Research Article

Modeling of Car-to-motorcycle Overtaking Maneuver Based on Comfort Zone Boundaries

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Abstract
Thailand has one of the world's highest road fatality rates, mainly on motorcycles. In mixed traffic, motorcycles coexist with other vehicles. The interaction between cars and motorcycles, such as overtaking due to speed differences, can lead to accidents. This scenario also has implications for autonomous vehicles interacting with motorcycles. To increase safety in such interactions, a model was developed that simulates overtaking maneuvers of car drivers with motorcycles, using the concept of comfort zone boundary and a four-phase classification. In a driving simulator, 648 overtaking maneuvers collected from 36 Thai drivers were recorded with different lateral positions and speeds of the motorcycles. A novel graphical method using steering wheel angle and steering wheel velocity signals facilitated the identification of the phases. Time-to-collision and lateral distance characterized driver comfort zones and served as an indicator for safety measures. The lateral position of the motorcycle has proven to be the most influential factor in the model. The results suggest that overtaking vehicles exhibit non-lane-bound driving characteristics and a risk for the sideswipe accident is identified. These results provide a foundational framework for advanced driver assistance systems and motion planning of autonomous vehicles, contributing to improved road safety.

Keywords: Comfort zone boundary, Driver behavior, Modeling, Overtaking maneuver, Steering intention

1 Introduction

Motorcycles are one of the most popular means of transportation in many regions of the world, especially in low- and middle-income countries such as Thailand, which has one of the highest rates of traffic fatalities in the world, with most deaths occurring on motorcycles [1]. Motorcycles tend to be more affordable than cars, and factors such as unmet transportation needs, urban congestion, cost-effectiveness, efficiency, and convenience contribute to their widespread use. Consequently, a significant proportion of motorcycles share the roads with other vehicles, leading to an increased risk of accidents due to interactions between them. This scenario is also relevant for autonomous vehicles when they become a common mode of transportation.

Autonomous vehicles can provide various potential benefits, such as improving road safety for all road users and reducing traffic congestion [2]. Autonomous vehicles are expected to become a prevalent part of the automotive landscape in the coming decades due to technological advancements. To be accepted by users, they must exceed the safety of the human driver, which is the most important benefit expectation of technological advancement. Furthermore, autonomous vehicles' ability to mimic human drivers' behavioral patterns is crucial for effective interaction, interpretation, and communication with other road users [3].

Autonomous vehicles can navigate safely through various traffic situations with the help of motion planning. Numerous methods and techniques have been introduced to determine feasible and optimal paths or trajectories while avoiding collisions with other vehicles and obstacles. These methods include graph search, incremental search, potential field, cell decomposition, optimal control, etc. [4], [5]. Although some of these methods take into account several constraints for comfortable driving (e.g., change in kinetic energy, jerk, lateral and longitudinal acceleration) [6]–[8], the resulting trajectories may differ from those of human drivers, which directly affects the on-board driving experience. Therefore, understanding driver behavior can improve the motion planning of autonomous vehicles.

Numerous studies have examined the behavior of drivers while driving, focusing primarily on interactions between cars, especially standard maneuvers such as following a car and changing lanes [9]. For more complex maneuvers, research has looked at the overtaking of a bicycle [10]–[15] and a pedestrian [16] by cars. Although the division of the overtaking maneuver into four phases (approaching, steering, passing, and returning) in combination with the concept of comfort zone boundary (CZB) allows the definition of safe and comfortable space around the bicycle or pedestrian, only the first three phases could be investigated due to technical limitations, especially when using LIDAR [12], [16] or the camera [13], [15] to measure the side of the overtaking vehicles.

In addition to vehicle position, dynamic information, such as steering wheel angle, steering wheel velocity, brake/accelerator pedal position, speed, heading angle, etc. can also be used as inputs to infer driver intent [17]. The use of these inputs varies. In some studies, inference was defined based solely on exceeding the fixed values of steering wheel angle [18]. The traffic context surrounding the vehicle, e.g. the speed of surrounding vehicles, is also used as a cue to infer the driver [19]. Artificial neural networks have been used to recognize drivers' intentions. Depending on the available input data, different techniques can be applied, including recurrent neural networks [20] and long short-term memory networks [21].

To the best of the authors' knowledge, the only study on overtaking of motorcycles by cars was conducted by Abe *et al*. [18]. This study investigated Japanese driving characteristics when overtaking a scooter using a driving simulator. In this study, the independent variables, i.e. the lateral position of the scooter and the speed, were limited to only two different values. The dependent variables focused exclusively on the time-to-collision (TTC) when the drivers started to steer, the maximum lateral distance between the car and the scooter, and the maximum passing speed. These variables cannot describe the entire overtaking process, and the chosen test conditions may not accurately reflect the particular driving behavior of motorcycles. These include the different choices of riding position on the road [22] and riding speed [23].

To improve the safety of autonomous vehicles, the understanding and modeling of human drivers have been extensively studied recently [9], [24]. Driver characteristics and accident prediction have been determined using different approaches such as theory-based, physics-based, and data-driven. Therefore, the main objective of this study is to develop a model that mimics the driver's maneuvers when overtaking a motorcycle, taking into account the influence of the motorcycle's lateral position and speed. Driver CZBs during overtaking maneuvers describe the comfort distances between the car and the motorcycle. The maneuver is divided into four phases and the distances around the motorcycle are systematically measured and recorded with a driving simulator. A new graphical approach is used to identify the steering intention which divides each phase. The results of this study have the potential to provide valuable insights for the improvement of autonomous driving strategies, especially in the area of motion planning.

2 Materials and Methods

2.1 *Definition of the overtaking maneuver and its phases*

In the middle of traffic, motorcycles generally maintain a slower speed than cars [23], which means that following car drivers often overtake slower motorcyclists. According to the observations, the drivers have two options to overtake a motorcycle: 1) to move to an adjacent lane and continue in the new lane, and 2) to move to an adjacent lane and then return to the original lane, as shown in Figure 1. This study focuses specifically on the second option.

This study adopted the four-phase model of

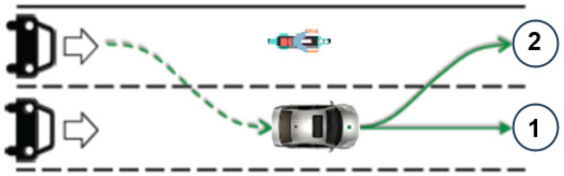

Figure 1: Two options for overtaking a motorcycle in the left-hand traffic system.

overtaking a bicycle [15]. The first phase of the overtaking maneuver on a motorcycle is the approaching phase. It begins when a car approaches behind the motorcycle and ends when the driver decides to steer away to avoid a collision. The second phase, steering away, then begins and ends when the driver steers the car in a straight direction again. The third phase involves a course adjustment, which allows the driver to correct the car's course considering the position of the motorcycle and successfully pass it. The returning phase, the fourth and final phase, begins when the driver decides to steer back to the original position in the lane. All phases of the complete motorcycle overtaking maneuver are shown in Figure 2.

The gaps around the motorcycle concerning the car, namely Gap_1, Gap_2, Gap_3, Gap_{Lat}, and Gap_4, quantify the driver's CZBs for phases 1 to 4. CZBs express the spaces where drivers do not feel uncomfortable and prefer to stay within [16]. Gap_1 and Gap_2 represent the distances between the rear of the motorcycle and the front of the following car in phases 1 and 2, respectively. Gap_{Lat} is the distance between the side of the motorcycle and the side of the car when they are parallel in the same longitudinal position. Gap_3 and Gap_4 are the distance between the rear of the car and the front of the motorcycle. These distances excluding GapLat can be quantified by Time-to-collision (TTC) between the motorcycle and the car according to Equation (1).

$$TTC_i = \frac{Gap_i}{\Delta V} \tag{1}$$

In Equation (1), $i \in \{1, 2, 3, 4\}$ indicates the phase in which TTC is calculated; Gapi is the longitudinal distance in each phase as defined in Figure 2, and ΔV is the speed difference between the leading and following vehicle.

2.2 *Measurement setup*

An experiment was conducted with the driving simulator of the Smart Mobility Research Center, Chulalongkorn University. The simulator is equipped with a six-degree-of-freedom motion base and uses sophisticated computer graphics to create a driving environment displayed on three screens (Figure 3). Visual and auditory stimuli were generated to represent changes resulting from the driver's inputs via a steering wheel, brake pedal, and accelerator pedal.

The overtaking scenarios were simulated on an urban road with left-hand traffic. The road consisted of four lanes with a one-meter wide island, as shown in Figure 4. The simulated motorcycle and the test vehicle measured 0.84 × 2.10 m and 1.83 × 4.58 m respectively. 36 drivers participated in this experiment, including 30 Thai males and 6 Thai females, with an average age of 36.33 years and a standard deviation of 5.82. All participants volunteered to participate in the experiment and had held a driver's license for more than 5 years. After they had given their consent, the participants were instructed in the tasks by the authors. Each driver had the opportunity to familiarize themselves with the driving simulator until they felt prepared. All drivers were instructed to perform the overtaking maneuver at their preferred speed. Participants were allowed to ask for breaks at any time during the experiment.

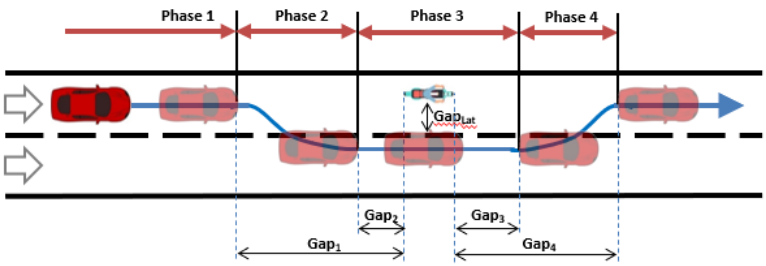

Figure 2: Four phases of the car-to-motorcycle overtaking maneuver.

Figure 3: A six-degree-of-freedom motion base driving simulator.

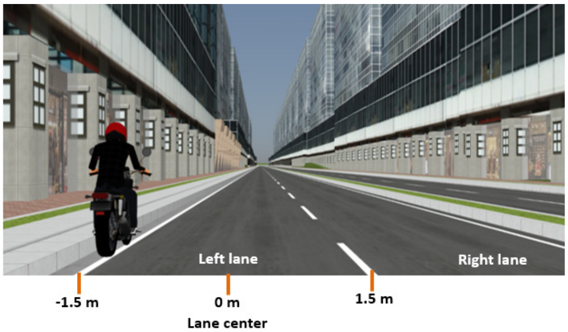

Figure 4: An urban-road driving scenario and a simulated motorcycle's position in the scene.

A driving scenario was created in which the motorcycle was ridden at different constant speeds and in different lateral positions. The motorcycle speeds (X_{mc}) were set at 20, 40, and 60 km/h. The motorcycle lateral positions (X_{mc}) varied from –1 m to 1.5 m in steps of 0.5 m, where 0 m was defined as the center of the lane, as shown in Figure 4. The negative sign of the lateral position indicates the left side of the lane center and vice versa. A total of 18 cases were considered in this scenario (3 speeds × 6 lateral positions).

In this controlled scenario, only the test car and the simulated motorcycle appeared in the scene, creating an open traffic situation. When the subject driver approached the simulated motorcycle at a certain distance, the overtaking maneuver was initiated. During the overtaking maneuver, the driver's behavioral data, including the steering wheel angle, steering wheel velocity, and passing speed (V_{pass}), were recorded with a sampling period of 0.1 s.

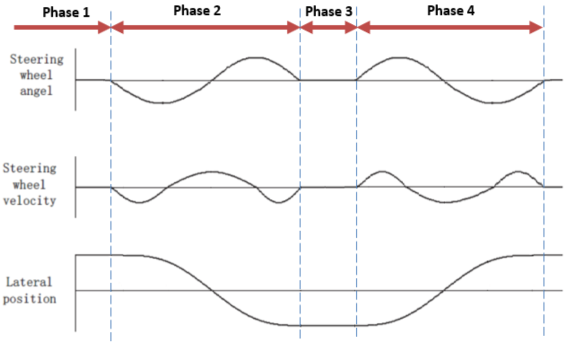

Figure 5: An idealized time course of the double-lane-change maneuver.

2.3 *Overtaking maneuver phase identification*

The overtaking maneuver can be conceived as a double-lane change maneuver. An idealized time course of the double-lane change maneuver is shown in Figure 5, where each phase is highlighted by both the steering wheel angle and the steering wheel velocity. However, the steering wheel velocity signal exhibited some distortions due to imperfect steering inputs from the subject driver, as shown in Figure 6 above. To address this, the steering wheel velocity values were converted to a –1, 0, and 1 signal, where the steering wheel velocity value less than zero was mapped to –1, the value equal to zero was mapped to 0, and the value greater than zero was mapped to 1, as shown in Figure 6 below. This change made it possible to identify the start and end of each phase.

2.4 *Data analysis and model development*

All data were analyzed using a descriptive analysis for each phase, supplemented by a graphical representation to determine the nature of the relationship. A correlation analysis was then conducted to determine whether X_{mc} and V_{mc} correlated across all variables, including statistical tests. Regression models were then developed for the identified relationships and validated by the coefficient of determination (R^2) for both linear and non-linear equations according to Equation (2).

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{2}$$

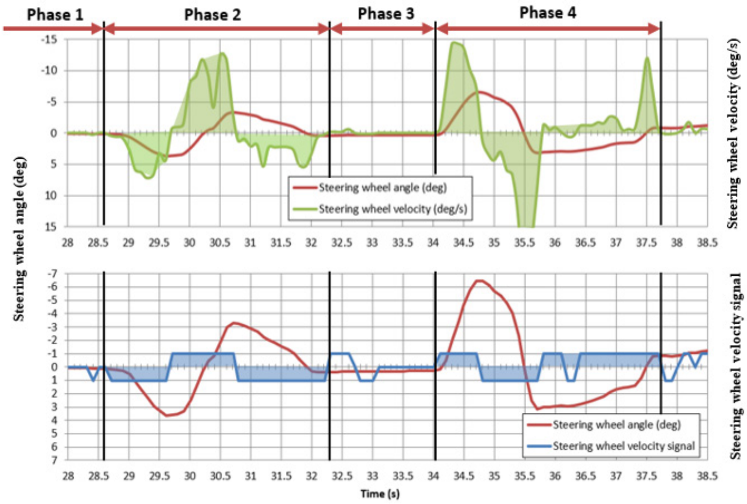

Figure 6: Time course of the steering wheel angle and steering wheel velocity when performing overtaking maneuver: raw data (above) and after signal conversion (below).

3 Results and Discussion

3.1 *Descriptive statistics and modeling*

A total of 648 overtaking maneuvers were captured and subjected to analysis. Three maneuvers were excluded due to difficulties in accurately identifying their phases. Table 1 summarizes the average values for TTC_1, TTC_2, Gap_{Lat}, V_{pass}, TTC_3, and TTC_4. The influence of X_{mc} and V_{mc} on the mean values and standard deviations of these parameters is visually represented in Figures 7 and 8, respectively.

Table 1: Average values of TTC_1, TTC_2, Gap_{Lat}, V_{pass}, TTC_3, and TTC_4

Phase	Variables	Average Values for all Test Conditions
1. Approaching	TTC_1	5.2–9.4 s
2. Steering away	TTC_2	1.3–2.1 s
3. Course adjustment	Gap_{Lat}	0.3–1.3 m
	V_{pass}	89–102 km/h
	TTC_3	–0.4–0.4 s
4. Returning	TTC_4	4.3–6.1 s

When considering the influence of X_{mc} across all motorcycle speeds ranging from 20–60 km/h, a linear increase in TTC_1 was observed with the lateral movement of the simulated motorcycle from the left to

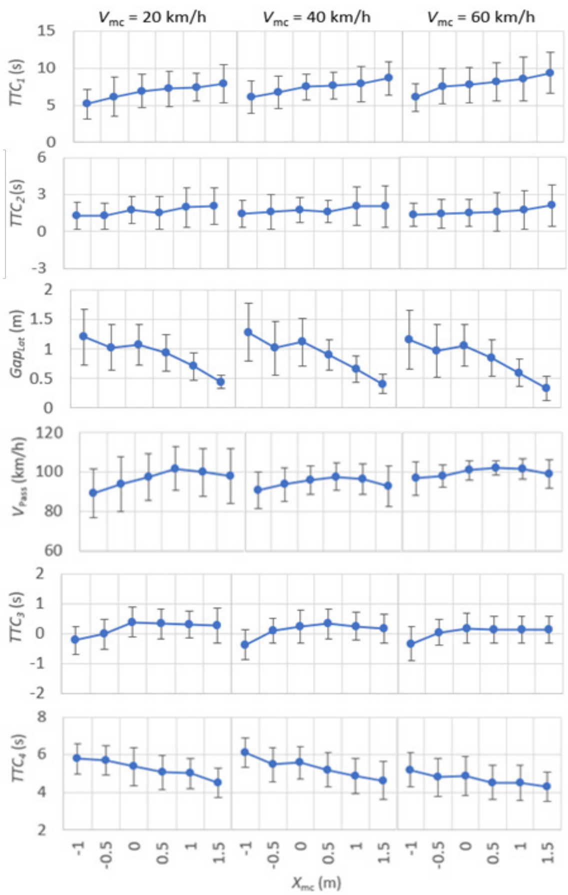

Figure 7: Effect of X_{mc} on CZBs in each phase.

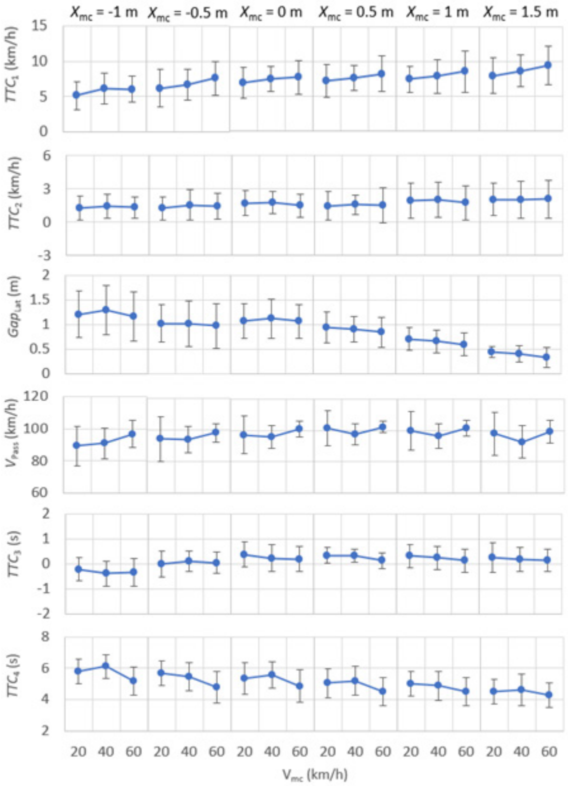

Figure 8: Effect of V_{mc} on CZBs in each phase.

the right of the lane. A similar linear trend was evident for TTC_2, demonstrating its increase with rising X_{mc} values throughout the considered speed range. A linear decrease in Gap_{Lat} was observed with increasing X_{mc} values across all motorcycle speeds. The passing speed (V_{pass}) demonstrated an initial increase followed by a decrease at X_{mc} = 0.5 m, regardless of the motorcycle speed. TTC_3 exhibited a continuous increase until reaching a near-constant state at X_{mc} values of either 0 or 0.5 m. A linear decrease in TTC_4 was observed with increasing X_{mc} across all motorcycle speeds.

The influence of V_{mc} on most data points for TTC_1 appeared to exhibit linear increases with rising V_{mc} across the entire motorcycle lateral position range (X_{mc}) from –1 to 1.5 m. In contrast to TTC_1, TTC_2 displayed relatively constant trends across the range of V_{mc} and X_{mc} values. Between X_{mc} = –1 and 0 m, Gap_{Lat} maintained consistent values. However, a downward trend emerged between X_{mc} = 0.5 and 1.5 m, indicating decreasing lateral gaps with increasing V_{mc}. Only when X_{mc} was at –1 m, V_{pass} exhibited a clear increasing trend. But for other X_{mc} values, no discernible trend was evident. Similar to V_{pass}, neither TTC_3 nor TTC_4 displayed any recognizable trend within the analyzed range of V_{mc} and X_{mc} values.

Table 2 presents the outcomes of the correlation analysis. Corroborating the observations from Figures 7 and 8, these results imply a significant impact of the motorcycle lateral position on each phase, albeit in varying degrees. The correlation of motorcycle speed, conversely, appears minimal. Consequently, the regression models for each phase, solely incorporating the motorcycle lateral position as a predictor, are outlined in Table 3.

Table 2: Correlation coefficients across all variables for X_{mc} and V_{mc}. * indicates p-value < 0.001

Variables	r	
	X_{mc}	V_{mc}
TTC_1	0.86*	0.44
TTC_2	0.88*	–0.01
Gap_{Lat}	–0.94*	–0.10
TTC_3	0.69*	–0.24
TTC_4	–0.79*	–0.45

Table 3: Regression model of each phase

Equations	R^2	p-value
$TTC_1 = 1.04X_{mc} + 7.12$	0.74	0.000
$TTC_2 = 0.28X_{mc} + 1.59$	0.78	0.000
$Gap_{Lat} = –0.31X_{mc} + 0.95$	0.88	0.000
$TTC_3 = 0.29\log_e(X_{mc} + 1.5)$	0.68	0.000
$TTC_4 = –0.46X_{mc} + 5.2$	0.62	0.000

Note: $X_{mc} \in$ {1, –0.5, 0, 0.5, 1, 1.5}

3.2 *Driver behaviors during overtaking*

This study on an urban multi-lane road revealed that the subject drivers initiated steering maneuvers for overtaking earlier, as indicated by larger TTC_1 values when the motorcycle was positioned to the right of the left lane center. Notably, the motorcycle's lateral position of –0.5 m from the center aligns with that employed in [18]. In this study, average TTC_1 values ranged from 6.2 to 6.7 s for motorcycle speeds of 20 and 40 km/h, respectively. These values are lower compared to the average of 7.2 s [18] for a motorcycle speed of 30 km/h. As discussed later, applying the steering intention identification technique from this study to the data in [18] would likely yield significantly higher TTC values at the onset of steering maneuvers. This finding suggests that Japanese drivers may initiate overtaking maneuvers considerably earlier than Thai drivers.

At the end of phase 2, the subject drivers completed the first steering maneuver, before their car's front reached the motorcycle's rear, within a very narrow time window averaging around 1.3 to 2.1 s across all motorcycle lateral positions and speeds.

The analysis of phase 3 revealed a distinct behavior by subject drivers. As the simulated motorcycle shifted laterally from left to right, they demonstrably reduced their lateral gap (on average, from 1.3–0.3 m) while maintaining very high passing speeds (ranging from 89–102 km/h). Notably, when the motorcycle occupied a lateral position of –0.5 m from the left lane center, the average lateral gap recorded for passing speeds of 93.8–98.1 km/h was approximately 0.97–1.02 m. This contrasts with the findings presented in [18], where an average lateral gap of 1.2–1.3 m was observed at a passing speed of 74 km/h under the same test conditions.

At the end of phase 3, the subject drivers initiated steering corrections earlier (approximately –0.4 s on average) when the simulated motorcycle was positioned –1 m from the left lane center. As the simulated motorcycle shifted laterally rightward, TTC_3 values initially increased. However, they stabilized around 0.1 to 0.4 s on average once the motorcycle reached the center of the left lane (0 m position).

The subject drivers generally completed their second steering maneuver in phase 4 after their car had already passed the end of the simulated motorcycle. This completion time ranged from 4.3 to 6.1 s on average across different motorcycle positions. With increasing lateral positions of the simulated motorcycle, the subject drivers exhibited a tendency to reduce the distance traveled during their return steering maneuvers. A direct comparison between phases 3 and 4 in this study and [18] is not possible. This is because the previous study did not record these specific phases in their experiment.

Intriguing results emerged when the subject drivers encountered the simulated motorcycle positioned 1.5 m to the right of the left-lane center, simulating a motorcycle riding on the lane dividing line. In this scenario, all drivers opted to overtake on the right side of the motorcycle, despite lacking instructions prohibiting unsafe overtaking maneuvers. This behavior suggests a natural inclination among Thai drivers to pass motorcycles on the right, even without explicit regulations forbidding it. Interestingly, the lateral gap recorded in this case was the lowest across all conditions, averaging a mere 0.3 m. This observation potentially indicates that Thai drivers are comfortable with very narrow gaps when passing motorcycles. This comfort level could be attributed to their familiarity with motorcycles frequently maneuvering around cars, particularly considering the widespread practice of lane-splitting in Bangkok and surrounding areas. Several factors might contribute to this overtaking behavior. The Thai regulation mandating motorcycles riding in the left lane might lead drivers to expect them only in that lane, prompting them to overtake on the right even with limited space. The driving simulator's inability to perfectly replicate real-life situations and perspectives [25] might also influence driver behavior. Additionally, drivers might be subconsciously aware the simulated motorcycle is not real and consequences like accidents are absent in the simulator environment. It is crucial to acknowledge that driver responses and lateral gap values may differ significantly in real-world scenarios, especially considering aspects like accident avoidance and wider roads (e.g., six lanes). Therefore, further studies are necessary to comprehensively understand these overtaking behaviors in real-world conditions.

Another interesting finding was the overtaking strategies employed by the subject drivers, potentially influenced by whether they followed lane-based or non-lane-based driving patterns. Lane-based driving signifies a tendency to stay close to the lane center [26]. To categorize driving behavior, the lateral position of the subject car in phase 3 was analyzed. If a driver significantly steered away from the original lane center, approximately 3 m towards the adjacent lane center, and maintained that position throughout the phase, this was considered full lane change, signifying lane-based driving. Conversely, any behavior demonstrating deviation from this full lane change was classified as non-lane-based driving. Figure 9 illustrates the average lateral positions of subject cars relative to the left lane center, influenced by various motorcycle lateral positions and across different motorcycle speeds. The observed steering-away distances from the lane center did not reach the full 3 m indicative of

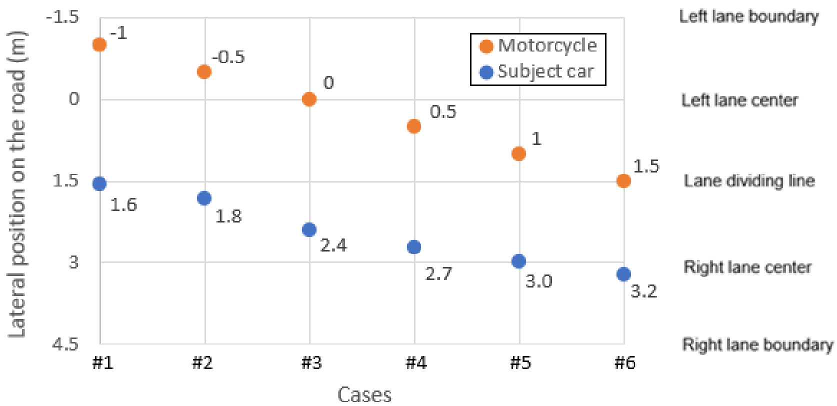

Figure 9: Average lateral positions of subject car and motorcycle in phase 3 in different conditions.

lane change. This finding suggests that subject drivers predominantly adopted a non-lane-based driving strategy during overtaking maneuvers. Although steering-away distances approached 3 m when the simulated motorcycle was positioned 1 and 1.5 m from the left lane center, this was still categorized as non-lane-based driving. This behavior can be attributed to the drivers' balance of the lateral gaps between the motorcycle and the right lane boundary. Notably, studies presented in [16], and [18] also categorize such driving patterns as non-lane-based.

3.3 *Behavioral data as the baseline of motion planning for autonomous vehicles and safety aspects*

This study offers valuable insights for designing safe and efficient autonomous vehicle overtaking maneuvers of motorcycles traveling in the same direction, potentially applicable to bicycles as well. By training artificial neural networks, particularly Recurrent Neural Networks, on empirical driver trajectories like those collected here, autonomous vehicles can learn and imitate human-like overtaking behaviors. These networks excel at handling time-series data involved in such maneuvers [27]. Another trajectory planning technique that can benefit from these results is the concept of virtual reference points positioned at specific distances from the lead vehicle [28]. However, prioritizing safety is paramount. Autonomous vehicles must incorporate both TTC for longitudinal safety (ensuring sufficient stopping distance) and lateral gap for lateral safety (maintaining a safe distance from the motorcycle) regardless of observed human driving behaviors, which may not always be safe [29]. This approach, coupled with a rigorous focus on ensuring safety, may pave the way for autonomous vehicles to develop smooth and safe overtaking capabilities.

Phase 1 emphasizes safety by acknowledging the need for sufficient space, or safe headway, between the subject car and the lead motorcycle to react and brake in case of emergencies like the motorcycle losing control. Real-world and simulated studies recommend a minimum TTC_1 of 4 seconds for human drivers, considering 1.5 s for reaction time and 2.5 s for braking [30], [31]. Only 8% of observed TTC_1 values in this study fell below this 4-second threshold, indicating that the subject drivers generally maintained a safe front headway when approaching the motorcycle. This adherence to safe following distances signifies responsible driving behavior.

Phase 3 highlights a potential safety concern in Thailand regarding lateral clearance when passing motorcycles. Unlike some countries like Australia and European nations with mandated minimum gaps (ranging from 1–1.5 m), Thailand lacks such legislation, similar to Japan [14], [15]. In this study, a concerning finding emerged: 89% of lateral gap measurements in phase 3 fell below 1.5 m, a violation of the Australian safety criterion used here. This suggests that subject drivers often pass motorcycles with less space than considered safe in other countries. Similarly, the lateral gaps observed in [18] would also be deemed unsafe based on the chosen criterion.

Phase 3 also reveals additional safety concerns related to TTC_3. While no established safety criterion exists for TTC_3, a value of zero might be acceptable when the overtaking car is faster than the motorcycle [32]. However, ensuring the following driver/rider feels comfortable and avoiding aggressive cut-in maneuvers necessitates additional space [33]. Unfortunately, no research has investigated motorcyclists' safety perceptions in this context. Therefore, this study employed a 0-second gap as a placeholder. 50% of TTC_3 values fell below 0 s, exceeding the assumed safety limit. This, combined with the very low Gap_{Lat} values observed, suggests a high risk of sideswipe accidents due to improper cut-in maneuvers. This finding potentially explains why sideswipe accidents are the second-highest cause of motorcycle accidents in Thailand [34].

If the model developed in this study is used for autonomous vehicle motion planning, particularly prioritizing safety, it might require modifications. Addressing these limitations is crucial for designing safe and responsible autonomous vehicle overtaking behaviors that prioritize the safety of all road users, including vulnerable motorcyclists.

3.4 *Steering intention inference method*

This study successfully employed a novel graphical method for identifying steering intention, achieving a 99.5% accuracy rate compared to 95.9 and 100% reported in previous studies using hidden Markov models [19] and fixed steering wheel angle values [18] respectively. The key strength of the graphical method lies in its ability to accurately detect the onset of steering maneuvers, particularly under low steering wheel angle magnitudes, which aligns well with the partial lane-changing behavior observed in Figure 10. Additionally, this method is simple compared to hidden Markov models, reducing computational complexity. However, the method was not infallible. Some cases presented challenges in classifying steering intention due to imperfect driver inputs and non-standard patterns. Variations in individual driving styles and potential inconsistencies in steering wheel control could introduce noise into the data. Also, deviations from expected steering wheel angle and velocity patterns could complicate the identification of clear dividing points between phases.

While the steering wheel angle and velocity effectively capture driver responses to their surroundings, they suffer from a crucial drawback, i.e. latency.

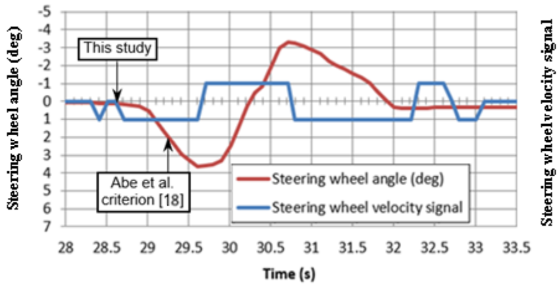

Figure 10: Comparison of steering initiating point.

Compared to direct observations of driver behaviors and real-time traffic context, data derived from steering inputs arrives with a slight delay, limiting its potential for immediate prediction of driver intentions [17]. Despite this limitation, the graphical method employed in this study demonstrates the utility of steering data for post-analysis purposes.

3.5 *Limitations*

This study offered valuable insights into driver overtaking behaviors for a motorcycle traveling in the same direction. However, acknowledging its limitations is crucial for interpreting the findings and guiding future research. The assumption of a straight-riding motorcycle may not fully capture real-world scenarios where motorcycles might swerve during overtaking. The influence of surrounding vehicles, such as the leading car and following car, was not investigated. The study did not consider the impact of nighttime conditions on visibility and driver decision-making.

In real-world scenarios, numerous additional potential overtaking situations exist, such as motorcycles stopping at the outer lane edge, decelerating in various lanes, parallel parking, double-stopping, or using the inner lane. Future research should investigate these expanded scenarios to gain a more comprehensive understanding of driver behavior and potential safety concerns during car-motorcycle overtaking.

4 Conclusions

This study explores driver behavior during car-motorcycle overtaking maneuvers in simulated left-hand traffic urban environments. Drawing upon the CZB concept, a model was developed to capture and describe the driver's decision-making process throughout the overtaking sequence. This model identifies four distinct phases within the maneuver and introduces a novel graphical method for identifying the driver's steering intention. Data for the study was collected from Thai drivers participating in a driving simulator that mimicked realistic urban road conditions.

This study presents a key finding regarding driver behavior during car-motorcycle overtaking. Motorcycle lateral position significantly outweighs motorcycle speed in influencing driver decisions. Notably, each phase of the overtaking maneuver was affected by the motorcycle's lateral position in unique ways. This emphasizes the crucial role of considering motorcycle position, beyond just speed, for understanding and predicting driver behavior during overtaking.

Furthermore, the study observed non-lane-based driving behavior, where drivers did not strictly adhere to the lane center, particularly in response to motorcycle position. Additionally, the results suggest a potential contributor to sideswipe accidents involving motorcycles. This finding underscores the need for further research and interventions to promote safe overtaking practices that prioritize the safety of all road users, including motorcyclists.

This study's findings can serve as a valuable baseline for developing advanced driver assistance system features like low-gap warnings and autonomous vehicle motion planning in motorcycle overtaking scenarios. However, it's crucial to acknowledge that the proposed models included some unsafe characteristics, such as car-motorcycle lateral distances falling below 1 m during overtaking and steering back before fully passing the motorcycle. The safety conditions should be considered to ensure the safe application of these findings.

Acknowledgments

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Author Contributions

S.S.: conceptualization, methodology, research design, investigation, data analysis, writing an original draft, visualization; S.K.: writing—reviewing and editing; G.P.: software, resources, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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