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Deceleration Planning Algorithm for Smart Regenerative Braking Reflecting a Driver's Characteristics through Online Learning Algorithm

Gyubin Sim[1], Kyunghan Min[1], Inseok Park[2], Jeamyoung Yeon[2], Myoungho Sunwoo[1]

[1]*Depaertment of Automotive Engineering, Hanyang University, 222 Wangsimni-ro, Seongdong-gu, Seoul 04763 Republic of Korea, gbcompany27@gmail.com*

[2]*Research & Development Division, Hyundai Motor Company, Hwaseong, Korea*

Summary

The extension of a driving range is one of the most important challenges to an Electric Vehicle (EV). One of the effective approaches to extend the EV's driving range is the Smart Regenerative Braking System (SRS). This paper proposes a deceleration planning algorithm and an online learning algorithm that generate a reference acceleration based on the driver's characteristics which is learned in real-time. These algorithms are validated through simulation using experimental data as inputs. The results demonstrate that the generated acceleration is highly similar to the experimental data of drivers and reflects the driver's characteristics by the online learning algorithm.

Keywords: Smart regenerative braking system, Deceleration planning, online learning algorithm, personalization, driver's characteristics

1 Introduction

EV has numerous advantages: they have powerful driving torque, produce zero emissions, and they are quieter than vehicles with combustion engines. However, EV lacks the driving range due to the limited capacity of the battery, which is one of the main concerns of producing EV. To extend an EV's driving range, extensive research regarding the improvement of efficiency of EV has been conducted[1]. SRS is one of the examples that extend the driving range of EV by saving the braking energy.

In the operation of SRS, the braking energy is converted to the electric energy by the regenerative braking. In addition to energy saving, SRS provides ease and convenience to the driver without the driver losing the fun of driving which usually comes from acceleration. For the driver's ease and fun of driving, SRS intervenes the longitudinal motion of the vehicle only when the vehicle needs to decelerate. As a result, a driver does not need to push the brake pedal when using SRS, which adds convenience.

To implement the SRS, reference deceleration is needed. The reference deceleration should satisfy the safety criterion to avoid collision with a preceding vehicle. In addition to this, harmonization of the reference deceleration with the driver's pedal input is essential. SRS operates when the driver steps off the accelerator pedal. For the driver to feel as though they are driving even in the operation of SRS, the intervention of SRS should be similar to a human's brake' pedal input. Therefore, after the driver steps off the accelerator pedal, SRS needs to increase the deceleration gradually, decelerate to the safe point, and then finish the deceleration steadily.

In the automated longitudinal control, a driver can feel discomfort due to the difference in the driver's characteristics and the automated longitudinal control's characteristics. One of the noticeable points where the driver can feel discomfort is, the distance to a preceding vehicle. Some drivers get close to a preceding vehicle, while other drivers prefer to keep a longer distance to a preceding vehicle. If a driver has a driving style to keep a long distance to a preceding vehicle, the driver feels discomfort when the automated longitudinal control keeps a short distance to it. Due to the discomfort by the automated longitudinal control, various research has been conducted to reflect the driver's characteristics to the controller[2]. SRS can also cause discomfort to the driver if the deceleration by SRS is different from the driver's deceleration pattern. Therefore, the personalization method is necessary. To reflect the driver's characteristics in real-time, SRS should be able to learn the driver's characteristics using the driving data whenever the deceleration by the driver's brake pedal input finishes.

Based on the two points mentioned above: harmonization with a driver's accelerator pedal input and personalization, this paper suggests a deceleration planning algorithm and an online learning algorithm to reflect the driver's characteristics. The deceleration planning algorithm is designed as a parametric model with four braking sections to simulate the human's deceleration pattern. The deceleration planning algorithm including the braking sections will be described in section 2. Then, section 3 will clarify the online learning algorithm which updates the learning vector representing a driver's characteristics. The simulation results of the deceleration planning algorithm including the online learning algorithm will be explained in section 4. Finally, section 5 discusses the conclusion and future works.

2 Deceleration planning algorithm

2.1 Split of deceleration profile

2.1.1 Analysis of deceleration profile

Deceleration profile was analysed in two different types of deceleration conditions: dynamic condition and static condition. Dynamic condition means deceleration condition caused by any dynamic object such as a preceding vehicle. Therefore, a car-following condition is an example of dynamic conditions. A static condition indicates the deceleration situation by the static object like a traffic light. Stopping in front of the traffic light and deceleration by the curved road are examples of static conditions.

The overall shape of the deceleration profile in both dynamic and static condition is similar as shown in Figure1. Based on the similarity between deceleration profiles, we split the deceleration profile into four braking sections: coasting, initial, adjustment, and termination section. Also, we defined four start points in the braking sections as shown in Figure1. Depending on these braking sections, we designed a deceleration planning algorithm and analysed drivers' characteristics in each braking section and point.

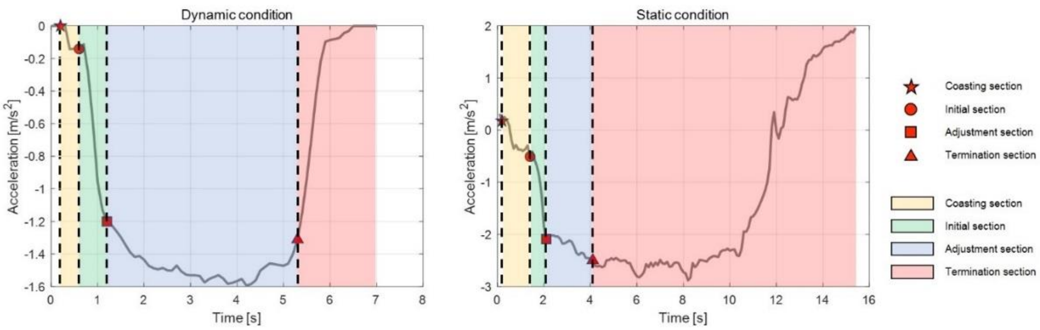

Figure1: Braking profiles in the dynamic and static condition

2.1.2 Definition of each braking section

Based on the driver's behavior in the deceleration condition, the braking profile can be divided into four sections. The first thing that drivers do is taking their foot off the accelerator pedal. This first section is defined as 'costing section'. In this section, the driver does not push both the accelerator pedal and brake pedal, so that deceleration of the vehicle is kept at a small value.

In the second section, a driver starts to push the brake pedal. This section is defined as 'initial section'. As the driver pushes the brake pedal more and more, the deceleration increases as shown in the green-colored part of Figure1. A remarkable feature in this section is that the deceleration becomes greater with a nearly constant slope.

Subsequently, what usually follows next, is that the driver keeps the degree of stepping on the brake pedal. In this section, the driver adjusts the degree of pushing the brake pedal to keep appropriate velocity and distance to dynamic or static object. We defined this section as 'adjustment section'.

In the final section, drivers step off the brake pedal gradually. As the degree of stepping the brake pedal decreases, the deceleration becomes smaller and finally reaches to a small value. This section is defined as 'termination section'.

2.2 Definition of model parameters

Several model parameters are defined which are used in the deceleration model. Some of them are constant regardless of the driving condition. Another model parameters change based on the driving condition such as the distance to the object and speed of the ego vehicle. The other model parameters depend on not only the driving condition but also drivers' characteristics, which are defined as learning parameters. The list of model parameters including the learning parameters is like the below.

Table1: List of model parameters

Parameters	
Initial acceleration slope	φ_i
Initial distance	d_i
Adjustment distance	d_a
Adjustment acceleration	a_a
Termination acceleration	a_t
Maximum acceleration	a_m
Reference acceleration	a_{ref}
Coast acceleration	a_c
Adjustment gain	K_a
Termination gain	K_t
Time step of the planning algorithm	T_s
Acceleration exponent	σ

2.3 Deceleration model

Under the operation of SRS, the acceleration depends on the driver, but the deceleration is automatically decided by SRS. Therefore, the deceleration generated by SRS should be harmonized with the acceleration generated by the driver's accelerator pedal input. To make the drivers feel like they're driving, the deceleration planning algorithm is designed based on the four braking sections. As a result, the deceleration generated by it is like the deceleration profile measured in the vehicle experiment.

To be harmonized with the driver's acceleration, the deceleration model was designed as a parametric model which is modified depending on the braking sections. The basic form of the parametric model is an intelligent driver model which is suggested by M. Treiber in 2000 (1)[3]. In this equation, there are two key factors influencing the acceleration: effective distance and reference velocity. The deceleration planning algorithm generates appropriate deceleration by modifying the reference velocity and effective distance according to the braking section and driving condition.

$$a = a_m \left(1 - \left(\frac{v}{v_{ref}}\right)^{\delta} - \left(\frac{d_{eff}}{d_{rel}}\right)^{2}\right) \tag{1}$$

The description of deceleration model consists of two parts. One part is descriptions of the condition for transitions between the braking sections, such as from the coasting section to the initial section. The other part is descriptions of modification of two key factors in the equation depending on the braking section. The results of the proposed algorithm are shown in Figure3

2.3.1 Coasting section

If a driver gets off the accelerator pedal, the deceleration model starts to generate a deceleration profile and the braking section in this time is in the coasting section. As mentioned in 2.1.1, the deceleration in the coasting section is kept at a nearly constant value. Therefore, the deceleration model in the coasting section generates deceleration which is kept at a fixed value called ‘coasting acceleration’. Coasting acceleration is set as the mean value of deceleration in the coasting section based on the vehicle experiment data. To keep coasting acceleration, deceleration model modifies the reference velocity and effective distance as shown in equation (2). With the modified equation, the deceleration is kept at the coasting acceleration.

$$v_{ref}(k) = 1/\left(1 - \frac{a_c}{a_m}\right)^{\frac{1}{\delta}} , \; d_{eff} = 0 \tag{2}$$

2.3.2 Initial section

In both dynamic and static condition, a driver starts to push the brake pedal as the distance to the object becomes smaller. The distance, in the coasting point and initial point, in the experimental data has a correlation so that the deceleration model can decide the start point of the initial section based on the initial distance calculated by the coast distance. The algorithm of calculating learning parameters, such as the initial distance, will be explained in 3.2.

According to the deceleration profile analysis, the deceleration in the initial section has a nearly constant value of the slope. Therefore, the deceleration model applies different reference velocity and effective distance as shown in equation (3) to keep the constant slope.

$$v_{ref}(k) = \hat{v}(k-1)/\mathit{\Gamma} v_i(k) , \; d_{eff} = 0 \tag{3}$$

$$\mathit{\Gamma} v_i(k) = \left(\left(\Gamma v_i(k-1)\right)^{\sigma} - \frac{\varphi_i T_s}{a_m}\right)^{\frac{1}{\sigma}} \tag{4}$$

2.3.3 Adjustment section

Even if the vehicle decelerates with the initial acceleration slope, the distance to the object becomes smaller. When the distance reaches a specific value, drivers start to keep the degree of stepping the brake pedal. The distance to object in this point is adjustment distance which is different by deceleration condition and drivers’ characteristics. The deceleration model calculates it based on the initial distance. If the distance to the object becomes smaller than the initial distance, the braking section changes to the adjustment section.

Based on the analysis of the braking profile, we found that the acceleration in the adjustment section tends to get closer to the reference acceleration. The reference acceleration is calculated by equation (5), which is a so-called constant acceleration (CA) model. Therefore, the deceleration model in the adjustment section was designed to conduct a role of I controller to follow the reference acceleration. The modified equation of reference velocity and effective distance is equation (6)

$$a_{ref}(k) = \frac{v_{pre}^2(k-1) - \hat{v}(k-1)}{d_{rel}(k-1)} \tag{5}$$

$$v_{ref}(k) = \frac{\hat{v}(k-1)}{\left|\frac{a_a}{a_m}\right|^{\frac{1}{\delta}}}, \; d_{eff}(k) = \hat{d}_{rel}(k-1)\sqrt{1 + \int K_a \frac{\hat{a}(k-1) - a_{ref}(k)}{a_m} dt} \tag{6}$$

2.3.4 Termination section

As the acceleration gets closer to the reference acceleration in the adjustment section, the acceleration becomes larger than the reference acceleration. Then, the braking section moves from the adjustment section to the termination section.

In the termination section, the deceleration generated by drivers' brake pedal input has similar value with the reference acceleration as described above. Therefore, the deceleration model in the termination section leads the acceleration to follow the reference acceleration. The modified equation of reference velocity and effective distance is comparable to equation (7). It is similar to the adjustment section but equation (7) has a bigger I-control gain.

$$v_{ref}(k) = \frac{\hat{v}(k-1)}{\left|\frac{a_t}{a_m}\right|^{\frac{1}{\delta}}},\ d_{eff}(k) = \hat{d}_{rel}(k-1)\sqrt{1 + \int K_t \frac{\hat{a}(k-1) - a_{ref}(k)}{a_m} dt} \tag{7}$$

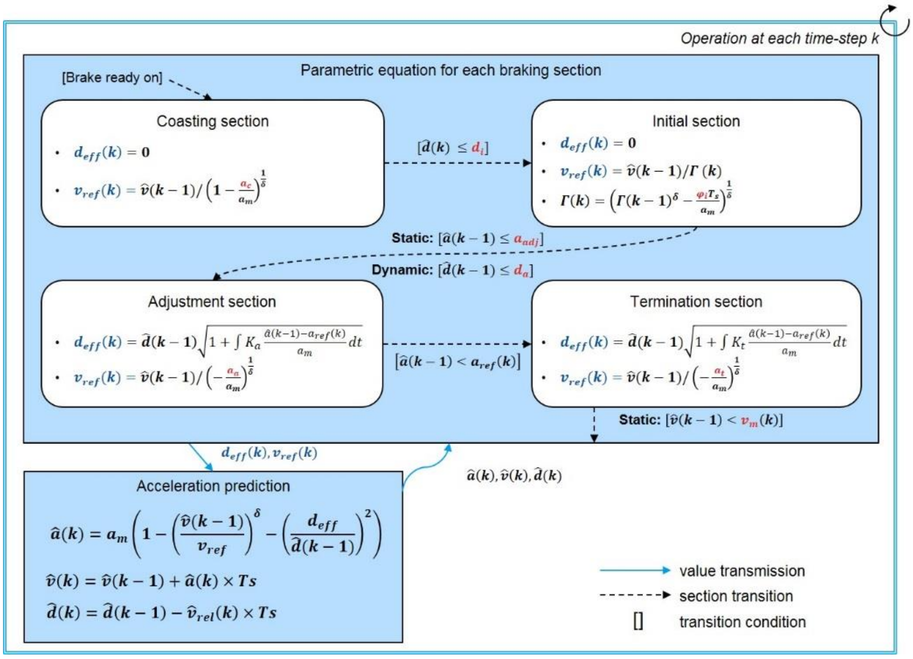

Figure2: The overall process of the deceleration planning algorithm

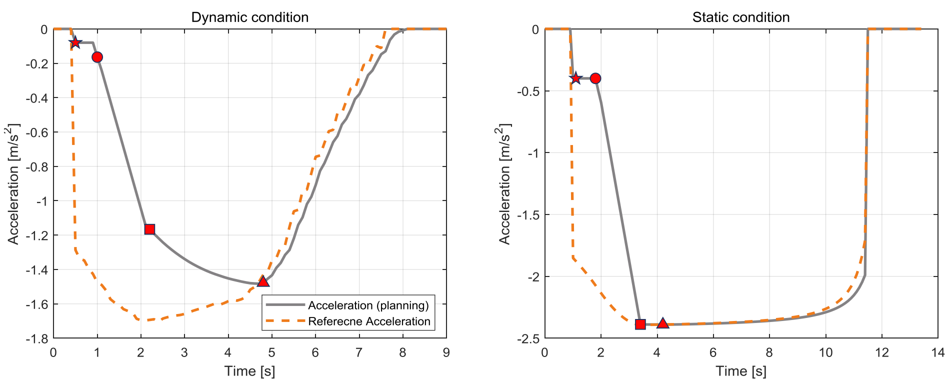

Figure3: Deceleration profiles generated by the planning algorithm

3 Online learning algorithm

3.1 Analysis of drivers' characteristics

As mentioned in 2.2, some of the model parameters are determined by not only the driving condition such as the distance to the object and velocity but also drivers' characteristics. These model parameters are defined as learning parameters. The set of learning parameters is different according to the deceleration conditions. The list of learning parameters and correlated index which influence the value of learning parameters in each deceleration condition is shown in Table 2.

Table2: List of learning parameters

Deceleration condition	Parameters		Correlated index
Dynamic condition	Initial acceleration slope	φ_i	Initial index
	Initial distance	$d_{rel,i}$	Coasting distance
	Adjustment distance	$d_{rel,a}$	Initial distance
Static condition	Initial acceleration slope	φ_i	Initial index
	Maximum acceleration	a_m	Coast index
	Adjustment acceleration	a_{adj}	Initial index

Figure4 and 5 show the correlation between the learning parameters and the index values in each dynamic and static condition. As shown in both figures, the value of learning parameters changes depending on the index values and the driver. Three drivers have similar deceleration style individually in both the dynamic and static conditions. For example, the driver3 has moderate deceleration pattern generally. In the Figure4, the value of the initial acceleration slope of driver3 is smaller than the other drivers, which means he usually pushes the brake pedal gradually. In the Fugure5, the driver3 has smaller maximum acceleration than the other drivers. In conclusion, the driver3 decelerates moderately in both the dynamic and static conditions.

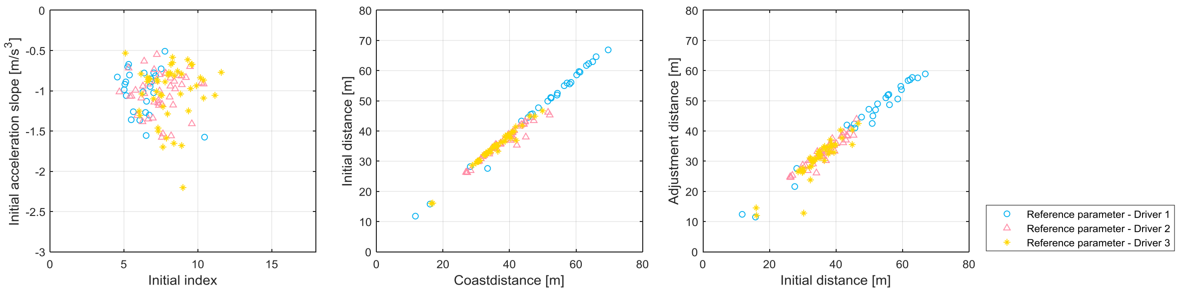

Figure4: Correlation of learning parameters depending on drivers in the dynamic condition

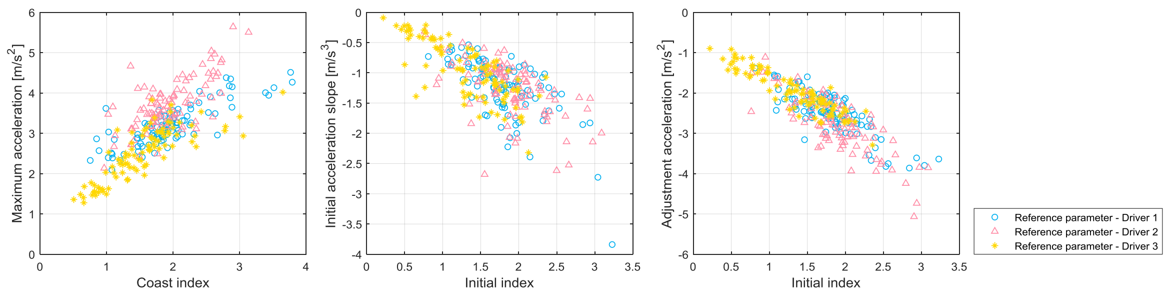

Figure5: Correlation of learning parameters depending on drivers in the static condition

3.2 Algorithm of calculating learning parameters in deceleration model

The overall process of the learning algorithm is described in Figure6. It consists of four small processes: parameter activation, measurement profile calculation, reference parameter calculation, and parameter vector update. In the four processes, parameter activation calculates learning parameters. The detail of the calculating process will be described in the next paragraph.

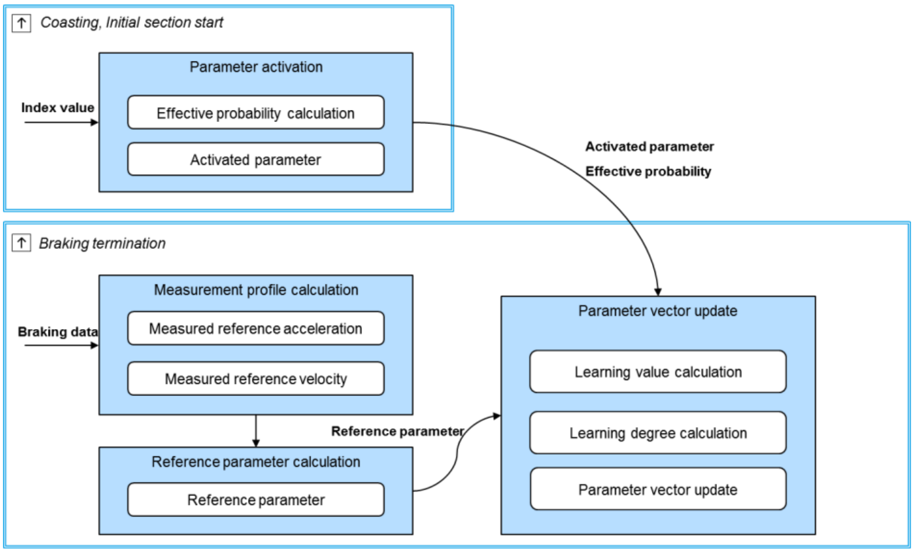

Figure6: The overall process of the online learning algorithm

Learning parameters are calculated by the dot product of two vectors: effective probability vector and learning vector. Whenever the coating section or the initial section starts, the index value such as the initial index is determined using vehicle driving data. Then, the Gaussian distribution is determined whose mean value is the index value. Based on the basic index vector, the Gaussian distribution is converted to the effective probability vector by normalization. Figure7 shows an example of this process when the index value is 7.5.

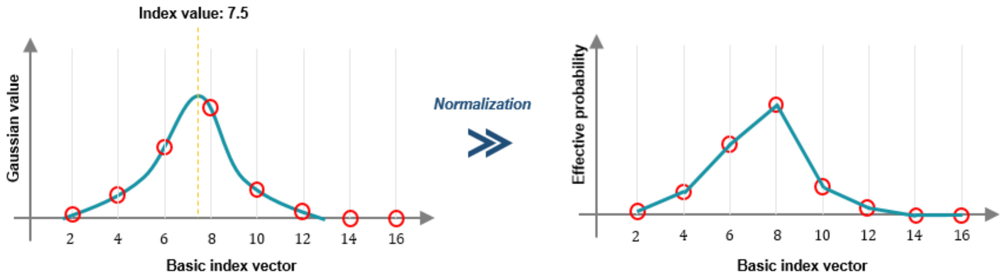

Figure7: The process of calculating the effective probability vector

After calculating the effective probability vector, the learning parameters are calculated by the inner product of the effective probability vector and the learning vector. Learning vector is a vector, which consists of learning parameter values appropriate to each index value in the basic index vector. This learning vector is updated whenever the deceleration profile ends.

3.3 Online learning algorithm to reflect a driver's characteristics

If the parameter activation and the reference parameter calculation is completed in Figure6, the value of the reference parameter reflects the driver's characteristics because it is directly extracted from the driver's driving data. However, the value of the learning parameter does not reflect the driver's characteristics because it is calculated by the learning vector which is not updated based on the driver's characteristics. Therefore, the learning parameter is different from the reference parameter. Using this difference and learning degree, the learning vector is updated to reflect the driver's characteristics. The learning degree is calculated based on the effective probability. The higher the value of the effective probability vector, the higher the learning degree is and the more the learning vector is updated.

4 Validation

The deceleration planning algorithm proposed in this paper was validated by software-in-the-loop simulation (SILs) using Simulink. For validation, vehicle experimental data is used as the input of the deceleration planning algorithm. Vehicle configuration used in the vehicle experiment and the experiment site will be described in the next part.

4.1 Condition for data acquisition

4.1.1 Vehicle configuration

For the experiment, KONA Electric of Hyundai was used. It has a radar sensor which can estimate the distance to the dynamic object in front of the ego vehicle and relative velocity. The detail information about it is described in Table3. The distance to the object and relative velocity is used in the deceleration planning algorithm for the dynamic condition. In addition, the vehicle is equipped with RTK-GPS. In the algorithm for the static object, the estimation of the ego vehicle position is essential. In the experiment, the location of the ego vehicle is highly accurately estimated by RTK-GPS.

Table3: Specifications of the radar sensor and RTK-GPS

Sensor	Specifications
Radar	Maximum range: 150m FOV +/- degrees over 60m, +/- degrees under 60m Update rate: 50ms
RTK-GPS	Accuracy (RMSE): 2cm Update rate: 20ms

4.1.2 Vehicle experiment site

The experiment was conducted in Yeongjongdo, Incheon in Korea. The experiment site for each dynamic condition and static condition is represented in Figure8. The experiment in the dynamic condition was conducted in the site where the road is nearly straight, and the slope is almost zero. Three test drivers drove the ego vehicle to acquire the data for the analysis of drivers' characteristics. Also, to make the driving condition for the dynamic condition, the other test driver drove the preceding vehicle. For the static condition, three test drivers drove the vehicle and stopped in front of every traffic lights.

Figure8: Vehicle experiment sites

4.2 Simulation results

The experimental data in each condition is used for the validation of the deceleration planning algorithm. The deceleration profile generated by the algorithm is compared with the measured deceleration in the experiment. In both the dynamic condition and the static condition, not only. The generated braking profile such as acceleration, velocity and distance to the object is compared with the measured data

As shown in Figure9 and Figure10, the deceleration profile generated by the algorithm is harmonized with the driver's accelerator pedal input. When the driver steps on the accelerator pedal, the algorithm dost not generate any deceleration. Then, if the driver steps off the accelerator pedal, the deceleration profile is generated based on the driving situation. The generated braking profile such as acceleration, velocity, and relative distance is very similar to the measured data in both the dynamic and static conditions. In the case of static condition, the distance to the traffic light reaches zero by the deceleration of the algorithm, which means that the vehicle stops at the exact position.

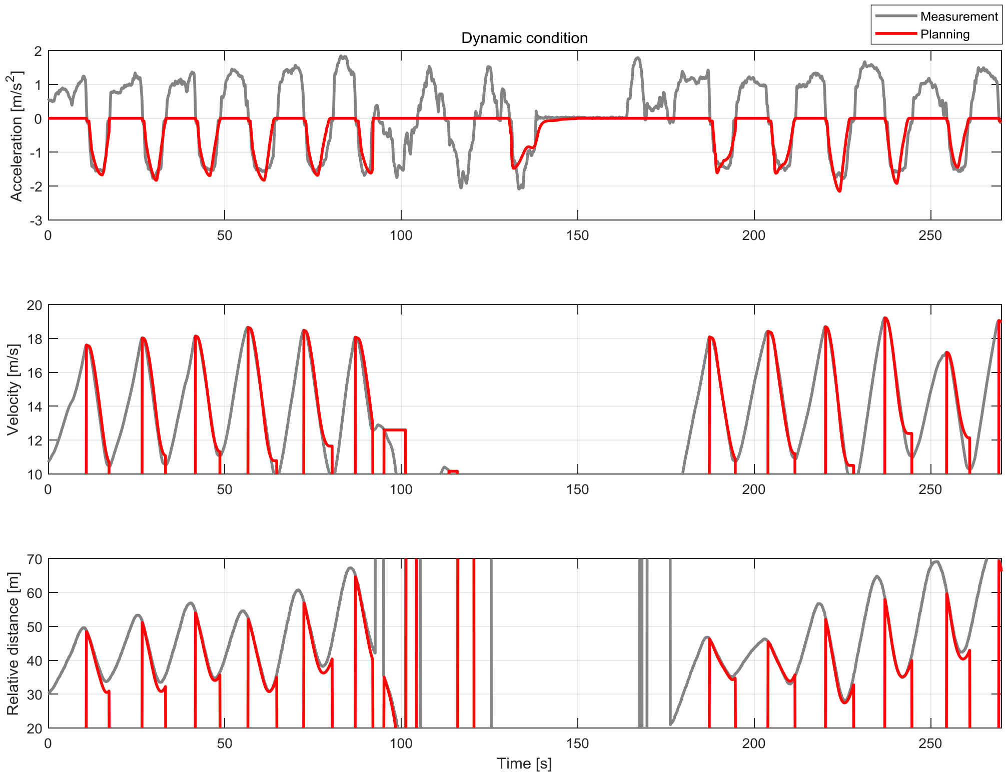

Figure9: Planning results in dynamic condition

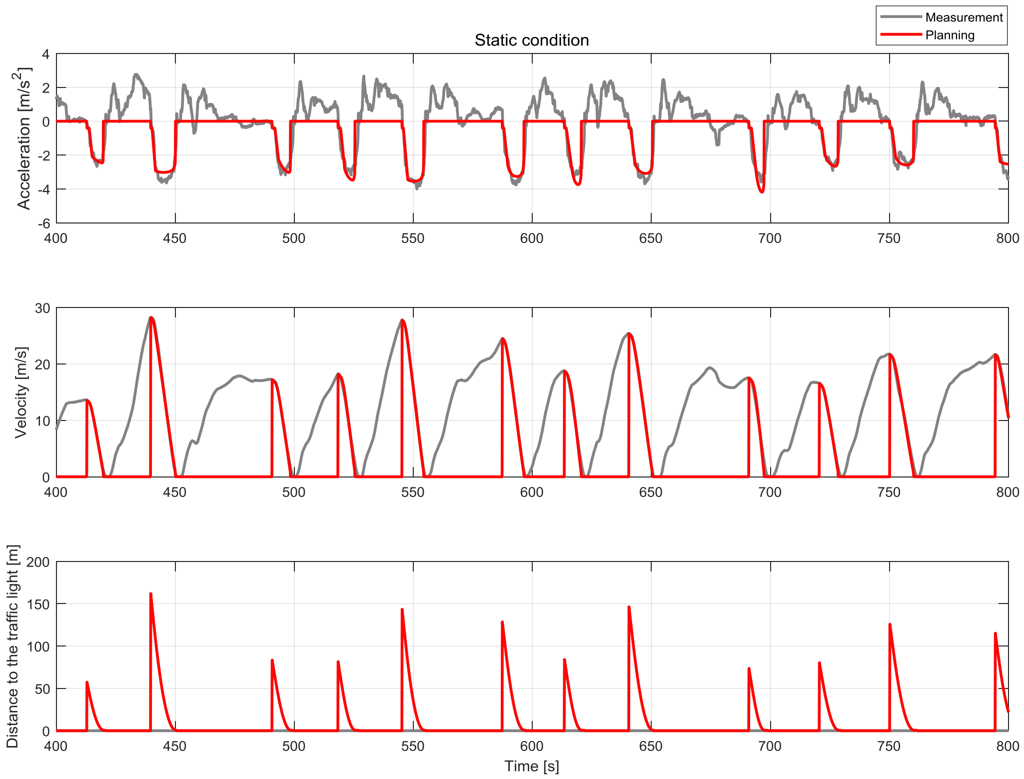

Figure10: Planning results in the static condition

The comparison of the generated braking profile and measured braking profile was conducted using the driving data of one driver. However, the validation of an online learning algorithm is conducted based on the results of three different drivers to check if the algorithm updates the learning vector appropriately. Figure11 shows the result of the updated learning vector for the initial acceleration slope in the dynamic condition. As shown in Fig11, the driver3 tends to have a smaller value of initial acceleration slope in the same situation than the other drivers. As a result, the updated learning vector of the initial acceleration slope of driver3 has a small absolute value generally. The result of online learning algorithm in the static condition is shown in Figure 12. As shown in Figure 12, the driver2 usually drive with a larger maximum acceleration than the other driver. Therefore, the updated learning vector of the maximum acceleration of driver3 has large value.

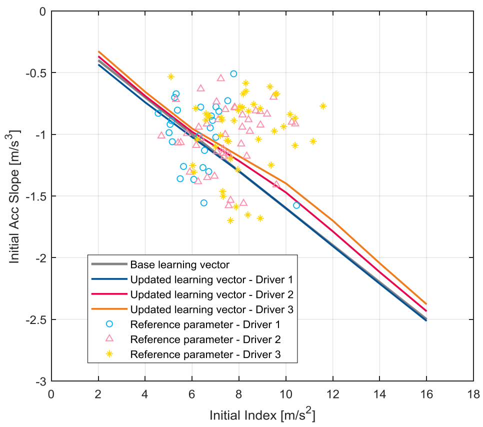

Figure11: Learning results of initial acceleration slope in the dynamic condition

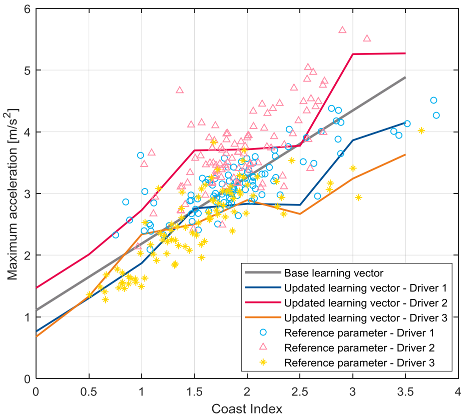

Figure12: Learning result of acceleration slope in the static condition

5 Conclusion and future works

In this paper, the deceleration planning algorithm and the online learning algorithm was proposed. Based on the analysis of the braking profile, the deceleration profile is split into the four braking sections. The deceleration planning algorithm generates a deceleration profile by modifying the reference velocity and the effective distance depending on the braking sections. It has learning parameters which can reflect a driver's characteristics. These parameters are updated through the online learning algorithm. The online learning algorithm updates the learning vectors based on the effective probability and learning degree. The deceleration planning algorithm and the online learning algorithm was validated in the SILs. The results of SILs show that the generated deceleration profile is comparable to the data measured in the experiment.

The proposed algorithm generates a reference deceleration profile for SRS. The proposed algorithm will be improved to be applied in more static conditions. The next step to implement SRS in the vehicle is controlling regenerative braking torque. Research of a robust controller to control the regenerative braking torque in diverse driving conditions will be conducted. Thereafter, SRS will be implemented in the vehicle by integrating the deceleration planning algorithm and torque controller.

Acknowledgments

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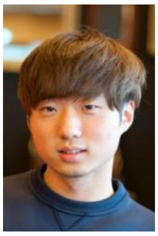

Gyubin Sim received a B.S. in Automotive Engineering from Hanyang University in 2018, and he is currently pursuing a master's degree in the Department of Automotive Electronic Control at the same university. He has researched the state estimation of the engine and powertrain control of electric vehicles as a member of Automotive Control and Electronics Laboratory. His current research activities include prediction of vehicle states, regenerative braking control and analysis of drivers' characteristics.

Kyunghan Min received a B.S. in Mechanical Engineering in 2011, and Ph.D. degree in Automotive Engineering in 2017 from Hanyang University, Seoul, Korea. His main fields of research are algorithm design of powertrain management system, real-time embedded system for control algorithm. His current research activities include prediction of vehicle states, regenerative braking control for electric vehicles based on driver characteristics.

Inseok Park received the B.S. degree of Electronics and Computer engineering from Hanyang University in 2005. M.S. and Ph. D. degree of Automotive Engineering from Hanyang University, Seoul, Korea, in 2007 and 2013, respectively. Currently, he is working on a department of eco-vehicle control development of Hyundai Motor Group R&D Center, Korea. His research activities include automotive software engineering and model-based software design. He has also done some work on nonlinear, robust and MIMO controller design for automotive powertrain systems such as spark ignition and turbocharged diesel engines. Currently, he is working on motion control and regenerative coasting strategies of electric vehicles.

Jeamyoung Yeon received the B.S. degree of Mechanical engineering from Hanyang University in 2002. M.S. and Ph. D. degree of Automotive Engineering from Hanyang University, Seoul, Korea, in 2004 and 2008, respectively. Currently, he is working on a department of eco-vehicle control development of Hyundai Motor Group R&D Center, Korea. His research activities include automotive software engineering and model-based software design. He has also done some work on holistic optimization strategy for ECU integration. Currently, he is working on a control system architecture for electric vehicles and many others.

Myoungho Sunwoo received a B.S. in Electrical Engineering from Hanyang University in 1979, and M.S. in Electrical Engineering from the University of Texas at Austin in 1983, and a Ph.D. in System Engineering from Oakland University in 1990. He joined General Motors Research (GMR) Laboratories, Warren, MI, in 1985 and has worked in the area of automotive electronics and control for 30 years. During his nine-year tenure at GMR, he worked on the design and development of various electronic control systems for powertrains and chassis. Since 1993, he has led research activities as a Professor with the Department of Automotive Engineering at Hanyang University. His work has focused on automotive electronics and controls (such as modeling and control of internal combustion engines, design of automotive distributed real-time control systems, intelligent autonomous vehicles, and automotive education programs).