Development of Aggressive Driving Detection Method for two-wheeled vehicles

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Abstract. In the rapidly growing two-wheeled vehicle industry, there is an increasing need to detect and prevent aggressive driving behaviors. In this study, we propose an effective method to identify aggressive driving behaviors of simulated two-wheeled vehicles using limited data from the Carla simulator. We focus on two types of aggressive driving behaviors: sharp turning and sharp lane changing. By utilizing acceleration, angular velocity, and position data, we establish a foundation for detecting these behaviors. For sharp turning, a multi-stage classification method is adopted using gyroscope and acceleration data. Sharp lane changings are detected using an XGBoost model.

Keywords. Two-wheeled vehicles, aggressive driving detection, sharp turning, sharp lane changing

1. Introduction

The rapid growth of delivery services calls[2] for improved safety measures for two-wheeled vehicles, given the substantial increase in their usage. Despite a decrease in overall traffic fatalities, fatalities involving two-wheeled vehicles are rising, indicating the need for enhanced safety precautions. Existing methods for assessing safe driving behaviors mainly focus on four-

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[2] In 2022, the delivery services market in South Korea reached approximately $23,000 million, exhibiting a remarkable growth of 973% compared to 2017, with a steep annual growth rate of 162% (Statistics Korea).

wheeled vehicles, leaving a gap for two-wheeled vehicles. The absence of data collection systems for these vehicles necessitates the use of simulation technology and AI to detect aggressive driving behaviors (Ministry of Land, Infrastructure and Transport, 2022). Such behaviors are difficult to assess due to limited data and the distinct nature of two-wheeled vehicles.

To address this gap, we aim to develop a method to detect aggressive driving behaviors in simulated two-wheeled vehicles using the limited available data. Given the limitations of onboard detection devices for two-wheeled vehicles, we rely on simulation data encompassing speed, acceleration, and angular velocity.

2. Aggressive Driving Detection

In this study, the detection criteria for aggressive driving on two-wheeled vehicles were narrowed down to sharp turning and sharp lane changing. *Figure 1* illustrates the temporal changes in the Z-axis gyroscope values for rapid turns and abrupt lane changes. During a rapid turn, the value experiences a maximal change over approximately 1 second, while during an abrupt lane change, a single significant change occurs over 0.5 seconds.
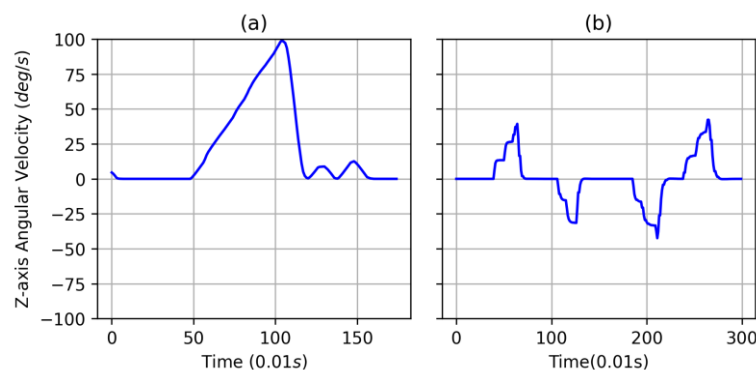

Figure 1. Z-axis gyroscope signals used for sharp turning(a) and sharp lane changing(b) detection.

To detect aggressive driving, sensor data(acceleration, angular velocity, and position information) extracted from the Carla simulator[3] was chosen considering the feasibility of onboard installation on real two-wheeled vehicles.

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[3] The Carla simulator is an open-source simulator designed for autonomous driving research. In this study, various aggressive driving scenarios and trajectory data that would be difficult to collect on actual roads were generated and analyzed using the simulator.

However, criteria for defining rapid turns and rapid lane changes can be subjective. In this study, the classification of rapid turns and abrupt lane changes was performed by dividing them into four categories. To achieve this, a labeling task was carried out by conducting a survey with 100 participants, including both ordinary individuals and traffic experts.
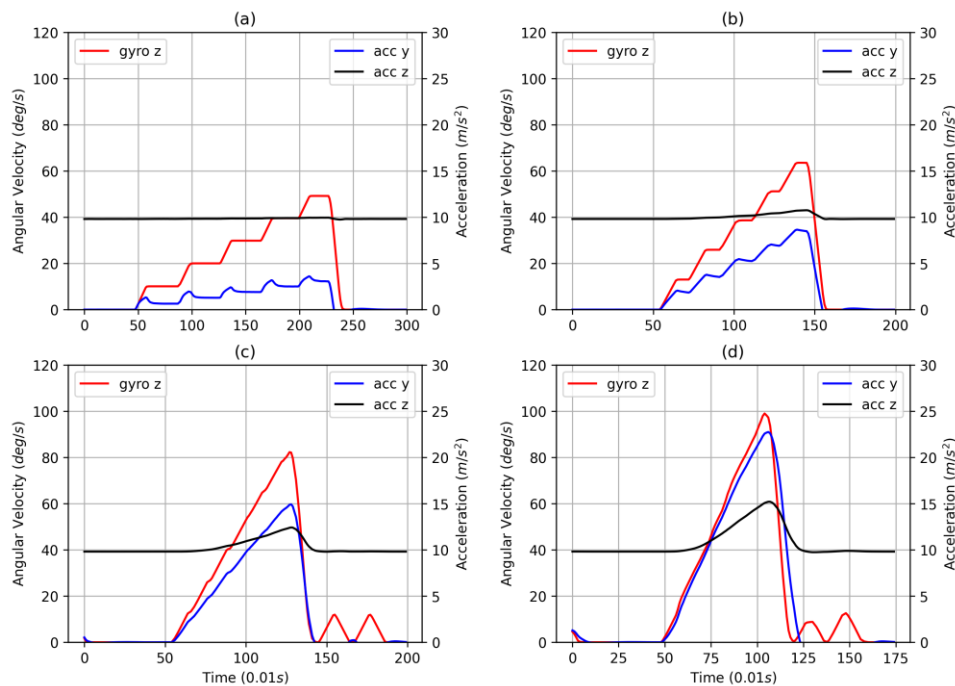
2.1. Rapid Turning

Figure 2. Inertial sensing data used for sharp turning detection. Data obtained from Carla simulator, and (a), (b), (c) and (d) are the level (1~4) of sharp turning defined in the survey, respectively.

	Time	Max. Gyro-Z	Max. Acc-Y	Max. Acc-Z
Sharp Turn (L1)	2 (s)	30 - 50 (deg/s)	0 - 5 (m/s^2)	-
Sharp Turn (L2)	1 (s)	50 - 70 (deg/s)	5 - 10 (m/s^2)	-
Sharp Turn (L3)	1 (s)	70 - 90 (deg/s)	10 - 15 (m/s^2)	10 - 12.5 (m/s^2)
Sharp Turn (L4)	1 (s)	90 - (deg/s)	15 - (m/s^2)	12.5 - (m/s^2)

Table 1. Table for sharp turning criteria.

Rapid turns can be detected using gyroscope and acceleration data (R. Gao et al., 2022). This study considers both the Y and Z-axis acceleration values in addition to the Z-axis gyroscope values to differentiate between stages of rapid turns. *Figure 2* illustrates the changes in Z-axis gyroscope, Y-axis acceleration, and Z-axis acceleration values across different stages of

rapid turns. As the stage of rapid turning increases, the Z-axis gyroscope value changes sharply, and both Y and Z-axis acceleration values demonstrate increased fluctuations. Based on these observations, this study defines the criteria for rapid turns as shown in *Table 1*.
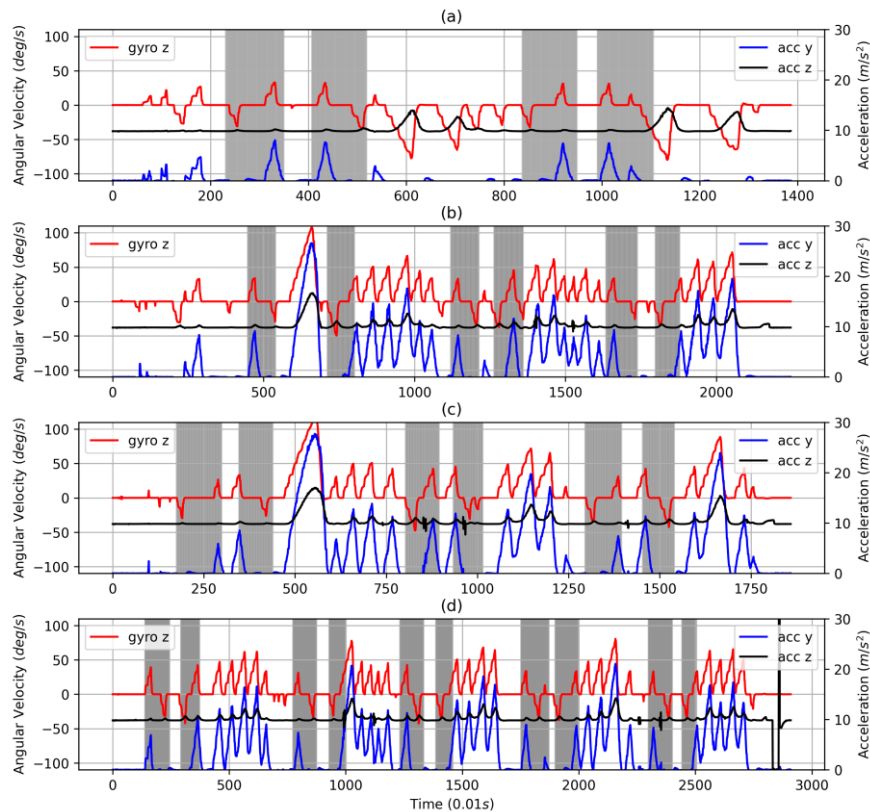
2.2. Sharp Lane Changing

Figure 3. Inerial sensing data used for sharp lane changing detection. Data obtained from Carla simulator, and (a), (b), (c) and (d) are the level (1~4) or sharp lane changing defined in the survey, respectively. The gray section judged to be a sharp lane changing in the survey.

Sharp lane changes exhibit a back-and-forth pattern due to the nature of vehicle movement (R. Gao et al., 2022). *Figure 3* illustrates the staged sharp lane changing. It's noticeable that the Z-axis gyroscope value oscillates around 0(deg/s) during sharp lane change segments(gray). However, there are many cases where the Z-axis gyroscope value oscillates but doesn't correspond to an abrupt lane change, and the acceleration value is also inconsistent. This indicates the difficulty of establishing a straightforward definition for abrupt lane changes due to their complex and non-linear na-

ture. Moreover, sharp lane changes tend to oscillate rapidly from left to right in a short period, making it challenging to define solely based on observation.

Because of these reasons, we propose an XGBoost model to detect sharp lane changing. The XGBoost classification model results for staged abrupt lane changes are presented in *Table 2*.

Class	Precision	Recall	F1-score	Class	Precision	Recall	F1-score
Normal	0.97	0.99	0.98	*LC (L3)*	0.97	0.84	0.90
LC (L1)	0.95	0.92	0.93	*LC (L4)*	0.85	0.88	0.87
LC (L2)	0.89	0.80	0.84				
Accuracy	0.95						

Table 2. Table for evaluating XGBoost classification model results for sharp lane changing. *LC* is a sharp lane change and *L1* to *L4* are in that level.

3.   Conclusion

In conclusion, we developed a method using Carla simulator data to detect aggressive driving behaviors. We focused on rapid turns and sharp lane changes as indicators of aggression. Our approach involved a multi-stage classification for rapid turns and an XGBoost model for sharp lane changes, both showing promising classification accuracy. To validate our findings, we plan to apply and test our method with actual riders, ensuring its practicality and effectiveness in real-life situations.

Acknowledgement

References

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