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DISTRIBUTED DRIVING CONTROL FOR MECHANICAL COMBINATION OF PERSONAL VEHICLES

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Abstract. *Recently, several vehicle manufacturers in Japan have unveiled the concept model of personal vehicles (PVs). PVs are small single- or double-seated electric vehicles and are specifically used for short trips. Considering the trend of vehicle use in Japan, PVs are appropriate for daily transportation. However, when several luggages or people need to be transported, multiple PVs, each with one driver, will be required. Thus, potential users of PVs select passenger vehicles because "larger vehicles also serve smaller purposes." Therefore, this study aims to solve issues in vehicle combination technology to expand the utility of PVs. In particular, a dynamic vehicle model is developed for mechanically combining vehicles using neural networks to accomplish distributed driving control. This combination of PVs is operated as a single vehicle. Then, simulation evaluations are performed on the developed model. The simulation evaluations validate the feasibility of the combination of PVs and clarify the relationship between driving distance and modeling accuracy.*
Keywords: Personal vehicle, Mechanical combination, Machine learning, Neural network, Dynamic modeling

1. **Introduction.** Recently, the use of PVs has gathered interest in Japan. PVs are small single- or double-seated electric vehicles and are specifically suited for short-distance trips. Target users of PVs are those who seek transportation for distances that are too long for walking or cycling and too short for using motorbikes or passenger vehicles. In Japan, the average number of people in a passenger vehicle is about 1.3/unit and the average distance of a trip is about 10 km. This statistic agrees with the above assumption regarding vehicle use in Japan.

PVs are expected to be used for pleasure or business trips within a region. In Japanese suburban areas, public transportation is inconvenient, and hence, visitors rent passenger vehicles or walk to their destinations. If they can rent PVs at a lower cost than passenger vehicles, they can conveniently explore the entire city instead of only visiting areas close to stations. Therefore, the use of PVs would lead to the revitalization of suburban cities. In addition, PVs can be customized depending on the characteristics of each city because they are cheaper than passenger vehicles.

Moreover, PVs are expected to be used for transportation from one's home or office, public transportation, and delivery services because they are faster and more comfortable than walking or cycling. PVs can be especially beneficial for delivery services because they can reduce operation costs, for example, fuel cost. In addition, PVs can enhance the brand image of a company because they reduce noise pollution and the environmental burden. Therefore, several Japanese municipalities are discussing the reconstitution of social transportation systems and are running trials of PVs within special zones.

However, PVs have a lower load capacity than passenger vehicles. This may be paradoxical. Although users of passenger vehicles need the performance of PVs, they choose passenger vehicles when they need to travel with many bags or when many people are traveling together even if this case is less frequent. In general, each PV requires one driver; therefore, many drivers are needed in the case of many bags or people. This limits the utility of PVs.

To solve this issue, this study proposes PVs that can be used in combination. Many important advantages of combination of vehicles have been reported [1-5]. We have been attempting to apply combination of vehicles to PVs as well as passenger vehicles and trucks. This paper mainly focuses on a mechanical method of combining PVs. Previous studies have developed and evaluated mechanical, semi-mechanical and electronic methods of combining vehicles. Concept of the mechanical combination and its feasibility evaluation have been reported [6]. As for the semi-mechanical combination method, a device, which measures V2V distance and its relative angle using a draw wire encoder and a slide rail, has been proposed and the device has been validated using actual vehicles [7]. As the electronic combination for trucks, an algorithm for stable V2V distance control has been proposed [8]. In addition, in order to complement reliability, which is a weak point of the electronic combination, a redundant system architecture using GPS and V2V communication has been proposed and evaluated [9]. A study on the electronic combination for PVs has proposed a vehicle following control algorithm, which can maintain V2V distance with error of about 15 cm [10].

If a combination of PVs can be operated as a single PV, the utility of PVs can be expanded. From the viewpoint of regulation, PVs combined by the mechanical method described in this study are easier to operate. However, a PV is assumed to be used as a single vehicle. Thus, improving the driving motor output of PVs to enable towing of other PVs when used in combination is not desirable. The combination of PVs should be under distributed driving control because this control can complement the output of a PV. To operate combined PVs as a single PV, the driving control should be designed such that the vehicles' driving characteristics do not drastically fluctuate after the combination.

This study develops a dynamic vehicle model for accomplishing distributed driving control for a combination of PVs using neural networks and evaluates the model through simulations. Distributed driving control aims to maintain the driving characteristics of the combined vehicles at the same level as that of a single vehicle by sharing vehicle state quantities via V2V communication. The vehicle modeling can be performed dynamically on the assumption that users get on/off the vehicle and load/unload their baggage.

The rest of the paper is organized as follows. Section 2 describes the dynamic vehicle model using a neural network. Section 3 presents the conditions and results of the simulation evaluation to validate the dynamic vehicle model using a neural network. Finally, Section 4 concludes the paper.

2. Simulation Modeling.

This section describes the system architecture of the dynamic model using neural networks for accomplishing distributed driving control of the combination of PVs.

2.1. System architecture.

As explained above, this study aims to solve technological issues of PVs to enable their operation in combination, and as a result, expand the utility of PVs. This study focuses on the mechanical method of combining PVs. When PVs are combined mechanically, they must be under distributed driving control to complement the output forces of the PVs. Moreover, the driving characteristics of the vehicles in combination must not drastically fluctuate in order to ensure operability of the driver of the leading vehicle. In particular, mechanical energy must not be transferred via the coupling device to the other PVs in the combination. This also decreases the vibration generated by the vehicle combination, thus improving ride comfort.

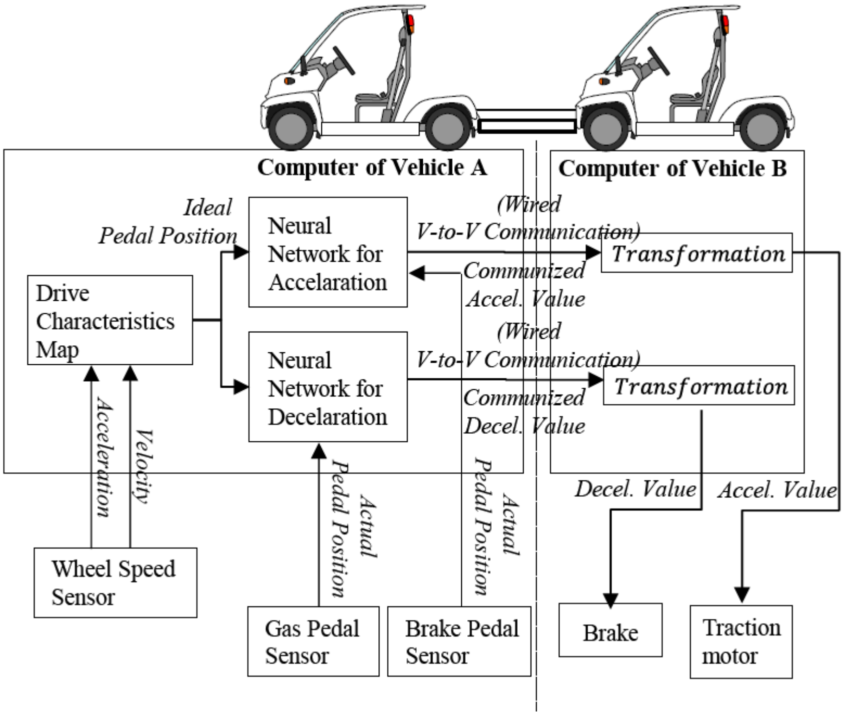

Figure 1. System architecture

The system architecture of the dynamic model designed in this study is illustrated in Figure 1. An example of combining two vehicles is shown in the figure. The leading vehicle is referred to as vehicle A and the following vehicle is referred to as vehicle B.

Vehicle A performs dynamic modeling of the PV combination using neural networks. All vehicle B has to do is transfer to command values of braking/driving received from vehicle A to the command values for vehicle B. This is because vehicle A's braking/driving characteristics map is used for dynamic modeling of the combination of PVs. In this study, the command values of braking/driving are the same for all vehicles and can be communicated to the actual command value for each vehicle. A standard for the command value would be needed before implementing this design in the actual operation.

Vehicle A uses its braking/driving characteristics when used alone as the standard and calculates the difference between the braking/driving characteristics of vehicles A and B. The calculated difference is used for machine learning by the neural network and communicated to vehicle B's command value of braking/driving. In other words, when vehicles A and B are combined, the model calculates the command value of braking/driving to make the braking/driving characteristics of vehicle B close to those of vehicle A operating alone. If more than three vehicles are combined, the middle vehicle should equip functions of vehicles A and B.

The braking/driving characteristics of vehicle A as a single vehicle must be provided by the manufacturer as the braking/driving characteristics map. However, it is not practical to share the braking/driving characteristics map via communication. Thus, in this study, almost all functions of the dynamic modeling of the combination of PVs are performed by vehicle A and are treated as a black box.

The dynamic modeling of the combination of PVs is assumed to be used as feedback control in a vehicle control system. If the influence of modeling errors or noise on the modeling is required to be close to zero, feedback control using sensors such as a force gauge equipped with a coupling device is required.

2.2. **Combination of vehicles using machine learning.** A dynamic model for combining PVs is designed using the selective desensitization neural network (SDNN) in paper

[11] as a reference. The SDNN can perform learning in lesser time and has a better generalization ability than other neural networks. To evaluate the performance of the SDNN, previous studies have developed and validated a dynamic model for combination of vehicles using monotonic acceleration [12-14]. This study expanded the dynamic model to combining PVs so that it can be employed in actual operation.

The dynamic modeling of combining PVs accomplishes a two-variable function approximator using two SDNNs. The input of the function approximator is the current velocity and braking/driving command value for the vehicle and the output is the braking/driving command value for vehicle B as common values. The neural networks for calculating the driving and braking command values are constructed separately because each communized command value is not continuous in most cases.

The basic structure of the SDNNs used in this study is shown in Figure 2. The structure of the SDNNs for the driving and braking command values is the same. The first layer of the SDNN consists of two elements. The inputs of the first layer are vehicle A's communicated command value (driving/braking) and velocity. The input values, zero to maximum value, are transferred at 512 resolution values. The second layer consists of two element groups, each consisting of 1024 elements. Each layer corresponds to the code patterns generated by the SDNN code pattern consisting of 1024 elements. Each element in the code pattern has a value of 1 or −1.

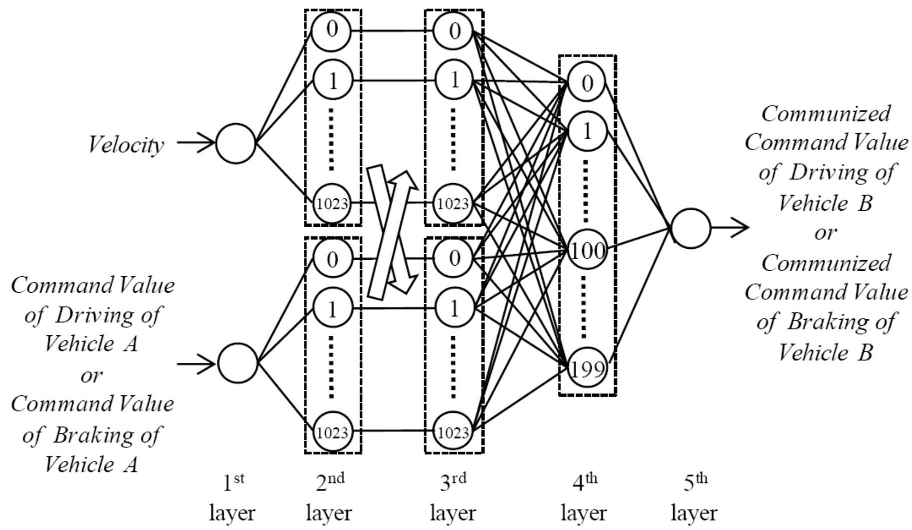

Figure 2. Basic structure of SDNNs

The third layer performs selective desensitization of the two element groups. Combination of each element in the second and third layers is randomly selected to avoid overlap. Each element of the third layer outputs a value of 1 or −1. This is to avoid deviation or unintended correlation in the pattern of neural activity in selective desensitization.

The fourth layer consists of 512 elements and builds a parallel perceptron with the third layer. Learning of the parallel perceptron is based on error correction training.

The fifth layer consists of one element and the element is connected to all elements in the fourth layer. The weight of a constant value determines the output z. The output z is the command value for vehicle B and is sent to vehicle B via V2V communication.

3. **Simulation Evaluation.** This section describes the conditions and results of the simulation evaluations of the dynamic model for combining PVs using the neural network described in Section 2.

3.1. **Evaluation conditions.** Two combined vehicles are simulated on a flat straight road to evaluate the dynamic vehicle model for combining PVs using a neural network.

The vehicle behavior model of the simulation only considers longitudinal control because this study assumes only driving on a straight road. The vehicle behavior model calculates vehicle acceleration, velocity, and position from the vehicle's weight, rotation resistance, air resistance, and the force generated from the tires. The force generated from the tires of each vehicle is calculated from the braking/driving characteristics map. The characteristics map is a matrix of the force generated from the vehicle, which consists of the command value and velocity.

Conditions of the simulation evaluations are classified into four patterns.

Pattern 1: Mass of vehicle B is 1.5 times that of vehicle A. The command values for vehicle B are calculated with the proposed system.

Pattern 2: Vehicles A and B have different driving characteristics. The command values for vehicle B are calculated with the proposed system.

Pattern 3: Mass of vehicle B is 1.5 times that of vehicle A. The command values for vehicle B are calculated without the proposed system and fixed to zero.

Pattern 4: Mass of vehicle B is 1.5 times that of vehicle A. The command values for vehicle B are calculated without the proposed system and fixed to the same values as those for vehicle A.

Under the above conditions, vehicle A is under proportional velocity control in order to simulate a typical PV driver's behavior of acceleration/deceleration. The target velocity of vehicle A is set at 10 km/h for 30 s after the beginning of the experiment and then set to 0 km/h. After driving for 55 s, vehicle A repeats the driving behavior from the beginning of the experiment, thus maintaining the learning state of the neural networks.

3.2. **Evaluation results.** Figures 3 to 5 show the simulation results. Figures 3 and 4 show the velocity fluctuation of the combined vehicles for 10 cycles. The deeper color of the solid lines indicates later cycles.

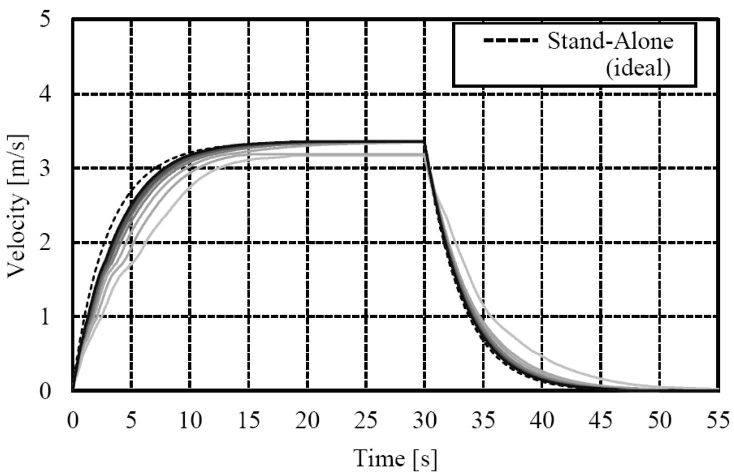

Figure 3. Simulation results (pattern 1)

Figure 3 shows the simulation results for pattern 1. The results show that before learning, the combination of vehicles has insufficient output power for acceleration/deceleration compared with that of vehicle A as a single vehicle. However, in later cycles, the output power for acceleration/deceleration of the combination of vehicles is closer to that of vehicle A as a single vehicle. This indicates that by using the proposed system, the driving characteristics of the combination of vehicles can become almost the same as that of vehicle A as a single vehicle even if the mass of the vehicle following vehicle A significantly fluctuates because of the weight of baggage or people getting on/off the vehicle.

Figure 4 shows the simulation results for pattern 2. In this experiment, vehicle B is set to have higher performance in acceleration. The result shows that before learning,

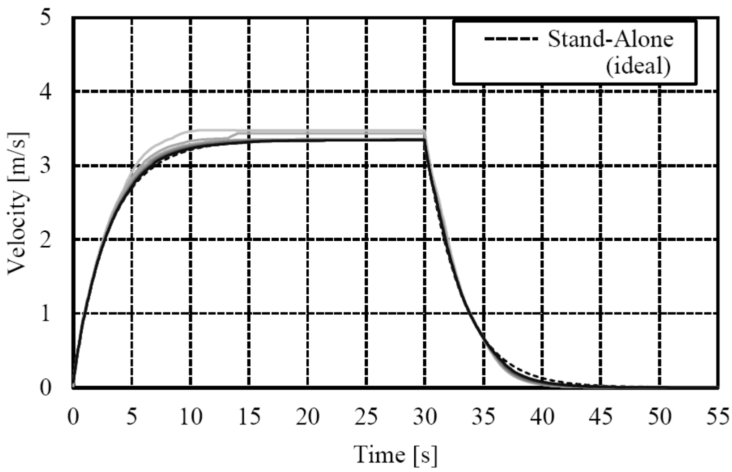

FIGURE 4. Simulation results (pattern 2)

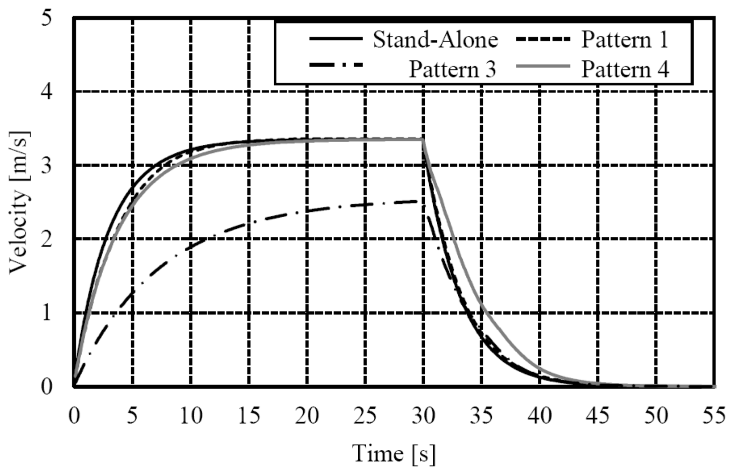

FIGURE 5. Simulation results (pattern 1, 3, 4)

the combination of vehicles performed acceleration at a greater output force than vehicle A as a single vehicle. However, in later cycles, the combination of vehicles performed acceleration/deceleration at closer output force to vehicle A as a single vehicle. This shows that by using the proposed system, the driving characteristics of the combination of vehicles can become almost the same as those of vehicle A as a single vehicle even if the performance of the vehicles in a combination is not the same.

Figure 5 shows the velocity fluctuation of vehicle A and the combination of vehicles in patterns 1, 3, and 4. The results for pattern 1 indicate the results after 10 cycles of learning. The acceleration/deceleration of the combination of vehicles is more gradual than that of vehicle A as a single vehicle. This is because vehicle B, in short of output power, is towed by vehicle A. In other words, pattern 3 would cause an accident, especially in deceleration, because the vehicles cannot perform deceleration as the drivers' intent. Pattern 4 shows more gradual acceleration/deceleration than pattern 3. In other words, operation of vehicles in pattern 4 is more difficult than in pattern 3. Finally, pattern 1 enables closer driving characteristics to vehicle A as a single vehicle. This means that the combination of vehicles in pattern 1 can be operated in the same way as vehicle A as a single vehicle. In addition, pattern 1 would perform less transference of mechanical energy. Less transference of mechanical energy enables better ride comfort because less vibration is generated in the mechanical combination of vehicles.

The above results validated that the utility of the distributed driving control for combination of PVs is higher in conditions of pattern 3 or 4.

4. **Conclusions.** This study developed a dynamic vehicle model for combining vehicles using neural networks and performed simulation evaluations on the developed model to validate the distributed driving control for the combination of PVs, which would expand the utility of PVs.

PVs that can be mechanically combined under distributed driving control are needed to increase their utility. Therefore, this study designed dynamic vehicle modeling for a combination of vehicles using SDNNs, which can perform learning in shorter time and have a higher generalization ability than other neural networks. Simulation evaluations were performed in four patterns to clarify the relationship among the learning performance, driving distance, and accuracy of the modeling method designed in this study. The results validated the modeling method for the distributed driving control for combination of PVs.

The author is planning to conduct demonstration experiments by installing the distributed driving control in actual PVs.

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