocity, our model estimates the safety distance to be about 9m smaller than the RSS model. Finally, when the leading vehicle is driving faster than the subject vehicle by more than 40km/h, the RSS model showed that the safety distance was 0, indicating no need to keep the safety distance.

In contrast, our model showed that a smaller distance than the required distance of the RSS had to be maintained. And to validate the safety of our model, we compared using the highD dataset, which is accident-free data. As a result of substituting the actual values of the dataset, the RSS model estimated a distance 10 to 30m larger than the actual inter-vehicle distance, and our model estimated a distance of 0 to 10m larger than the real inter-vehicle distance. It shows that both the RSS and our models are safe models that prevent crashes. Therefore, although the RSS model has a low accident probability, we could affirm that the trade-off between traffic flow and safety is significant by estimating a relatively large safety distance.

5 CONCLUSIONS & FUTURE WORK

This paper evaluated the RSS model by comparing the RSS model with the safety distance model found through Graph Neural Networks (GNNs) based on a real road dataset. In the previous safety distance models, there is a representative RSS model. However, it is inefficient for traffic flow to estimate the safety distance longer than necessary. Most studies have evaluated the RSS model through simulations or proposed a model with a slight modification of the RSS model to solve the problem. Unlike previous studies, we proposed a new model through machine learning rather than a mathematical car-following model. First, we trained GNNs using data obtained from real road environments. After that, edge weights, which are the correlations of nodes representing each vehicle obtained through GNNs learning, were extracted. Finally, the optimized formula was derived through symbolic regression using the extracted edge weights.

The formula we found estimates a relatively short safety distance compared to the RSS model when the velocity of the leading vehicle is comparable to or slower than the velocity of the subject vehicle. Conversely, the results showed that the minimum safety distance should be maintained even when the speed of the leading vehicle is significantly faster than that of the subject vehicle. In addition, compared with accident-free data to verify safety, there was little error between our safety distance and the actual distance. As a result, our model can reduce the safety margin between safety and traffic flow compared to the RSS model. Therefore, we conclude that the RSS model needs improvement.

Like the follow-up studies on the RSS model, we will verify our model through various additional simulations (Chai et al., 2020; Xu et al., 2021).

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