Prediction of Collision Avoidance Ability of Two-wheeled Vehicle Riders Using Driving Behaviors and Emotional States

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ABSTRACT: In recent years, the traffic accidents rate and fatality are decreasing year by year. In comparison, the accident rate and fatality caused by two-wheeled vehicles are not decreasing trends. It is also a problem that the development of the safety systems for the two-wheeled vehicles is insufficient compared to that of the four-wheeled vehicles. Therefore, this study has the purpose modeling to predict the collision avoidance ability in case of a risky situation by using driving behaviors that can be obtained in real-time. For the experiment, a dynamic riding simulator that can control rolling motion was constructed, and the experiment was conducted with 18 test subjects (Mean age = 21.83, S.D. = 1.34). In the experiment, the driving behaviors of each emotional state were investigated based on an emotional model consisting of two axes of valence and arousal with sound stimulation and driving conditions. Driving behaviors were quantified using lateral control ability, head motion as confirmation behavior, and emotional state. The correlation between driving behaviors and collision avoidance ability was investigated. Lane position, one of the indicators of lateral control ability, has a quadratic functional correlation of $R^2 = 0.568$, which is more correlated than other indicators. Moreover, multiple regression analysis was conducted using driving behaviors to predict overall collision avoidance ability. As a result, a model was constructed using driving behaviors with real-time measurement, to predict the rider’s collision avoidance ability when risky situations occur ($R^2 = 0.685$, $R^2_{adj} = 0.655$).

KEY WORDS: safety, driving ability, performance, behavior observation / Collision avoidance ability [C1]

1. Introduction

Developments and researches in Advanced Driver Assistance System (ADAS) and Human-Machine Interface (HMI) for vehicle safety is a very active field, and the pace of product introduction is accelerated. Studies of ADAS for four-wheeled vehicles are especially numerous, but studies for Advanced Rider Assistance System (ARAS) for two-wheeled vehicle riders are less common, although the number of fatalities due to traffic accidents is almost double. The accident rate of two-wheeled vehicle riders has significant differences depending on the rider’s driving skill, and the driving experience is required to reduce traffic accidents. Novice two-wheeled vehicle riders have a three to eight times higher frequency of injury in traffic accident than four-wheeled vehicle drivers (1). The fatality of the four-wheeled vehicle accident was significantly decreased. Richer, M., et al (2005) were studied the relationship of improvement of car design for safety and injury level using traffic accident data of the 1970s and 1990s. They clarify the improvement of the car safety system is effective to decrease the injury level when a collision accident occurred (2). This suggests the development and introduction of ADAS have supported to reduce the traffic accidents. However, the fatality of the two-wheeled vehicle accident does not decrease relatively. Fortunately, studies of ARAS and On-Bike Information System (OBIS) have been started by some research teams and the practical use of ARAS will accelerate (3). Prior to the development of a safety system for the two-wheeled vehicles, it is necessary to propose an algorithm in consideration of the driving characteristics of the two-wheeled vehicle riders. There are many well-known algorithms such as TTC algorithm (4) and Stop Distance Algorithm (SDA) (5) as the driving characteristic algorithm of a four-wheeled vehicle for the safety system. These make the safety system for the four-wheeled vehicle easy to construct. In the previous study, the rider’s driving performance was defined as an index then the defined index was applied to the four-wheel vehicle driving characteristic algorithm to propose an algorithm which is suitable for the characteristics of two-wheeled vehicles (6). However, in order to apply this algorithm to the safety systems, problems such as the selection of an index suitable for the characteristics of the two-wheeled vehicles, real-time measurement, and low measurement cost are still remaining. Furthermore, it was confirmed that driving behavior was changed depending on the riding style when riders using ARAS (7). These differences are larger than four-wheeled vehicle drivers. Many ADAS algorithms used the driver’s reaction time and deceleration of the vehicle for setting the trigger threshold. The average drivers’ brake reaction time was clarified that between 0.2 to 2.5 seconds (8) but using assumed driver’s behaviors is not suitable for all risky situations and all drivers, especially two-wheeled vehicle riders. Therefore, future ARAS needs to be personalized because driving behaviors have significant variations in their riding style. Therefore, the purpose of this paper is below:

1) The investigation of the relationship between real-time driving behaviors and collision avoidance ability
2) The proposal of driving behavior model to predict the collision avoidance ability for designing the personalized ARAS

2. Riding simulator experiments to investigate driving behaviors of two-wheeled vehicle riders at ordinary driving and risky situation

2.1. Riding simulator

In this study, the driving behaviors of two-wheeled vehicle riders were quantified to investigate the relationship between under ordinary driving situations and risky situations. For investigating the driving behaviors, the riding simulator experiments were conducted considering scenario manipulation. Fig. 1 shows the constructed Riding Simulator (RS) to investigate driving behaviors. This RS was constructed with two PC for calculating the vehicle dynamics and transmitting the graphics, Head-Mounted Display (HMD) for simulating, the electrical fan for increasing the reality of driving velocity, and simulator chassis. The simulator chassis can detect the steering angle, the opening level of the accelerator, the pressure level of the brake handle, and the rolling angle of the vehicle (Maximum rolling angle = ±15 degree). Controlling the experimental conditions and calculating the motorcycle dynamics was simulated using MatLab R2013a-Simulink linked Car-Sim 8.2.2. The platform software for driving simulation is DS-nano by Misaki-design.

2.2. Experiment conditions

2.2.1. Stimulation method of emotional states

In the experiment, the rider’s emotional states were induced with sound stimulation and driving conditions to investigate riding performance as broad as possible. The ability to perform task are depending on the emotional state, and it has an inverted U-shaped relationship (9) according to two emotional states: arousal and valence. This relationship shows the same trend in driver performance in four-wheel driving (10). Many human emotional state models have been proposed by psychologists. Among many emotional models, Russell’s emotional circumplex model defined that human emotions have continuous two-dimensional space that represents valence and arousal (11). Fig. 2 shows the relationship between Russell’s emotional circumplex model and emotional state in this study. Many methods were used to stimulate and induce the emotional state, and the acoustic sound is also used as one of the stimulating methods. The emotion inducing method using pictures (IAPS: International Affective Picture System) and the method using movie clips have a high induction effect. However, in this study, it is necessary to induce emotions to test subject with driving tasks for about 20 minutes, simultaneously. Therefore, valence level was controlled using acoustic sound in this study. Several light and active movie music sounds were selected to stimulate positive valence, and the crying baby sound was used to stimulate negative valence. The advantage of the stimulation method using sound is that it can stimulate emotions while performing tasks, so the stimulation effect during the experiment can be relatively constant. The traffic volume and surrounding road environment have an effect on the level of arousal while driving (13). In order to stimulate arousal level, the road environment and the traffic volume of dummy vehicles were controlled. The same road dimensions such as the width of the same road and the composition of the entire course were set for each emotional state.

2.2.2. Driving course and collision course design

The driving course including a sharp curve of R 50 meters was set, and a vehicle that assumed a side collision at an intersection was reproduced in about 20 minutes of experiment driving as shown in Fig. 3 (a). The test subjects performed sufficient practice driving before starting the experiment. When the experiment began, subjects drove for 18 to 20 minutes on the road without any risky situations, in order to make subjects sufficiently accustomed road condition and experience at each emotional state. For 2 minutes before the occurrence of a risky situation, the test subjects’ driving behaviors such as lateral control and head motion as confirmation behavior were investigated. The experiment was finished when the subject’s vehicle control completely stopped after a risky situation. In this study, the correlation between driving behaviors before a risky situation and driving behavior to avoid a risky situation like collision avoidance behavior was investigated to predict the collision avoidance ability in real time.

The test subjects were instructed to drive in the virtual center lane while maintaining 60 KPH as possible on the priority lane without any traffic signals. The virtual center line was visually presented during driving as shown in Fig. 3 (b). The reason for
this instruction is to measure the test subject’s lateral control ability and to induce a collision between the ego vehicle and the crossing vehicle in the collision course as much as possible. In the crash course, the crossing vehicle was designed to suddenly come out in 70 KPH without decelerating from the left side of the intersection, and it was also designed to collide if the test subject drives without decelerating action at the intersection.

\[
\text{Lanex} = \frac{\sum_{i=1}^{n} \theta(x_i)}{n}
\]

Where:

\[
\theta(x_i) = \begin{cases} 
1 & \text{if } x_i < x_L \\
1 & \text{if } x_i > x_R \\
0 & \text{otherwise}
\end{cases}
\]

Subjects were instructed to drive while maintaining a virtual center lane in the experiment, and \text{Lanex} was used to evaluate how they followed the instructions. The width of the \text{Lanex} was set to 1 m, and the position of the virtual line center was set to 0 m, negative to the left side, and positive to the right side. Therefore, \(x_L\) was set to -0.5 m, and \(x_R\) was set to 0.5 m, defines the left and right lane boundary, respectively.

3.1.2. Lateral position and Lateral velocity

The lateral position (LP) and the lateral velocity (LV) are the common parameters to investigate the driving performance (16). In this study, the LP and LV were defined as the change of lateral distance and lateral velocity from the virtual lane center, respectively. It was calculated using the absolute value of the distance from the virtual center lane \((x_L, x_R)\). The average value of LP and LV were quantified by Eq. 3 and Eq. 4.

\[
LP_{avg} = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{2}(\left|x_L\right| + \left|x_R\right|)
\]
\[ U_{\text{avg}} = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{2} (|x_L| + |x_R|) \] (4)

3.1.4. Visual behavior

The visual behavior (VB) in terms of head motion was quantified by Eq. 5 to investigate VB of test subjects while approaching intersections. The VB was defined as the left and right viewing angles relative to the front. In order to evaluate only VB when test subjects approached the intersection, the VB of the road section without intersection was not included, and VB was quantified as the average of the left and right confirmation action angles while approaching the intersection.

\[ VB_{\text{avg}} = \frac{1}{n} \sum_{i=1}^{n} |VB_i| \] (5)

Where:

\[ VB_i = \begin{cases} \text{VB}_i \text{ if vehicle at intersection} \\ 0 \text{ if vehicle driving straight} \end{cases} \] (6)

3.1.5. Time-To-Collision

The time to collision (TTC) was investigated as the rider’s collision avoidance ability at the risky situation. The risk event in this study is a side collision also known as T-bone collision at an intersection as shown in Fig. 5. The TTC was defined by Eq. 7 as a minimum value of TTC between ego-vehicle and crossing-vehicles at the risky situation.

\[ TTC_{\text{min}} = \min\left(\frac{S}{V}\right) \] (7)

Where:

\[ S = \sqrt{dx^2 + dy^2} \] (8)

\[ dx = X_o - X_E \] (9)

\[ dy = Y_o - Y_E \] (10)

\[ V = |V_o \cdot (\cos \psi_E \cdot \cos \psi_E + \sin \psi_E \cdot \sin \psi_E) - V_E| \] (11)

Here, \( S \) is the relative distance between ego-vehicle position \((X_E, Y_E)\) and crossing-vehicle position \((X_o, Y_o)\). \( V \) is the relative velocity of ego-vehicle and crossing-vehicle. Here, \( V_E \) is the ego-vehicle velocity and \( V_o \) is the crossing-vehicle velocity. \( \psi_E \) and \( \psi_o \) is global heading angle of ego-vehicle and crossing-vehicle, respectively. In this experimental study, TTC was calculated by the center of vehicles, so the collision was judged \( TTC_{\text{min}} \) under 0.12 sec.

3.2. Emotional states

3.2.1. Self-Assessment Manikin

The emotional states were evaluated as the level of valence and arousal. Each emotional state was evaluated on image-based 9 scale using Self-Assessment Manikin (SAM) (17). SAM has been used not only in psychological studies but also in driving safety studies (18). The SAM can evaluate the test subject’s emotional state in Russell’s emotional circumplex model by choosing an illustration similar to their emotional state. The SAM was presented to test subjects after the risky situation occurred, and the test subjects were instructed to verbally answer with a number of the illustration that is most similar to the emotional state prior to the occurrence of the risky situation, not the emotion they felt in the risky situation. This is to investigate whether the emotional state during ordinary driving, that can be acquired in real-time, not the emotional state at risky situations.

3.2.2. Physiological signals

The physiological signals such as Galvanic Skin Response (GSR) and Electrocardiogram (ECG) were investigated to clarify the physiological changes with emotional state. The GSR signal has been used as a quantitative indicator of arousal by measuring the conductance according to the amount of moisture generated in the skin sweat glands activity (19). The GSR signals were sampled at 1,024 Hz from the sensor attached to test subjects’ foot in order not to disturb the driving. As the main indicator among the variables that can be obtained from the GSR signal, the average amplitude (Micro Siemens) during driving was investigated to estimate an arousal state.

The balance of the Autonomic Nervous System (ANS) is highly related to emotional valence state such as positive and negative states (20, 21). Therefore, the ECG signals were used to investigate the valence state during driving. The ECG signals were sampled at 500.5 Hz from the four bipolar limb lead located at RA, LA, RL, LL, and one unipolar lead located at Vz on the chest. Frequency domain analysis of heart rate activity was performed as an indicator of the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PSNS). Physiological signals were sampled from two minutes before the risk event to just before the event. Sampled signals were grouped and analyzed based on the result of SAM. GSR and ECG sensors of Shimmer’s development kit were used in this investigation.

4. Results & Discussion

4.1. Results

4.1.1. Results of TTC

Fig. 6 shows \( TTC_{\text{min}} \) in each emotional state (valence and arousal), and each group was modified into three scales by nine scales of SAM result. Emotional states were equally re-scaled as...
low arousal/valence from 1 to 3, natural arousal/valence from 4 to 6, and high arousal/valence from 7 to 9 from the SAM result. In this study, $TTC_{\text{min}}$ was used as an evaluation index for riding performance in terms of traffic safety, and the long $TTC_{\text{min}}$ means that the rider could stop at a safe distance in a risky situation. It is possible to evaluate the overall performance by the reaction time and deceleration operation for the risky situation. The result of the one-way ANOVA confirmed a significant difference for each group ($F (2, 59) = 5.01, p = 0.008$) in $TTC_{\text{min}}$ according to the valence level. In order to confirm the homogeneity of variances, Levene test was conducted, and it was confirmed that the variance of each group was heteroscedasticity ($p < 0.001$). As a result of the post-hoc analysis (Games-Howell test), it was confirmed that the $TTC_{\text{min}}$ was longest when riders have a neutral valence level (Low valence and neutral ($p < 0.001$), Neutral and high valence ($p < 0.001$)). These results suggest that driving in an emotional state of too enjoyable/excited or too depressed/annoyed has a problem of decreasing riding performance in a driving. The result of the one-way ANOVA shows that there is no significant difference in each group ($F (2, 59) = 3.136, p = 0.0508$) in $TTC_{\text{min}}$ according to the arousal level. There was no significant difference but the average $TTC_{\text{min}}$ was the longest in the low arousal state, followed by a natural and high arousal state.

4.1.2. Results of lateral control

To investigate the relationship between normal vehicle control ability and collision avoidance ability in a risky situation, the regression analysis was performed in each parameter as Fig. 7. In order to quantify the collision avoidance ability, the dependent variable was the $TTC_{\text{min}}$, and the independent variable was each parameter. In order to clarify the relationship between each parameter and the collision avoidance ability, a regression analysis was performed with linear and polynomial (quadratic) function. As a single indicator, the linear relationship with $LV_{\text{avg}}$ ($p < 0.001, R^2 = 0.465$) and nonlinear relationship ($p < 0.001, R^2 = 0.568$) have the highest relation with collision avoidance ability. $Lanex$ and $LV_{\text{avg}}$ do not have a high correlation with the collision avoidance ability. In particular, it was confirmed that $Lanex$ had a nonlinear relationship compared to other parameters. The result that $LP_{\text{avg}}$ had a higher correlation than other variables suggest the $LP_{\text{avg}}$ has a wider tendency of the lateral direction movement than other variables. Therefore, these results suggest that $LP_{\text{avg}}$ has a higher possibility than other variables as a parameter to evaluate the concentration for the driving of two-wheeled riders. $Lanex$ and $LP_{\text{avg}}$ have a negative correlation with their collision avoidance ability, which shows the higher driving concentration that does not deviate from the course caused the high collision avoidance ability in dangerous situations. $LV_{\text{avg}}$ has a positive correlation with the collision avoidance ability, which suggests that the higher speed of leaving or returning from the lane, the higher collision avoidance ability. A high speed leaving the lane is not good in terms of driving concentration but returning quickly to the lane is considered to indicate the concentration on driving in the correct course.

4.1.3. Results of visual behavior

Fig. 8 shows the relationship between the rider’s visual behavior when approaching an intersection and collision avoidance ability as a linear and quadratic function. “Turning the face and doing confirmation action” is very important for safe driving for two-wheeled vehicle riders. However, it was confirmed that $VB_{\text{avg}}$ and $TTC_{\text{min}}$ show a very low correlation ($p < 0.01, R^2 = 0.192$) in this experiment. This result suggests that
the collision avoidance ability increases as the test subject certainly confirms the surrounding driving situation when approaching the intersection. However, the low relationship shows how their effort to confirm has no significant effect on stopping the two-wheeled vehicle in a risky situation. In addition, it was confirmed that the deviation was large in this relationship, and a lot of data was concentrated at a low angle (30 degrees or less). We measured the motion of the subject's head using the acceleration sensor of the HMD, but there is a possibility that the visual behavior was performed using eye movement or peripheral vision. Therefore, additional measurements or experiments using eye-tracking are required.

In the correlation of the quadratic term, a correlation was confirmed (p < 0.008, R² = 0.195), but it was confirmed that the correlation was significantly lower than that of other parameters. As in the results of one-way ANOVA between the test subject’s arousal level and TTC in Section 4.1.1, a significant correlation (p < 0.001, R² = 0.195) was confirmed as shown in Fig. 9. This result suggests that the collision avoidance ability increases as the arousal level decreases, as in the result of ANOVA, but the effect was confirmed to be insignificant.

### 4.1.5. Overall performance for avoiding collision

To evaluate the overall collision avoidance ability, multiple regression analyses were performed as shown in Table 1. The model has three main driving behaviors representing lateral control as three variables, visual behavior as one variable, and emotional state as one variable. All parameters were used as independent variables and confirmed the model accuracy at $R^2 = 0.685$ and $R^2_{adj} = 0.655$. The adjusted R-square ($R^2_{adj}$) compensates for the disadvantage of increasing $R^2$ when the number of independent variables used in the model increases. The $R^2_{adj}$ can be calculated from $R^2$, the number of independent variables (predictors), and the total number of samples. Tolerances and variation inflation factor (VIF) of the model were tested to check for multicollinearity problems. For all parameters, the tolerance is greater than 0.1 and the VIF is less than 10, so the model has been confirmed to have no multicollinearity issues. It was confirmed that the impact on the collision avoidance ability when a risky situation occurs was in the following order: $LP_{avg}$ (Beta = -0.891), Lane $x$ (Beta = 0.516), $V_B_{avg}$ (Beta = 0.326), $LV_{avg}$ (Beta = 0.222), and Arousal (Beta = -0.217). This suggests that lateral control ability has a higher impact on collision avoidance ability in risky situations than other driving behaviors.

The lateral control ability has been evaluated in terms of driver’s arousal and effort to awake for driving ([22, 23]). However, in this study, there was no correlation between arousal and lateral control ability, and the relationship between arousal level and collision avoidance ability has a low correlation. Unlike four-wheeled vehicles, the rider drives outside of the vehicle, and the vehicle is unstable in terms of kinematics. Therefore, it is considered that the riders of the two-wheeled vehicle have less change in arousal level than drivers of the four-wheeled vehicle ([24]). In addition, since a two-wheeled vehicle is very sensitive to rolling maneuvers, it is considered that the lateral control ability is related to the rider’s driving concentration and riding skill. The alcohol consumption and extreme fatigue may induce the two-wheeled vehicle rider’s emotion to very low arousal as like the four-wheeled vehicle driver. Driving a two-wheeled vehicle in these conditions is more dangerous and it could reduce the ability to avoid accidents ([25, 26]).

### 4.2. Results of emotional state and physiological signals

In order to analyze physiological signals according to emotional states, we classified emotional states into four emotions using the SAM results. Each emotional state is the emotion marked red in Figure 2, and the criteria for the classification of the emotional state are shown in Table 2. The emotional state was analyzed by classifying it into “Happy”, “Relaxed”, “Angry”, and “Sad”, which can be represented in Russell’s emotional circumplex model.

#### 4.2.1. Result of arousal level based on GSR signal

The result of the one-way ANOVA of amplitude for each group was significantly different (F (3, 151) = 8.694, p < 0.001) as Fig. 10.
Table 1 Multiple regression analysis table for investigating each driving behavior and collision avoidance ability and modeling the statistical models to predict the collision avoidance ability

| Driving behaviors | Parameters | Estimate | Beta | Std. Error | t value | Pr(>|t|) | Tolerance | VIF | $R^2$ | $R^2_{adj}$ |
|-------------------|------------|----------|------|------------|---------|---------|-----------|-----|-----|------------|
|                   | (Intercept)| 0.312    | 0    | 0.059      | 5.289   | ***     | 0.685     | 1.0 | 0.655|             |
| Lateral control   | $L_{ae}$   | 0.002    | 0.516| 0.001      | 3.038   | **      | 0.206     | 4.848|     |             |
|                   | $L_{pv}$   | -0.894   | -0.89 | 0.171      | -5.240  | ***     | 0.206     | 4.864|     |             |
|                   | $L_{av}$   | 25.005   | 0.222| 10.441     | 2.395   | *       | 0.693     | 1.442|     |             |
| Visual behavior   | $V_{Bav}$  | 0.002    | 0.326| 0.001      | 4.069   | ***     | 0.926     | 1.080|     |             |
| Emotional state   | Arousal    | -0.012   | -0.217| 0.005      | -2.582  | *       | 0.844     | 1.185|     |             |

Table 2 Classification of emotional states for physiological signal analysis

<table>
<thead>
<tr>
<th>Emotional state</th>
<th>SAM result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Happy</td>
<td>Arousal $\geq$ 6 Valence $\geq$ 6</td>
</tr>
<tr>
<td>Relaxed</td>
<td>Arousal $\leq$ 5 Valence $\geq$ 6</td>
</tr>
<tr>
<td>Angry</td>
<td>Arousal $\geq$ 6 Valence $\leq$ 5</td>
</tr>
<tr>
<td>Sad</td>
<td>Arousal $\leq$ 5 Valence $\leq$ 5</td>
</tr>
</tbody>
</table>

The post-hoc analysis (Games-Howell test) was performed to confirm the difference between each group (Levene test: $p = 0.007$). Post-hoc results show the amplitude of GSR of “Happy”, “Angry” groups, and “Relaxed”, “Sad” groups were significantly different ($p < 0.01$). This result can be confirmed that the physiological indicator was a relatively high arousal level like the emotional state of the riders’ feeling.

4.2.2. Result of valence level based on ECG signal

LF that can indicate the SNS and PSNS simultaneously was not significantly different at each emotional state ($F (3, 140) = 0.649$, $p = 0.585$). However, there was a significant difference ($F (3, 141) = 2.920$, $p = 0.036$) in HF that can indicate the PSNS. The average HF was the highest in the case of “Happy”, and “Relaxed”, “Angry”, and “Sad” were almost the same, but the lowest in the case of “Relaxed” state as Fig. 11. As the result of post-hoc analysis (Bonferroni test, Levene test: $p = 0.036$), the HF when riders feel “Happy” and “Relaxed” was significantly different ($p < 0.05$). In the case of the LF/HF ratio representing SNS, a significant difference was confirmed in each emotional state ($F (3, 154) = 4.934$, $p = 0.003$). As the results of post-hoc analysis (Games-Howell test, Levene test: $p = 0.004$), on the basis of “Happy”, a significant difference was confirmed with “Angry” ($p <0.05$) and “Sad” ($p <0.001$).

As generally known, in the high valence states like “Happy” and “Relaxed” state, the parasympathetic nerve was activated and the sympathetic nerve was deactivated. The results were able to confirm the same results in the “Happy” state. However, the result of the group who answered “Relaxed” shows paradoxical results of their ANS that parasympathetic activity is suppressed, sympathetic activity is activated. It means the test subjects feel both comfortable and mentally stressful at the same time because
they have to drive in a low arousal state, and it suggests that they are striving to stay awake to focus on controlling the vehicle. This paradoxical result shows the same tendency as some of the studies on arousal level and driving behavior [27,28]. As commonly known, in the group who answered “Anger” and “Sad”, sympathetic nerves were activated with low valence, but mental stress in the group of “Sad” is considered that not only from the low valence state but also from the effort to awake in the low arousal state.

4.3. Discussion and limitation

The driver’s emotional state, especially in terms of arousal, is very sensitive to driving performance, and the accident rate changes very much according to the change in arousal level of drivers. It has been known for a long time that in general, human performance and arousal have a relationship of inverted-U shape [29]. These concepts can be applied not only to general performance but also to driving performance. In this study, the collision avoidance ability according to valence showed an inverted-U shape correlation, but there was no significant correlation to the rider’s arousal level. However, the mean comparison and regression analysis seem to decrease arousal level was helpful to the increasing of \(TTC_{\text{min}}\), even there was no significant difference. Although the braking reaction time of each emotional state in a dangerous situation did not significantly different \((F (3, 62) = 0.31, p = 0.276)\), the braking distance was shortened. This suggests that the driving speed was lower than that of the instruction 60 KPH, because of low arousal, or there was a high concern about the collision at driving. Samuel, O. et al. (2019) conducted an on-road test with 18 test subjects regarding driving the two-wheeled vehicle while driving, and confirmed that the test subjects changed from negative emotion to positive emotion [30]. In this study, the changing of the test subject’s emotional state along the valence axis was very significant, and it was also found that it was significant to change from a low arousal state to a high arousal state. These results are the same as those of this study, which suggests that it is difficult for two-wheeled vehicle riders to become a low-arousal state than four-wheeled vehicle drivers. From this result, it is confirmed that two-wheeled vehicle driving has characteristics of maintaining a high arousal state while driving. This is considered that safety systems such as monitoring a driver’s arousal level and maintaining a high arousal state are inadequate considering the characteristics of two-wheeled vehicle driving. Rather, the collision avoidance ability of riders is significant in the feelings of pleasure/unpleasantness.

A two-wheeled vehicle is an unstable transportation that includes a rolling motion, and the risk is higher than the four-wheeled vehicles. Therefore, the development of a safety system is indispensable, but it is inappropriate to directly apply the safety system of the four-wheeled vehicles. In this study, we confirmed that two factors are important to design the safety system for the two-wheeled vehicle the based on this paper. 1) Valence level is significantly important for riding performance more than the arousal level. 2) Lateral control ability including rolling maneuver is most important among the driving behaviors for the two-wheeled vehicle. It is considered the dynamical safety system that can give riders an accomplishment such as the system using game theory will help to improve the performance of the two-wheeled vehicle riders rather than the statical safety systems of the four-wheeled vehicle. Such safety systems using game theory are introduced to help drivers’ decision making mainly lane changing and lane merging [31]. Game theory is a mathematical theory about interaction of decision-making. In this theory when individuals or companies perform certain actions, the outcome is determined not only by their actions but also by the actions of other participants such as games. As two factors for improving the riding performance of motorcycles defined in this study, the system using game theory is considered to increase the collision avoidance ability of motorcycle riders.

In order to predict the rider’s collision avoidance ability before a risky situation occurs, parameters that can be measured in real-time were selected and modeled. In general, variables such as reaction time to verify the rider’s performance cannot be measured unless a risky situation occurs, and the measurement time is also limited within a few seconds before a risky situation occurs. Therefore, in this study, modeling of riders’ risk avoidance behavior was performed focusing on the lateral control ability of two-wheeled vehicle driving that can be measured in real-time during all driving times. The total 19 variables such as accelerator and brake operation, and driving heading errors were also measured with measurement of lateral control ability. However, these variables have no significant relationship with collision avoidance ability. Therefore, we focused on the lateral control ability in this study. The lateral control ability correlates with collision avoidance ability, but other driving behaviors should also be considered for increasing the accuracy of the model.

5. Conclusion

This study quantitatively evaluated the rider’s driving behaviors and emotional states in order to predict the collision avoidance ability of the two-wheeled vehicle riders. The RS experiment with 18 test subjects was performed to investigate the driving behaviors that can be obtained in real-time. Investigated driving behaviors were compared with collision avoidance ability in risky situations for modeling to predict collision avoidance ability. The conclusions of this study following blew:

1) The investigation of the relationship between real-time driving behaviors and collision avoidance ability

Driving behaviors were investigated in terms of the main three performances like lateral control ability, visual behavior, and emotional state in driving. Lateral control ability has a high correlation with collision avoidance ability than other parameters. The confirmation behavior at intersections and arousal level has a significant correlation with collision avoidance ability but the correlation was very low.

2) The proposal of driving behavior model to predict the collision avoidance ability for designing the personalized ARAS

In order to evaluate the overall performance of the collision avoidance ability, the modeling of rider behavior was performed using variables with significant correlations. In the overall evaluation, it was confirmed that the lane position had a much
higher influence than the other variables. This could be used as an index to evaluate the overall concentration of driving the two-wheeled vehicle riders.

References