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Longitudinal Control Model of Curved Roads for Autonomous Vehicle: Privacy-Preserving Approach to Reflect Driver Tendencies Using Federated-Learning

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Executive Summary

This paper proposes a longitudinal control model for autonomous vehicles on curved roads. After that, we conduct federated learning using a dataset of 10 drivers and compare the results with the longitudinal control model. Unlike the existing method that determines the target speed according to a speed profile generated using map configuration, the speed profile is determined with only one parameter that integrates the characteristics of several parameters. This approach can reflect driver tendencies and the hardware characteristics of each vehicle. Then, we verify that this model shows stable performance in high-speed and low-speed driving using virtual environments (CarMaker) and vehicles (Avante, Niro).

The initial parameters and model are distributed to each client, and each conducts LSTM (Long-Short Term Memory) with different driving data. As a result, the weight lists of each client are transferred to the central server. By aggregating weight lists, we can upgrade the model, which is then distributed back to the client using this information. This communication between the server and clients is repeated, and the model can accurately reflect the driver's tendency over time.

Employing federated learning to calculate longitudinal velocity guarantees individual privacy by using non-centralized data, and the learning speed can be significantly increased. In addition, since there are multiple clients in federated learning, it is possible to reflect different driving tendencies for each driver, region, and country. Conclusively, we compare the performance indicators of two driving data using this model and goal velocity determined by federated learning.

Keywords: autonomous vehicle, control system, training, user behaviour, V2V(vehicle to vehicle)

1 Introduction

Lv4 Autonomous driving, which does not require driver intervention, is a hot issue worldwide. In order to implement an autonomous driving system that users can be satisfied with, a stable vehicle controller is required. Context-sensitive controllers are needed to improve commonly used values such as lateral acceleration, path tracking accuracy, and jerk as performance indicators of ride comfort. In particular, to improve path-tracking accuracy, many put efforts into improving the performance of the lateral controller. However, the longitudinal controller is also essential, as well as the lateral controller. Because several lateral controllers have their own critical speeds, when these speeds are exceeded, the controller's performance rapidly declines. In addition, if a vehicle exceeds the critical speed during turning, the tire will slip, and the vehicle's behavior will be nonlinear. This will no longer allow stable control of the vehicle. Therefore, studies on longitudinal control to increase ride comfort are being conducted worldwide.

As one of the ways to calculate longitudinal goal velocity, a speed profile has been generated using the map configuration given when driving on a curved road, and a target speed has been determined accordingly. Young-bae Kil calculated the critical safety speed by a curvature and friction coefficient based on vehicle dynamics and generated a velocity of profile[1]. Similar to this study, the speed profile was commonly created based on global path shapes[2][3]. In addition, using the bearing angle of 3~5 points on the local path, a velocity profile that decelerates following the value for a curve above a certain threshold(1.25°) is created[4]. Even one of the additional functions of the produced car by Hyundai Motor, NSCC-C(Navigation-based Smart Cruise Control-Curve), uses navigation map information to generate a speed profile[5].

However, it is important to move quickly and accurately from the starting point to the destination for autonomous driving. However, it is also very important to ensure it is similar to existing human driving, which directly affects the ride comfort experienced by users. This is because it is directly related to the ride comfort felt by users. Therefore, in this study, unlike the method in which the target speed was determined based only on the configuration of the map when driving on the curved road, a longitudinal model was created that could reflect the driver's tendency and the vehicle's hardware characteristics. There have also been studies to reflect this in the longitudinal model using machine learning, but the driver's tendency is a non-quantitative variable that can vary not only from driver to region and situation. This study proposes a simple model to tune by unifying the parameters that make up the model. This has the advantage of being able to reflect the driver's tendency and the vehicle's hardware characteristics and being commonly used in various lateral controllers. In addition, it has been successfully reflected in the winning team of the "2022 College Autonomous Driving Competition, Daegu, Republic of Korea".

Since the driver's tendency is different not only by the individual but also by region and country, it is necessary to apply a longitudinal model suitable for individual groups. Due to this need, several studies applied deep learning to make a model suitable for each driver's tendency. But in the case of central deep learning in which data were collected in an aggregation server for parameter tuning, and so on, several problems must be solved. For example, since each driver's data is large, communication with the aggregation server takes time and energy, leading to system delay. In autonomous vehicle control, requiring a quick response, a system delay greater than a certain level may lead to user risks, such as accidents.

There is also a privacy concern that people are sensitive to around the world. Over time, many sensors are attached to the body for the automation of vehicles. Furthermore, the problem of the security of data collected from those sensors is emerging. In fact, data collected by users is collected on a central server to upgrade the vehicle machine learning model, which was also a military and political issue. In order to respond to this problem, this study aims to employ federated learning[6]. In fact, many studies have been conducted to apply federated learning to autonomous vehicles, including S.R. Pokhrel and J.Choi enabling efficient communication using blockchain-based FL mode(BFL) and minimizing system delay[7]. In addition, Zhang, Hongyi, et al. used federated learning to calculate steering angles as outputs of learning using image data to improve latency with low bandwidth[8].

Additionally, Ford Motor Company trained the turn signal, one of the representative elements of driver orientation, using federated learning, and implemented a similar performance to that of centralized data[9]. Based on these studies, this study aims to use federated learning for the curve dependency model and handle a large amount of data while respecting individual privacy. In conclusion, we compared the trained model to the previous longitudinal model. Also, to conduct federated learning, we must use multiple drivers' driving data. Therefore, we used data from 5 drivers, and the total driving distance is about 950km.

2 Environment/Parameters

Establishing both a virtual environment and a real-vehicle test environment allows for the testing and validating of algorithms and control systems under controlled conditions before deploying them in the real world.

Standardizing environmental variables during comparative verification is also crucial n scientific experimentation, as it helps isolate the effect of the longitudinal controller being tested. Therefore, we used Stanley and Pure Pursuit as lateral controllers.

Federated learning allows for training models on decentralized data without requiring that the data be shared or centralized. To train the model with different clients' data, we used CUDA 11.3, a parallel computing platform that accelerates the training of machine learning models on GPUs.

2.1 CarMaker

Table 1: CarMaker Test Environment

Category	Detail
Vehicle Model	Niro EV
Testbed	Katri (K-city) AMG SpeedWay

2.2 Real-Vehicle

Table 2: Real-Vehicle Test Environment

Category	Detail
Vehicle Model	Avante AD Niro EV
Testbed	Katri (K-city) KIAPI

2.3 Federated Learning

Table 3: Federated Learning Parameters

Category	Detail
Vehicle Model	Niro EV
Testbed	AMG SpeedWay
Framwork	FLOWER
Local Model	LSTM
Aggregation Strategy	FedAvg
Input Size	7
Hidden Size	32
Output Size	1
Number of layers	2
Dropout	0.1
Number of Clients	5
Local Epoch	3
Local Batch	64
Learning Rate	0.001
Number of Round	3
Num Client Gpus	1

3 Longitudinal Model for Curved Road

3.1 Calculation of Critical Speed(V_c) according to Road Configuration

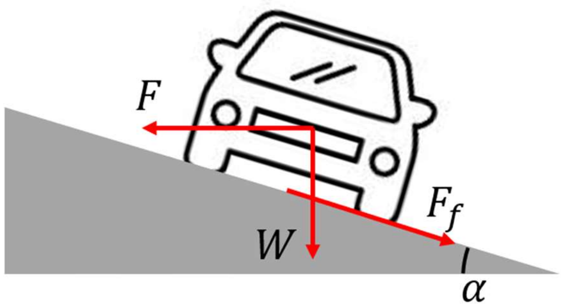

Figure 1: FBD of Vehicle on Curved Road

Vehicle dynamic analysis is required to make stable turns on curved roads. When the vehicle exceeds the static friction force and moves into the kinetic friction force, the friction curve changes nonlinearly, making it difficult to control the vehicle. Therefore, when turning on a curve, the safety-critical speed should be calculated by considering road and vehicle characteristics such as superelevation, friction coefficient, and vehicle weight, as shown in Figure 1. Equation (1) shows that slip can be prevented from increasing rapidly only when the lateral friction force is maintained at a value greater than the centrifugal force.

$$Fcos\alpha - Wsin\alpha \leq f(Fsin\alpha + Wcos\alpha) \tag{1}$$

Curved roads are usually designed with superelevation($tan\alpha$) to make stable driving of the vehicle. However, in this study, a flat road with zero α (2) is assumed.

$$\left(\frac{W}{g} \times \frac{V^2}{R}\right) \leq f \times W \qquad R \geq \left(\frac{V^2}{g} \times \frac{1}{f}\right) \tag{2}$$

Using this method, it is possible to calculate V_C, the maximum speed at which the vehicle can safely turn on a curved path. The calculated V_C corresponds to V_{min} in the longitudinal model, which is a parameter that determines the speed at which the vehicle should decelerate when entering the curve. In equations (1) and (2), f represents the lateral slip friction coefficient, which is set to 0.16 in this study following the criteria of the American Association of State Highway and Transportation Office(AASHTO).

3.2 Set Predict Point(D)

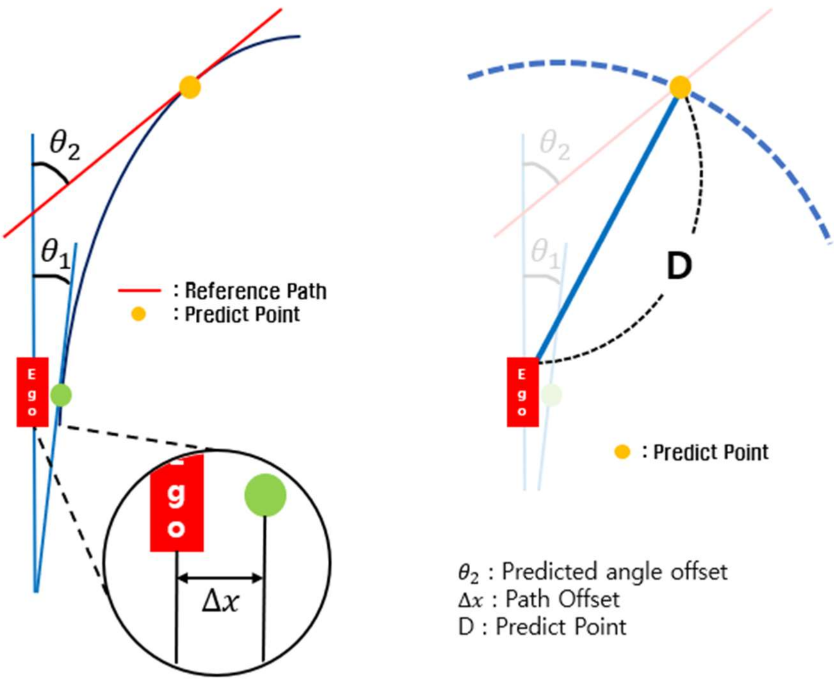

Figure 2: Parameters to make longitudinal control model

When turning the curved road, the driver's tendency is determined by the timing and how much braking is performed. The predicted distance(D), which is explained in Figure 2, was set as a parameter to indicate this. As shown in equation (3), a value proportional to the current speed(kph) can be applied, and the k value can be tuned to apply a longitudinal model suitable for the situation.

$$D(predict\ distance) = V_{Current} \times k \tag{3}$$

3.3 Longitudinal Control Model for Curved Road with Predicted Angle Offset

The longitudinal control model was developed using the provided parameters, as shown in equation (4). This model offers several advantages, including the ability to specify our maximum and minimum speed ranges, account for driver characteristics, and accommodate hardware characteristics such as delay in the vehicle.

As is commonly known, when turning on a curved road, speed, and ride comfort, including lateral acceleration and jerk, are in a trade-off relationship. It is natural that by reducing speed, we can increase the stability of the path following. However, the most significant advantage of this model is that it allows for the imitation of a driving style that suits the inclination of each driver by adjusting a single parameter.

Conclusively, Figure 3 shows a comparison between the target speed of the longitudinal control model and the data-driven by a person.

$$V_{goal} = V_{max} - |\theta_2| \times \frac{(V_{max} - V_{min})}{C} \tag{4}$$

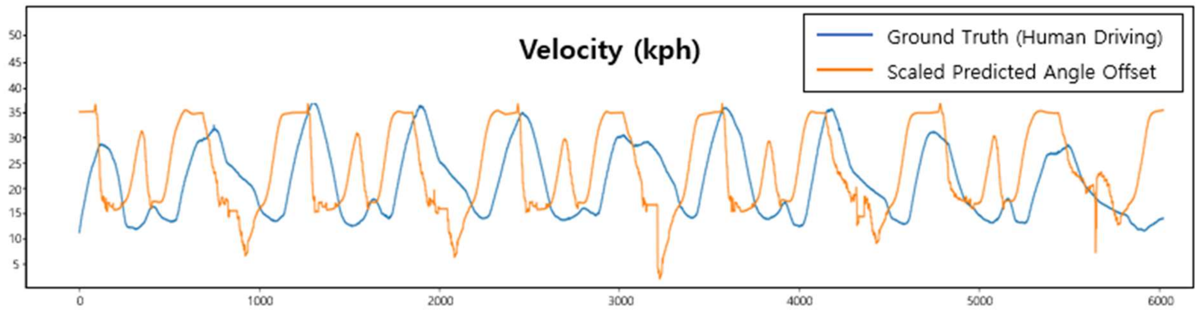

Figure 3: Comparison between Target Speed of Longitudinal Control Model and Human Driving Data

4 LSTM with Federated Learning

4.1 Federated Learning

Federated Learning(Collaborative Learning), as shown in Figure 4, is one of the machine learning methods that use decentralized data instead of central server-based machine learning to train each client's data. The advantages of not aggregating each data by communicating between the clients and the central server are as follows.

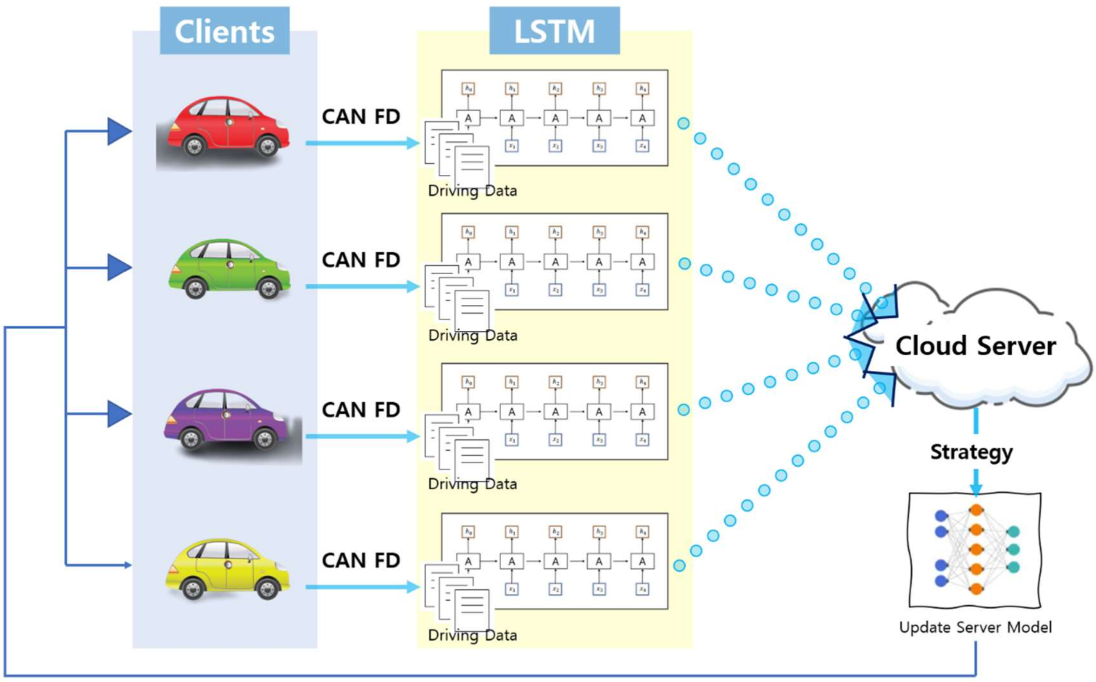

Figure 4: Schematic Diagram of Federated Learning

- **Fully Decentralized Learning**
  Federated learning offers significant advantages in terms of privacy as it does not concentrate each client's data on the server for learning but performs learning locally and then aggregates only the training results(weights) on the server. Developing autonomous driving algorithms for each vehicle is essential to usher in the era of autonomous driving. However, it is also essential to control them through server communication, which can be achieved through cluster vehicle control. In this regard, federated learning is expected to contribute to the era of autonomous driving significantly.
- **Non-iid Data**

Since learning is conducted separately on each client, there is an advantage that even if the data is imbalanced, it can be reflected in the overall model by assigning weights. In this study, which conducts federated learning tailored to the driving habits of each region, the advantage of using non-IID data is decisive.

- **Effective Communication between the clients and the server**
  In collecting all data and learning through communication with the server, a vast amount of data must be exchanged between the server and clients, which requires significant time, money, and energy. As a result, there is a high possibility that the real-time guarantee, which is essential for cluster vehicle control, may not be ensured. However, communication efficiency can be improved since only local learning results are exchanged with the server.

The block diagram illustrating the flow of federated learning is shown in Figure 5.

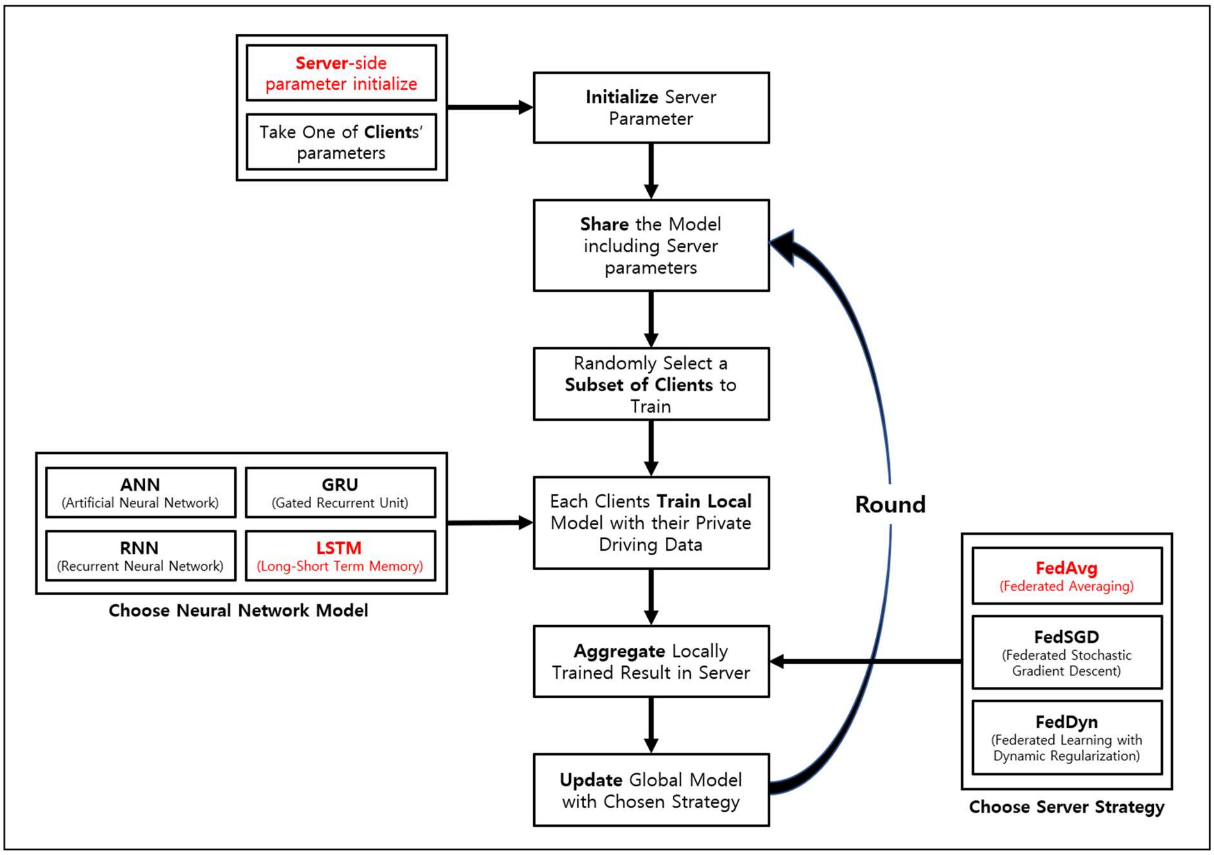

Figure 5: Block Diagram of Federated Learning with LSTM

5 Result

5.1 Longitudinal Control Model for Curved Road with Predicted Angle Offset

We created a longitudinal control model for a curved road that can be easily tuned according to the driver's tendencies by unifying parameters and verifying its performance.

First, when comparing the case of turning at a constant velocity during a right turn with the case of turning using the longitudinal control model, the results are shown in Figure 6. As shown in the graphs, driver comfort can be improved when we use the longitudinal control model.

Secondly, we output the speed profile according to the value of k, which can reflect the driver's tendencies, as shown in Figure 7. The k value, which determines the predicted distance, can reflect the safe driving tendency of a driver who decelerates in advance when it increases, while it can reflect the aggressive driving tendency of a driver who decelerates only when getting closer to the curve when it decreases. If a k value higher than a certain threshold is used, the level of deceleration remains constant, thus ensuring safety regardless of the driver's tendency. However, if a k value that makes the predicted distance shorter than the length of the curve is chosen, the degree of deceleration decreases, which could lead to unpredictable behavior.

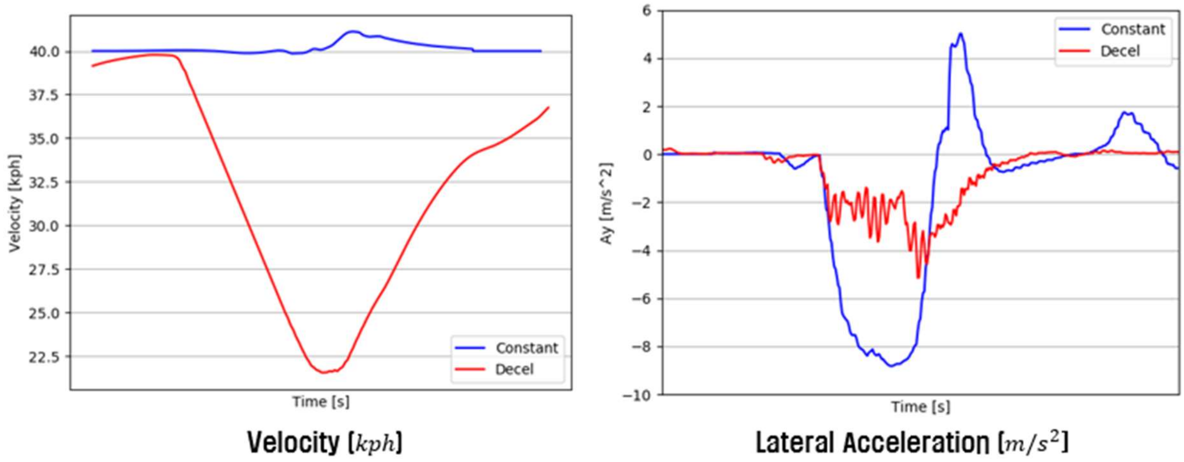

Figure 6: Velocity&Lateral Acceleration Result Plot

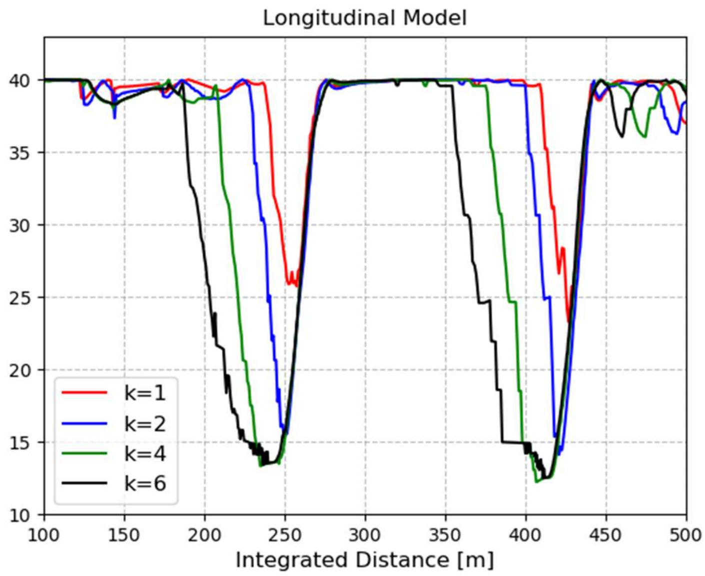

Figure 7: Velocity Profile of Longitudinal Control Model with Different k

5.2 Federated Learning with Driving Data

We performed the task of transplanting the LSTM, a time series prediction model, into a federated learning model. The results were obtained based on the data from five clients' driving. Figure 8 shows the plotted results. Although we cannot say that the performance of the federated learning model is significantly better when looking at the velocity profile, it is still significant that we were able to perform vehicle control while considering the aspect of privacy protection.

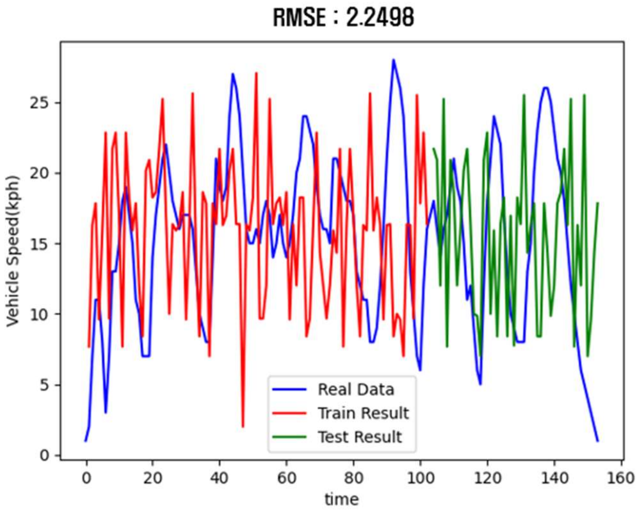

Figure 8: Comparison Training Result with Real Data

6 Conclusion

In this study, we developed an easily-tunable longitudinal control model for curved roads that can reflect driver tendencies and vehicle hardware characteristics and attempted to achieve dependency control through federated learning (FL) without centralization. Unlike previous machine learning methods, FL respects personal privacy by not collecting data on the aggregation server and has the advantage of efficient data utilization and minimized system delay. In this study, we had to conduct local training for clients serially using a single PC and used the FLOWER federated framework[11] for the process. If we proceed with federated learning using multiple workstations, we can conduct research that better aligns with the purpose of federated learning and open up possibilities for real-time vehicle control applications.

7 Future Work

Using deep learning methods that rely on centralized data can result in communication delays and create a burden for exchanging vast amounts of data. However, it is natural that their performance is better than that of federated learning methods. This study emphasizes the use of a learning approach that aligns with the global trend of protecting personal information in its longitudinal control model. We can upgrade the federated learning model as future work to surpass the performance of the centralized model.

Secondly, there is a severe problem~~,~~ in which the central server can decline the performance of the local model on purpose by sharing a model with adversarial data. By improving adversarial training, we can approve the safety of federated learning.

In addition, in this study, we used accumulated data for learning and applied it to vehicle control. We will attempt to secure real-time capabilities by taking advantage of reduced communication delays between the central server and clients through federated learning. We can conduct research by using multiple actual vehicles to attempt V2V and V2s communication in real-time and control vehicles, not only in simulations.

Acknowledgments

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Presenter Biography

Hyobin Kim received a B.S. degree in Mechanical Engineering from Sungkyunkwan University, Suwon, Korea, in 2022. He is currently studying for M.S. degree in Mechanical engineering at Sungkyunkwan University. His research interests include autonomous vehicle control system using artificial intelligence.

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