Satisfactory Driving Mode Classification based on Pedal Operation Characteristics

Yuntae Kim, Seibum B. Choi, *Member, IEEE*, Jiwon J. Oh and Jeongsoo Eo

***Abstract*—Since the vehicle's response according to the driver's gas pedal operation varies greatly depending on the driving mode, the selection of the driving mode significantly affects the driver's satisfaction. This paper presents a satisfactory driving mode classification that enhances the driver's satisfaction by providing a suitable driving mode to the driver. Unlike the conventional algorithm based on driving style recognition, the proposed approach determines the changes required for the current driving mode, such as mode-up, -stay, and -down. Features suitable for classification are extracted from the driver's pedal operation characteristics during specific situations, such as launch and acceleration while driving. The performance of the proposed algorithm is evaluated through nested cross-validation and compared with conventional algorithms based on driving style recognition, demonstrating its superiority and generality. The proposed algorithm is event-based and operates in real-time while driving. As a result, it provides a more reliable and effective solution for enhancing driver satisfaction by providing an appropriate driving mode.**

***Index Terms*—Classification, driving behavior, driving mode, driving style**

I. Introduction

INTELLIGENT vehicles (IVs) have emerged as a promising and attractive area of research within the automotive domain [1]. Within this domain, research topics that focus on human drivers, such as personalization, human-machine interaction, and human-like systems, have garnered considerable attention due to their potential to enhance driver satisfaction and overall driving experience [2]–[4]. In particular, in the case of personalization, driving satisfaction can be significantly enhanced by reflecting the individual driver's driving characteristics to the system. Consequently, efforts are being made to apply personalization to driving assistance systems, including safe driving systems, driver monitoring systems, and in-vehicle information systems [5], [6].

This paper addresses the topic of personalization for driving mode. Production vehicles offer different driving modes such as eco, comfort, and sport, each with a distinct response to the gas pedal operation. For instance, sport mode generates greater driving torque and faster response compared to other modes when the same pedal is applied. Since each driving mode has different characteristics, the satisfactory driving mode is different for each driver. Here, the satisfactory driving mode is the most comfortable and preferred mode for drivers to control the vehicle with the gas pedal. If a satisfactory driving mode is not provided to the driver, the driver feels that the vehicle shows an excessive or insufficient response and is dissatisfied with the vehicle. Therefore, it is crucial to provide a suitable driving mode to the driver because it can improve the driver's satisfaction. However, current production vehicles rely on direct driver selection of the mode, which is less frequently utilized due to drivers' unfamiliarity with each mode and the inconvenience of switching modes. Consequently, there is a need for an algorithm that can analyze driver behavior based on driving data and provide a satisfactory driving mode.

To the authors' knowledge, studies on providing a satisfactory driving mode have yet to be conducted. The most straightforward and intuitive approach is to utilize driving style recognition to determine the driver's driving style and select a suitable driving mode accordingly. For instance, sport mode may be suggested for aggressive drivers, while eco mode may be recommended for mild drivers. Since driving style recognition can be applied to various fields within IVs, its importance is growing [7], [8]. Driving style recognition can be categorized into three types: rule-based, supervised learning, and unsupervised learning. In rule-based methods, the driving style is recognized based on thresholds for statistics of driving data [9] or through a fuzzy inference system [10], [11]. However, these methods are limited in their application and require substantial effort in parameter tuning. In supervised learning approaches, collected data is labeled with driving style categories, such as aggressive, moderate, and mild, based on surveys or expert evaluations [12], [13]. A machine learning-based classifier is trained using this labeled data and features representing driving style. These features include descriptive statistics for velocity, acceleration, jerk, and relative distance and coefficients for Fourier and wavelet transforms [14]–[16]. Other features that can be considered are the driver's dynamic demand based on the vehicle model [17] and the vector encoding of multivariate time series [18]. Machine learning-based classifiers like support vector machine (SVM) [19], Gaussian hidden Markov process [20], random forest (RF) [21], and k-nearest neighbor (kNN) [22] are employed for classification.

In unsupervised learning methods, data is labeled based on clustering results using algorithms such as hierarchical clustering analysis (HCA) [23], Gaussian mixture model (GMM) [24], and k-means. The driving style is then recognized using Euclidean distance or a learned classifier [25], [26]. However, since driving style recognition based on clustering is highly influenced by the distribution of driving style among participants and the distribution of drivers' driving styles is close

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to a continuous normal distribution, clustering-based methods may not be a clear solution.

Previous studies face limitations in two aspects: 1) labeling for driving style and 2) feature extraction. Firstly, these studies classify data into abstract categories such as aggressive or mild based on participant surveys or expert evaluations. However, since each individual has a different classification criterion for driving style and comparing own driving style with other drivers is impossible, it is impossible to determine which driver belongs to which of the discrete categories. Therefore, this labeling method lacks objectivity. For example, even if a driver claims to be aggressive, it cannot be sure that their driving style is aggressive compared to other drivers. If there is a significant difference in the criteria for driving style, even this aggressive claimed driver's style may be closer to mild. Thus, this labeling method provides an estimated value rather than an actual value. Therefore, a new approach is needed to provide a satisfactory driving mode.

Secondly, most studies extract features for the entire driving scenarios [27]. However, driving data contains redundant information, and many situations do not exhibit driving style, such as maintaining a constant speed. Therefore, the methods were proposed to categorize driving events into situations like stop, acceleration, deceleration, and maintenance and extract features for each situation [28], [29]. Although most studies use descriptive statistics of velocity and acceleration as features, which also apply to research on driving condition recognition [30]–[32], these features are strongly influenced by driving conditions such as congested, urban, and highway scenarios. Consequently, these features primarily reflect the characteristics of the driving scenario rather than the driving characteristics of the driver [33]. Utilizing these features results in learning specific scenarios and does not guarantee performance in unseen driving scenarios. Hence, extracting features that reflect the driver's driving characteristics is necessary for classification.

In addition, to change the driving mode based on the driving style recognition, additional study is needed to determine the relationship between the classified driving style and driving mode. As the characteristics of the driving mode differ among vehicle types in production vehicles, the method of changing the driving mode based on driving style has low applicability.

This paper proposes a classification algorithm for determining a satisfactory driving mode based on the driver's gas pedal operation characteristics. The main contributions of this paper are threefold.

1) Suggesting a novel approach for providing a satisfactory driving mode.
2) Obtaining simple and practical features based on analyzing the driver's pedal operation characteristics.
3) Developing a more robust and accurate satisfactory driving mode classification algorithm than a conventional algorithm based on driving style recognition.

The above contributions are described in more detail as follows. Firstly, as shown in Fig. 1, a new approach is proposed to provide a satisfactory driving mode directly to the driver instead of providing a driving mode based on driving style recognition. The proposed algorithm classifies the required changes for the current driving mode, such as mode-up, -stay, and -down. To achieve this, participants in the experiment complete a survey after experiencing all driving modes, and the driving data is labeled based on the most satisfactory driving mode. Labeling driving style is considered an estimation because it is determined by an individual's subjective criterion for abstract categories. In contrast, the proposed approach provides an actual value based on the experience of existing driving modes. This change in approach transforms the problem of assessing the driving style of group members into the problem of judging individual satisfaction and dissatisfaction.

Secondly, features suitable for this new approach are extracted to reflect driving characteristics. Different driving behaviors are identified by specifying situations, and the driving characteristics of the driver who controls the longitudinal behavior of the vehicle using the gas pedal are analyzed. The proposed features are validated to be suitable for the proposed approach based on the results of the boxplot analysis. Finally, a classification algorithm is developed using supervised learning-based classifiers and evaluated using nested cross-validation. The performance of the proposed algorithm is analyzed by comparing it with a conventional algorithm based on driving style recognition. Unlike the conventional algorithm, the proposed algorithm exhibits high classification accuracy even for unseen driving scenarios.

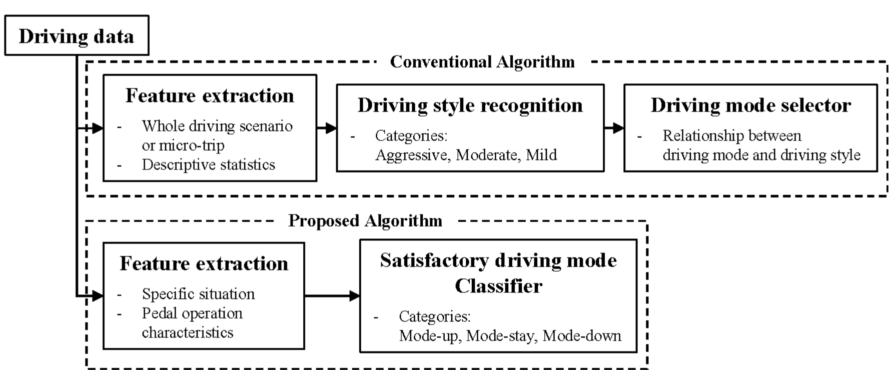


Fig. 1. Comparison between conventional algorithm and proposed algorithm

Fig. 2. Driving circuit

The remainder of this paper is organized as follows. Section 2 describes the experimental configuration and data labeling to determine the satisfactory driving mode. Section 3 presents an analysis of the driving data and feature extraction methods reflecting driving characteristics. Section 4 proposes a satisfactory driving mode classification algorithm for driver satisfaction and analyzes the classification results. Finally, Section 5 presents the conclusion of the paper.

II. Experimental Setup and Data Labeling

In this section, we introduce the experimental setup to acquire the data used in this paper and a novel approach to improve the limitations of existing driving style recognition-based methods.

The data used in this paper was obtained through the Controller Area Network (CAN) of the Kia Soul EV. The data include measurements for in-vehicle sensors such as longitudinal velocity, acceleration, pedal rate, and base torque. Base torque refers to the torque accessible from the Motor Control Unit (MCU) and is obtained through a map between the gas pedal and traction torque. Each measured value is sampled at 100 Hz.

The driving experiment was conducted at the Hyundai Namyang Research Center in Korea on a driving circuit that depicts city driving. The circuit is divided into five routes, as shown in Fig. 2, with a total mileage of 2.3 km. The driving scenario consisted of a launch-driving-stop process for each route. The maximum length of the route is 860m, and the minimum length is 282m. Data from all routes, except for Route 0, aimed at adapting to the driving mode, are analyzed. As shown in Table I, participants experienced all driving modes, including eco, comfort, and sport. The rate limit for the base torque and the torque gain, which is a coefficient between the gas pedal and traction torque, are changed depending on the mode. As the torque gain increases, the traction torque increases for the same pedal input. As the rate limit increases, the response of traction torque becomes faster for the same change in base torque. Even if the driver performs the same pedal operation, the longitudinal behavior of the vehicle is entirely different depending on the driving mode. A total of seven drivers participated in the experiment, and the experiment was conducted after one preliminary run.

After the experiment, the drivers were asked to complete a questionnaire about their most satisfied driving mode. Based on the questionnaire results, the data for each driving mode is labeled as mode-up, mode-stay, or mode-down. For instance, if a driver answered that he/she was most satisfied with the comfort mode, the corresponding driver's comfort mode data is labeled as mode-stay. Data for the eco mode is labeled as mode-up, while data for the sport mode is labeled as mode-down.

TABLE I
Experiment Configuration

Test number	1	2	3	4	5	6	7	8	9
Driving mode	E	C	S	E	C	S	E	C	S

(*) E : Eco, C: Comfort, S: Sport

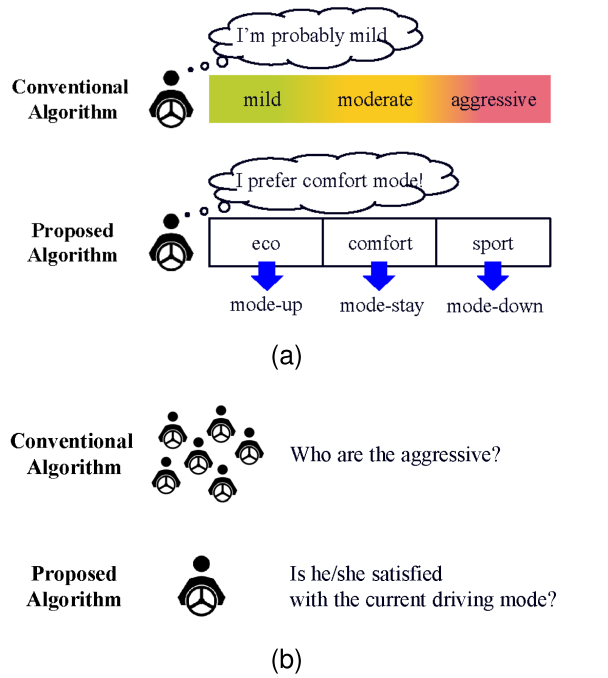


Fig. 3. (a) Comparison between conventional algorithm and proposed algorithm in terms of labeling (b) Comparison between conventional algorithm and proposed algorithm in terms of the problem to solve

This novel approach differs from providing a satisfactory driving mode based on the existing driving style recognition, as shown in Fig. 3. The existing approach for labeling driving styles as mild, moderate, and aggressive is based on a survey of drivers or expert evaluation. In this method, drivers are asked to categorize their driving style, or experts determine it based on their criteria. However, this method lacks objectivity since each individual has different criteria for driving style. Even if a driver claims their driving style to be mild or an expert determines that a driver is mild, it is uncertain whether the driver truly belongs to the mild category. The exclusion of comparisons with other drivers further reduces the objectivity of the existing approach. The proposed system, in contrast, does not have these limitations because the driver decides their preferred mode based on their experience with all driving modes. As a result, whereas the labeling of driving styles only provides an approximated value, the proposed method provides an actual value.

The novel approach changes the problem to be solved. The existing driving style recognition-based method aims to determine the driving style category to which a driver belongs. Therefore, it is crucial to extract features that express differences in driving style among drivers. However, as mentioned earlier, the labeling of the driving style is unclear, and the extracted features do not show a clear separation by category. Consequently, conventional algorithms rely on classifier learning. Due to the excessive learning for experimental scenarios, they have low generality and applicability. In contrast, the proposed algorithm determines whether the driver is satisfied or dissatisfied with the current driving mode and identifies which mode change is required. Therefore, extracting features that express individual satisfaction and dissatisfaction is essential. The conventional algorithm requires additional research on the correlation between the classified driving style and driving mode. Even if a driver's driving style is classified as aggressive, it is not sure that the driver will be satisfied with the sport mode. Additionally, since the characteristics of the driving mode vary for each vehicle type, the conventional algorithm has low applicability to production vehicles. In contrast, the proposed algorithm directly contributes to providing a satisfactory driving mode without additional work because it determines the satisfaction of the current driving mode.

III. Analysis of Driving Data and Feature Extraction

This section explains the analysis of the collected data and the extracted features. First, we specify the situations that require analysis since not all moments of driving data are meaningful. After that, we analyze the driving characteristics of drivers in these situations and extract features based on this analysis. We confirm that the features based on the pedal operation characteristics show significant differences for each category.

A. Determining the situation for data analysis

Previous studies have focused on extracting features for the entire driving scenario or micro-trip between two starting points and training the classifier. However, there are many situations where driving characteristics are not revealed, such as when speed is maintained in the driving data. These situations disturb extracting features for accurate classification. Furthermore, algorithms that rely on long-driving data may not be suitable for the target algorithms, which require real-time mode changes. Thus, we must specify the situations in which driving characteristics are revealed and develop an event-based classification algorithm through data analysis.

Satisfaction with the current driving mode and driving style is closely related. Therefore, it is essential to analyze data demonstrating driving style differences among drivers. The difference index is defined as follows.

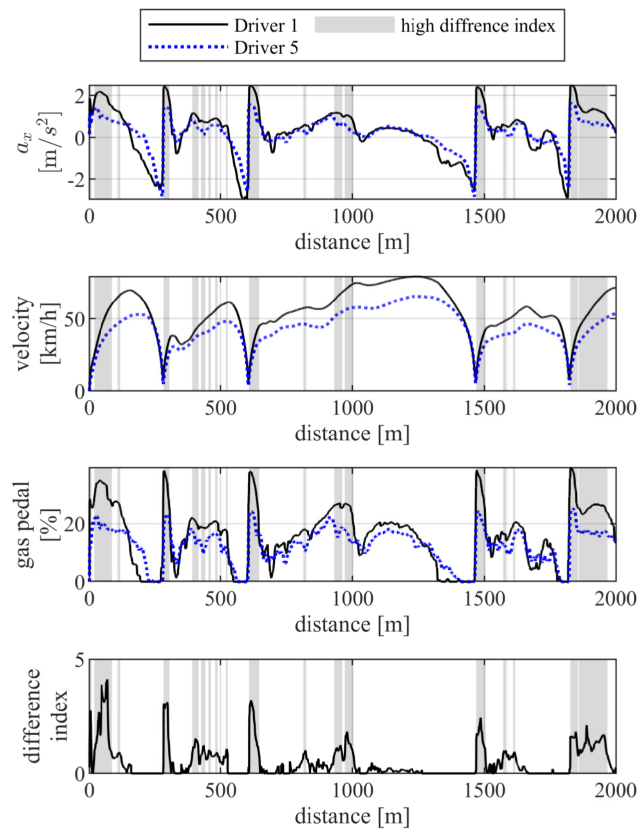


Fig. 4. Difference index for Driver 1 and Driver 5

$$X_{diff,ij}(d_k) = \frac{|\text{mean}(X_i(d_k)) - \text{mean}(X_j(d_k))|}{\text{std}(X_i(d_k)) + \text{std}(X_j(d_k))} \quad (1)$$

$X_i\,(d_k)$ represents the measured value at distance $k\,(d_k)$ of the (i)-th driver. These measurements include longitudinal velocity (v), longitudinal acceleration (a), and pedal rate (θ_p). Since each driver spends a different amount of time driving the circuit, a difference index is defined for the distance domain to enable comparison between drivers. This index demonstrates how different the driving of two drivers is using the mean and standard deviation of the measured values. A comparison of the difference index for all driver combinations revealed that longitudinal velocity has the highest value on average, followed by longitudinal acceleration and pedal rate in that order. Since velocity is an integral value of acceleration, when the difference between the two drivers in acceleration is accumulated, the difference in velocity is naturally high. Also, since velocity is more greatly affected by the driving condition than the driver's driving characteristics, it is inappropriate to use it to determine the satisfactory driving mode. Hence, data analysis for acceleration is required. The acceleration situation, such as launch and acceleration while driving, is where the difference index for acceleration is high, as shown in Fig. 4. Drivers generally judge satisfaction with a vehicle when their control is significantly involved, such as in an acceleration situation in which a pedal is operated.

Launch and acceleration while driving occur repeatably. The criterion for the launch is defined as follows.

$$
\begin{aligned}
X_l(t) &= \{X(t) \mid t_1 < t < t_2\} \\
t_1 &= \{t[k] \mid \theta_p[k] > 0 \;\;\&\;\; v[k] \simeq 0\} \\
t_2 &= \underset{t}{\operatorname{argmax}}(a(t)), t_1 < t < t_3 \\
t_3 &= \Big\{ t[k] \mid \dot{\theta}_p[k] < 0 \;\;\&\;\; \dot{\theta}_p[k+1] \geq 0 \\
&\qquad \& \;\; \frac{c_1 - \theta_p[k]}{c_1} > c_2 \Big\} \\
c_1 &= \max(\theta_p(t)) \\
c_3 &= \max(a(t)), t_1 < t < t_3
\end{aligned}
\tag{2}
$$

$X(t)$ means driving data for each route and c_2 indicate parameter that determine the situation. Launch refers to the time from when the vehicle starts to the point at which it reaches its maximum acceleration. The definition of t_3 includes conditions for excluding small perturbations. Next, the criterion for the acceleration while driving is defined as follows.

$$
\begin{aligned}
X_d(t) &= \{X(t) \mid \bar{a}(t) > c_4 \;\;\&\;\; \Delta t = t_e - t_s > c_5\} \\
\bar{a}(t) &= \frac{a(t)}{c_3}
\end{aligned}
\tag{3}
$$

t_s and t_e mean the start and end time of the acceleration while driving. This represents a situation where moderate acceleration has occurred for a sufficient time. Since each driver has a different scale for acceleration, normalized acceleration using the maximum acceleration at launch is utilized. The terms c_4 and c_5 indicate parameters that determine the situation and are set through tuning.

B. *Features for launch and acceleration while driving*

The driving characteristics are analyzed using boxplots to visualize data distribution. Boxplots consist of the data's median, first quartile, third quartile, maximum, minimum, and outliers. The interquartile range (IQR), which is the size of the box, is determined using the first and third quartiles. The maximum and minimum values are obtained based on the IQR and are drawn as whiskers. The box size will appear small if the data is distributed over a narrow range.

Fig. 5 shows a boxplot based on the maximum acceleration at launch. The x-axis represents each driver, and a boxplot is obtained. Since each boxplot has a different distribution, it indirectly shows that participants with various driving styles were recruited. In particular, Driver 5 and Driver 7 show significant differences in driving style. Fig. 6 shows the acceleration and pedal rate distribution for each driving mode for drivers 1, 3, and 5. As shown in Fig. 6, the acceleration distribution for each driver is not affected by the driving mode, but the distribution of the pedal rate changes significantly. The driver's pedal rate decreases when changing from eco mode to sport mode. These results suggest that the driver has the desired acceleration at launch and controls the pedal to reach the desired value. Moreover, since the pedal operation changes the most according to the change in the driving mode,

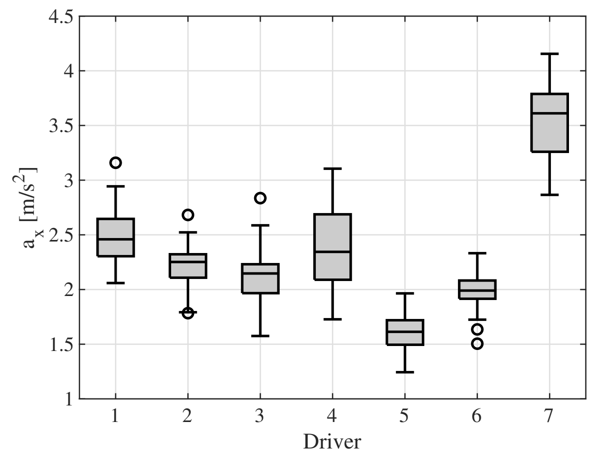


Fig. 5. Distribution of maximum acceleration for all drivers

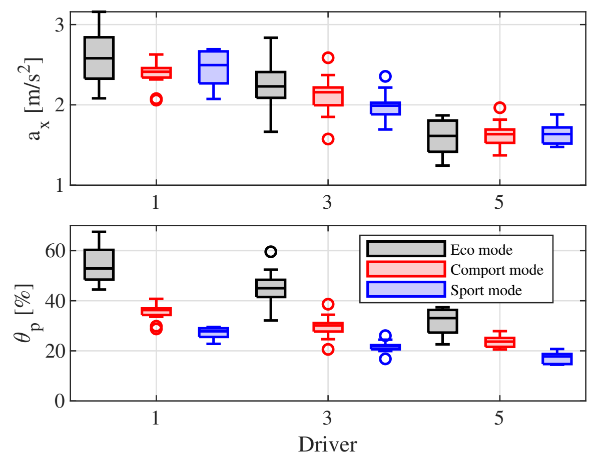


Fig. 6. Distribution of acceleration and pedal rate for drivers

it is necessary to analyze the pedal operation characteristics to determine the driver's satisfaction with the driving mode.

Since drivers have different desired accelerations, the normalized acceleration, $\bar{a}(t)$, utilized in Eq. 3, is introduced for comparison. $\bar{a}$ has a range of 0 to 1. Fig. 7 shows the pedal operation distribution of drivers to reach the desired acceleration for all drivers' launch data. Each color represents a different category, such as mode-up, -stay, and -down. The solid line represents the data median, similar to a boxplot, and the dotted line represents the first and third quartiles. Each colored patch contains 50% of the data for each category. As shown in Fig. 7, the distribution of each category is separated from the other. To further illustrate this point, Fig. 8 shows the boxplot of each category for the point where $\bar{a} = 0.8$. Similarly, the distribution of each category is disjoint.

As drivers have different driving styles and preferred driving modes, it can be challenging to determine individual satisfaction using the entire dataset. However, as demonstrated in Fig. 7, even when all drivers' data are included, the distribution of each category is disjoint. Thus, features extracted from the $\bar{a}$-θ_p domain can effectively contribute to providing a satisfactory driving mode. Based on the above observations, the features

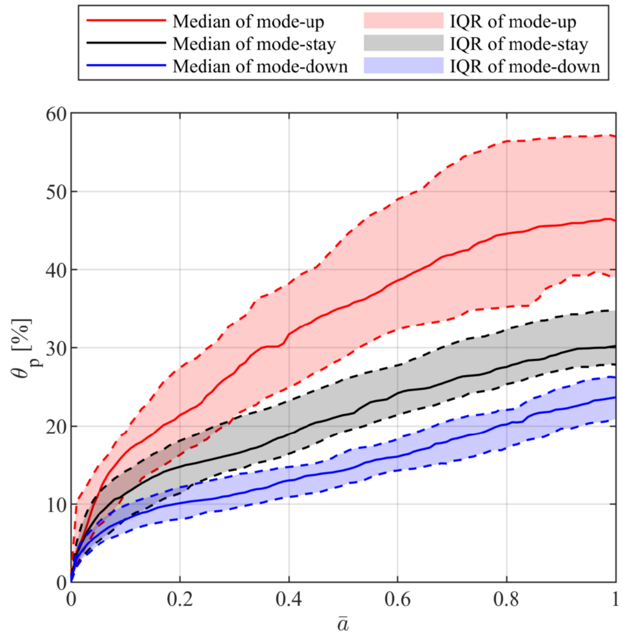


Fig. 7. Pedal operation distribution for all drivers' launch data

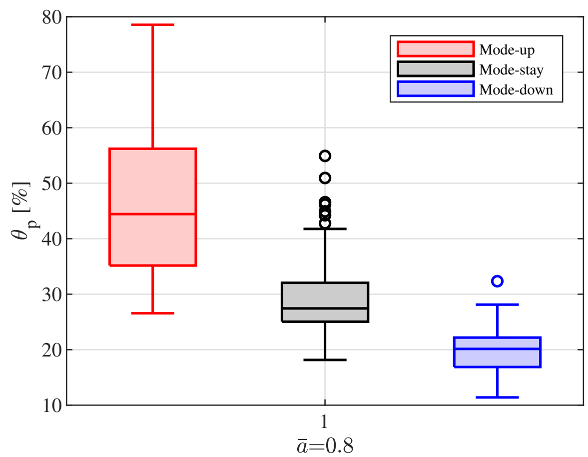


Fig. 8. Pedal operation distribution for $\bar{a} = 0.8$

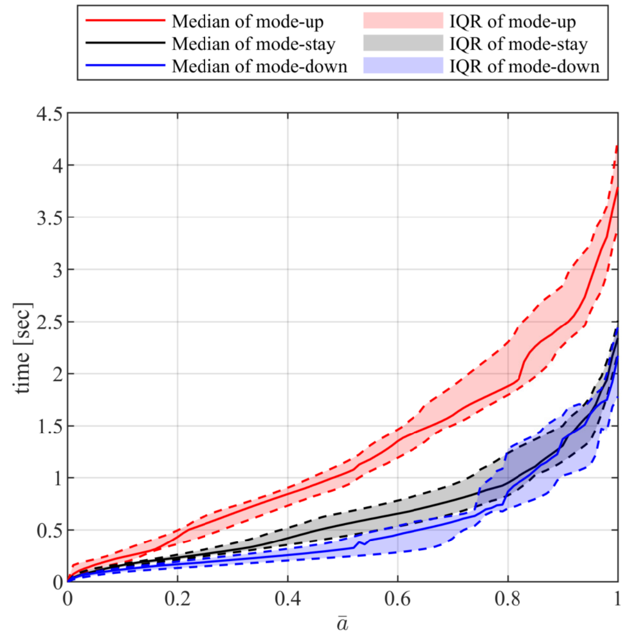


Fig. 9. Time distribution of Driver 3 for the launch

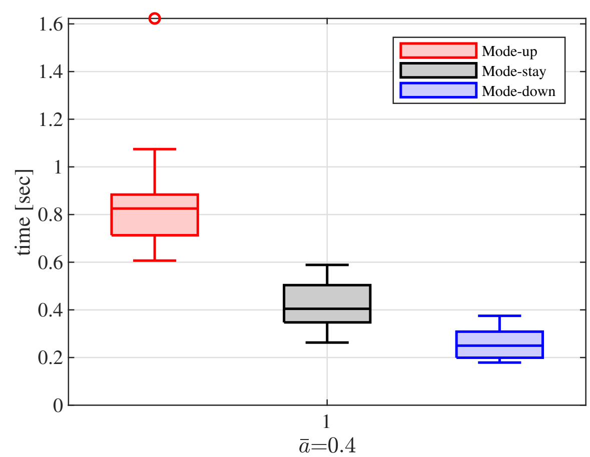


Fig. 10. Time distribution of Driver 3 for $\bar{a} = 0.4$

are obtained as follows.

$$\text{Pedal feature} = \{\theta_p(\bar{a}) \mid \bar{a} = 0.1, 0.2, \cdots 1\} \tag{4}$$

Also, Fig. 7 suggests that drivers are satisfied with the proper pedal operation range for generating acceleration. Usually, if a vehicle's longitudinal response is frustrating, the driver tends to step on the pedal more. Conversely, drivers tend to adjust the pedal more carefully if the car overreacts. Therefore, the driver's satisfaction with the driving mode appears through pedal control. As shown in Fig. 7, each category is separated at higher $\bar{a}$ values than at lower $\bar{a}$ values. Since a high $\bar{a}$ represents a situation where the driver's control is almost complete, this pedal feature indicates overall satisfaction with driving.

Several studies aim to minimize jerk, the derivative of acceleration, as an index for driver satisfaction during vehicle control [34], [35]. Fig. 9 shows the data distribution for Driver 3. The x-axis represents normalized acceleration, and the y-axis shows time. It indicates jerk as it shows the time required to generate $\bar{a}$. Each color represents a category, such as mode-up, -stay, and -down. The solid line indicates the median of the data corresponding to each category, and the dotted line indicates the first and third quartile, where 50% of the data for each category is distributed within each colored patch. Fig. 10 displays a boxplot of time for each category at the point where $\bar{a} = 0.4$.

Unlike the previous pedal feature, the distribution of each category is separated at low $\bar{a}$. As soon as the driver operates the pedal, if the vehicle responds quickly, the driver is surprised and stops operating the pedal. However, if the vehicle responds slowly even though the driver operates the pedal, the driver applies more pressure on the pedal. As a

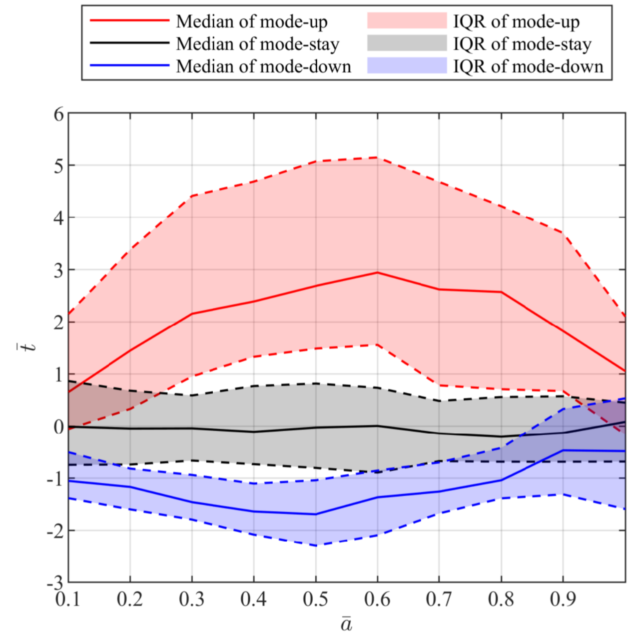


Fig. 11. Normalized time distribution for all drivers' launch data

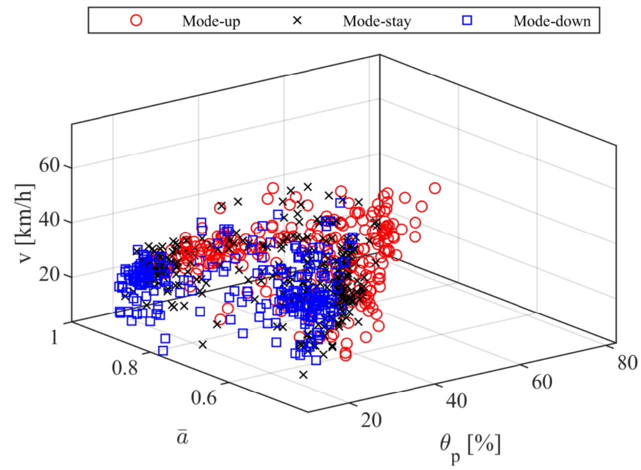


Fig. 12. Features for acceleration while driving

result, when the driver applies the pedal, there is an expected acceleration response: a satisfied jerk level. The driver satisfies the driving mode that meets this expectation. The driver's expected response is the gray area in Fig. 9. If the vehicle's response is faster than this expectation, that is, if it takes a short time to generate $\bar{a}$, the driver wants to mode-down. Conversely, the driver wants to mode-up if the vehicle's slow response takes a long time to generate $\bar{a}$. Therefore, as shown in Fig. 9, the distribution of each category is separated at low $\bar{a}$, and the features extracted from this $\bar{a}$-time domain represent immediate satisfaction.

However, the features extracted from $\bar{a}$-time domain cannot be immediately utilized since drivers have different satisfied jerk levels. Additionally, as depicted in Fig. 7, the separation of distributions for all drivers' data needs to be confirmed. Hence, the features are defined as follows through z-score normalization.

$$\text{Normalized time feature} \\ = \left\{ \frac{t\left(\bar{a}\right) - \mu_j\left(\bar{a}\right)}{\sigma_j\left(\bar{a}\right)} \mid \bar{a} = 0.1,\, 0.2,\, \cdots 1 \right\} \tag{5}$$

Here, σ_j and μ_j represent the mean and standard deviation of the data for the Driver j's mode-stay. Information about the driver's mode-stay is assumed to be known in advance. The validity of this assumption is further explained in the classifier's results later. The distribution of this normalized time feature for all drivers' data is illustrated in Fig. 11. Despite the data from drivers with different driving styles and preferred modes, the distribution of each category is noticeably separated. Therefore, the normalized time feature can effectively contribute to providing a satisfactory driving mode.

Next, the feature for acceleration while driving is extracted from the existence of an appropriate pedal operation range that the driver is satisfied with when generating acceleration. Since the map between pedal and traction torque varies with velocity, the feature for acceleration during driving is defined as follows.

$$\begin{aligned} \text{Driving feature} &= \left\{ v\left(t_d\right),\, \bar{a}\left(t_d\right),\, \theta_p\left(t_d\right) \right\} \\ t_d &= \frac{t_s + t_e}{2} \end{aligned} \tag{6}$$

t_s and t_e represent the start and end points of the acceleration while driving. According to Eq. 3, this situation appears as several subsequences for one micro-trip, with each point of subsequence having a redundant meaning. Therefore, the value located at the center of the subsequence is used as the feature. Fig. 12 displays the scatter plot for driving feature. As each category is distributed differently, this feature can be used to provide a satisfactory driving mode.

IV. Satisfactory Driving Mode Classification

This section focuses on the satisfactory driving mode classification algorithm based on the extracted features. The algorithm's hyperparameter selection and performance evaluation are conducted through nested cross-validation. The proposed algorithm's results are compared with conventional algorithms based on driving style recognition.

A. Feature sets construction

This paper proposes three features for providing satisfactory driving modes: the pedal and normalized time feature at launch and the driving feature at acceleration while driving, each with distinct characteristics. Launch features are extracted once for one micro-trip while the driving feature can be extracted multiple times for one micro-trip according to Eq. 3. The acceleration while driving occurs from a minimum of 0 to a maximum of 4 times for one micro-trip in the collected data. The normalized time feature is only available when the driver's satisfied jerk level is known. Since these proposed features

TABLE II
LABELING FOR CONVENTIONAL ALGORITHM

Preferred mode	Driving style	Current driving mode	Driving mode changes
Eco	Mild	Eco Comfort Sport	Mode-stay Mode-down Mode-down
Comfort	Moderate	Eco Comfort Sport	Mode-up Mode-stay Mode-down
Sport	Aggressive	Eco Comfort Sport	Mode-up Mode-up Mode-stay

have different characteristics, three feature sets are composed as follows: Set 1 includes pedal feature, Set 2 includes pedal and normalized time features, and Set 3 includes driving feature. A classifier is constructed for each feature set, and the resulting classification results are analyzed.

Conventional algorithms utilize driving style recognition, composed of features expressing driving style and labeling of driving style. The features are extracted based on micro-trip, including the mean and standard deviation of velocity, acceleration, and jerk [19]. Table II shows the labeling process of driving style and driving mode change for the conventional algorithm. The data is labeled as driving styles, such as mild, moderate, and aggressive, based on the preferred driving mode. For example, if drivers prefer eco mode, their data is labeled as mild. Based on these features and labeling, driving style recognition is constructed, named Set 4 - style. Regarding the change of driving mode, the data is classified into mode-up, -stay, and -down compared to the current driving mode based on the classification result of this driving style recognition. For example, if a driver's driving style is classified as moderate and the data used is eco mode data, it is determined as mode-up. The result of changing the driving mode through this conventional algorithm is named Set 4 - mode.

B. Algorithm structure and design

The classification algorithm for each feature set is constructed using a supervised learning-based classifier. The accuracy of classification dramatically depends on the hyperparameters' settings. Nested cross-validation is used for hyperparameter tuning and performance evaluation. Nested cross-validation comprises an outer loop and an inner loop. The inner loop cross-validation evaluates various hyperparameters' performance, selecting the optimal classifier. The outer loop cross-validation is used to evaluate the selected classifier's performance.

The paper applies the classification algorithm structure as shown in Fig. 13. The entire dataset is divided into folds based on the experimental scenario route. Each route has a different velocity profile, as shown in Fig. 14. Route 1 and Route 3 have similar profiles, while Route 2 has different velocity profiles. This route-based data partitioning enables the cross-validation results to show performance for unlearned driving scenarios. This method can verify the classification algorithm's generality and production vehicle applicability. The classifiers utilized in this paper are the Gaussian kernel classifier, k-nearest neighbor (KNN), linear classifier, and support vector machine (SVM).

Feature extraction suitable for classification is the most crucial task in constructing a classification algorithm using machine learning. Therefore, a simple classifier to verify performance proves the proposed feature's superiority based on the driver's pedal operation characteristics. The hyperparameters of each classifier are selected through inner loop cross-validation. The selected classifier's performance is evaluated through outer loop cross-validation. Classifier learning and performance evaluation are implemented through MATLAB.

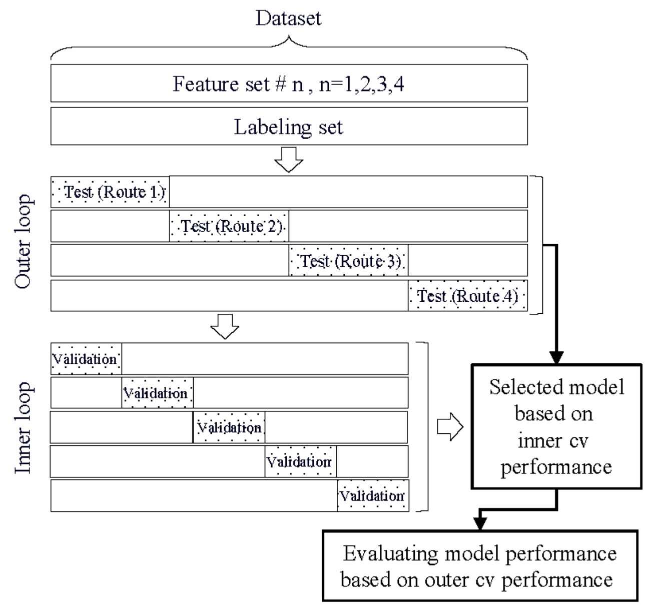


Fig. 13. Structure of classification algorithm based on nested cross-validation

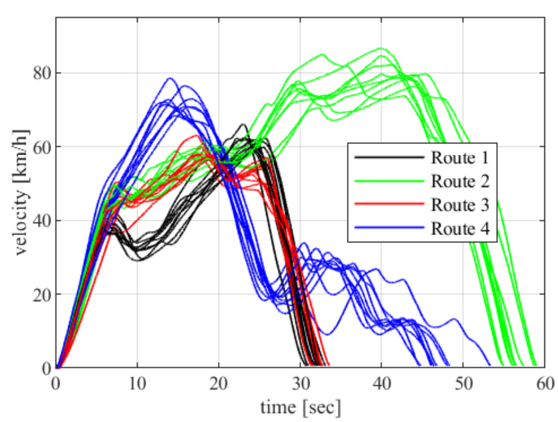
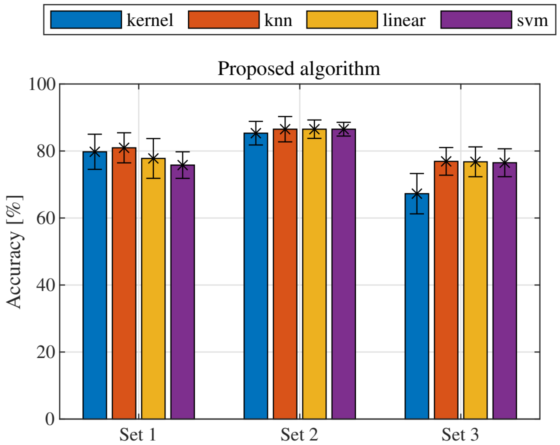


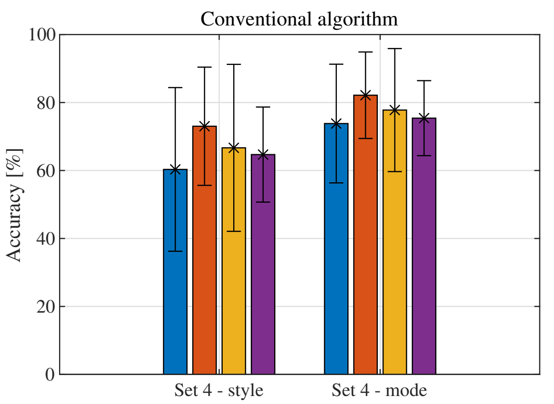
Fig. 14. Velocity profiles of each route for Driver 1

C. Classification performance evaluation

Fig. 15 displays the classification results obtained through nested cross-validation. The proposed algorithm produces three different results depending on the feature set used, as shown in Fig. 15a. The conventional algorithm, as demon-



(a)



(b)

Fig. 15. (a) Cross-validation results for the proposed algorithm (b) Cross-validation results for the conventional algorithm

strated in Fig. 15b, produces a classification result for driving style and another for change in driving mode. Each bar in the graph represents a classifier type, and the average cross-validation result is plotted with error bars based on the standard deviation.

Set 1 in Fig. 15a shows the classification result using only the pedal feature of launch, and Set 2 presents the classification result using the normalized time feature of launch and the pedal feature. The classification result using Set 2 is more accurate and has a lower standard deviation than Set 1. This result is achieved because the normalized time feature provides additional information. The pedal and normalized time features have different properties, as shown in Fig. 7 and Fig. 11. The pedal feature displays a separation of categories at high $\bar{a}$, while the normalized time feature separates into categories at lower $\bar{a}$. As these two features have separate meanings, the normalized time feature can provide additional information in classification. However, the driver's satisfied jerk level must be known to extract the normalized time feature. The classification result using Set 1, which does not include this feature, has a high accuracy of nearly 80%. Therefore, after obtaining the driver's satisfied jerk level through Set 1, an algorithmic structure that secures higher classification accuracy can be constructed through Set 2.

TABLE III
CROSS-VALIDATION RESULT FOR SELECTED MODELS

Accuracy [%]	Proposed algorithm			Conventional algorithm	
	Set 1	Set 2	Set 3	Set 4 - style	Set 4 - mode
Classifier	KNN	SVM	KNN	KNN	KNN
Fold 1 (Route 1)	87.30	87.30	76.19	82.54	87.30
Fold 2 (Route 2)	80.95	84.13	79.09	47.62	63.49
Fold 3 (Route 3)	77.78	85.71	71.43	85.71	92.06
Fold 4 (Route 4)	77.78	88.89	80.90	76.19	85.71
Mean	80.95	86.51	76.90	73.02	82.14
SD*	4.49	2.05	4.13	17.39	12.72

*SD: Standard deviation

Set 3 in Fig. 15a is a classification result using the driving feature of acceleration while driving. The classification result using Set 3 shows a relatively lower accuracy than that of Set 1 and Set 2. However, Set 1 and Set 2 can only be obtained once for one micro-trip, while Set 3 can be obtained many times. Therefore, the launch classifier with high accuracy can complement the acceleration while driving the classifier with lower accuracy but higher frequency. The ensemble of these two classifiers can improve the accuracy in production vehicle applications.

Fig. 15b shows the classification result of the conventional algorithm. The accuracy for driving mode change classification is higher than for driving style classification because the category for driving mode change has a more comprehensive meaning, as shown in Table II. For instance, if a driver has a mild driving style and is currently in sport mode, the labeling for a change in driving mode would be mode-down. If the classifier judges the driving style as moderate, the driving style would be incorrectly classified, but the driving mode change would be correctly classified as mode-down.

Both cases of this conventional algorithm have lower accuracy and higher standard deviation than the proposed method. A high standard deviation means that it is inappropriate to apply this algorithm to unlearned driving scenarios, and the generality of the algorithm is not secured. Also, the proposed algorithm is less affected by the type of classifier, unlike the conventional algorithm. In the case of the proposed algorithm, even though simple classifiers are used, the accuracy of each classifier is high, and the accuracy difference between classifiers is slight. It means that the features used in the proposed algorithm are very effective for classification.

Table III shows the classification results for the classifier with the highest accuracy in each set of Figure (fig. cv result). In the applied nested cross-validation, the classification accuracy for each fold is obtained because the outer loop is divided into folds according to the route. In the case of set 2, which uses the pedal and normalized time feature of launch, it shows an average accuracy of 86.51% and a standard deviation of 2.05% based on SVM. The proposed algorithm shows better classification performance than the conventional algorithm. In addition, set 1 and set 3 show an accuracy of 80.95% and 76.9%, respectively, with significantly lower standard deviation than conventional algorithms.

The high standard deviation of the conventional algorithm is due to its low accuracy for Route 2. As shown in Fig. 14, Route 2 has a distinctly different profile from other routes. Since Route 1 and Route 3 have a similar shape, it is possible to respond to the rest if one is used for learning. Therefore, the classification accuracy for Routes 1 and 3 in the conventional algorithm is relatively high. From these results, it can be inferred that conventional algorithms are vulnerable to unlearned scenarios. On the other hand, since the accuracy of the proposed algorithm remains mostly the same depending on the route, it can correctly classify new driving scenarios that have not been learned. That is, the proposed algorithm is suitable for production vehicle applicability. This result is possible because the proposed algorithm extracts features for specific situations, such as launch and acceleration while driving, instead of using the entire driving scenario and uses the proposed features that separate each category. In addition, the conventional algorithm works when the data for one micro-trip is accumulated, whereas the proposed algorithm is event-based classification, so it operates in real-time while driving and has high production vehicle applicability.

V. Conclusion

This paper presents a satisfactory driving mode classification algorithm based on the pedal operation characteristics of the driver. Providing a suitable driving mode can enhance driver satisfaction because the vehicle's longitudinal response to the driver's pedal input varies depending on the driving mode. Based on driving style recognition, the conventional algorithm suffers from unclear labeling and does not reflect driving characteristics in the features used for classification. To address this issue, we propose a new approach that determines which changes are necessary for the driver's satisfaction, such as mode-up, -stay, and -down for the current driving mode. According to the new approach, experiments are designed for acquiring data, and the collected data are analyzed.

The situation requiring data analysis is specified, which includes launch and acceleration while driving. Unlike the conventional algorithm that utilizes simple statistics, three types of interpretable features, such as pedal features, normalized time features, and driving features, are extracted based on the driver's pedal operation characteristics. Even though the data of drivers with different driving styles are gathered, the extracted features separate individual satisfaction and dissatisfaction.

The proposed algorithm undergoes hyperparameter tuning and performance evaluation through nested cross-validation. The cross-validation results for each feature set show that the proposed algorithm has higher classification accuracy than the conventional algorithm, even for unlearned driving scenarios. In addition, the proposed algorithm is less affected by the type of classifier and shows consistently high classification accuracy, even for simple classifiers, unlike the conventional algorithm. This indicates that the proposed feature significantly contributes to providing a satisfactory driving mode. Using the pedal and normalized time features for launch, the proposed algorithm shows an average classification accuracy of 86.5% and a standard deviation of 2.05% based on SVM.

Additionally, the proposed algorithm is highly applicable in production vehicles, as it can classify satisfactory driving modes in real-time while driving and directly contribute to providing satisfactory driving modes without analyzing the correlation between driving style and driving mode.

Acknowledgement

This research was supported by the Hyundai Motor Company; the BK21 FOUR Program of the National Research Foundation Korea(NRF) grant funded by the Ministry of Education(MOE); Technology Development for Future Automotives Tuning Parts (P0021036, Development of a smart damper system for electric vehicles capable of tuning damping force while driving) funded by the Ministry of Trade, Industry & Energy (MOTIE, Korea) and the Korea Institute for Advancement of Technology (KIAT);the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIP) (No. 2020R1A2B5B01001531);the Technology Innovation Program (20014983, Development of autonomous chassis platform for a modular vehicle) funded By the Ministry of Trade, Industry & Energy(MOTIE, Korea);Autonomous Driving Technology Development Innovation Program (20018181, Development of Lv. 4+ autonomous driving vehicle platform based on point-to-point driving to logistic center for heavy trucks) funded by the Ministry of Trade, Industry & Energy(MOTIE, Korea) and Korea Evaluation Institute of Industrial Technology(KEIT)

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