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Can Variations of Vehicle Driving Status Provide Accurate Predictors of Discomfort? A Study on the Actual Driving Test

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ABSTRACT The ride comfort of bus passengers is a critical factor that is recognized to attract greater ridership towards a sustainable public transport system. However, it is challenging to predict bus passenger comfort due to the complex non-linear interaction among various factors. In an application-based study, 18 real driving tests were conducted to analyze the correlation between factors induced by motion sickness and the driving status of the vehicle. We used the user's feedback module (UFM) to record the feelings of passengers, and the six degrees of freedom (6-df) motion parameters were obtained by the accelerometer in the micro electro mechanical system (MEMS) of the smartphone. Then, the data were discriminated and analyzed, and thresholds of the variables affecting the discomfort of passengers in different conditions were obtained. Finally, we established a prediction model of motion sickness duration based on the driving status of vehicles. The result shows that passenger's comfort is most sensitive to vertical acceleration changes when the vehicle is decelerated, and the duration of motion sickness (DMS) can be effectively predicted (79.8%) by the vehicle's lateral acceleration, roll, and pitch angular velocity indicators. The findings of this study provide insights into the potential theoretical basis for policymakers to improve the adjustment of the driving strategies and path trajectory of city buses.

INDEX TERMS Acceleration, Lasso regression, motion sickness, passenger comfort, traffic engineering.

I. INTRODUCTION

Comfort is a significant factor that affects passengers' choice of public transportation. Compared with cars, buses will accelerate and decelerate more frequently because the passengers get on and off, which may bring challenges to passenger comfort. With the development of public transportation, the pursuit of buses is no longer limited to safety, and the improvement of comfort is unavoidable. In addition, there is a strong correlation between the comfort and utilization of buses [1]. At present, there are more and more passengers with motion sickness. According to a new international survey on motion sickness, about four thousand people from China, the UK, Brazil, and Germany were surveyed about their experiences of motion sickness and found that 59% of them indicated they had experienced motion sickness in the past five years as a passenger in a car, including childhood experiences [2]. The highest and lowest incidence of motion sickness were reported in China and Germany, respectively. However, if we can understand the factors affecting passenger comfort, and improve the driving strategy and optimize the interaction between buses and passengers accordingly, the frequency and degree of motion sickness of passengers will be effectively reduced, and the riding comfort of passengers will be improved.

Research on passenger comfort as well as motion sickness is in full swing. Existing research on passenger comfort has mainly concentrated on the physiological mechanism of motion sickness, the driving behavior of the driver, and the interior environment of the vehicle. Bles *et al.* [3] put forward the subjective vertical conflict theory, which assumed that motion sickness is caused by the accumulation of conflicts between the vertical direction of the body perceived by the sensory organs and the movement predicted by the central nervous system. Based on the theory of sensory conflict, Morimoto *et al.* [4] added visual stimulation to the

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vehicle display, which can reduce the severity of motion sickness. Wada *et al.* [5], [7] and Fujisawa *et al.* [6] derived a mathematical model of motion sickness caused by head motion in 3D space based on subjective vertical conflict, and a vehicle control method for minimizing dizziness was proposed. These results strongly suggest that the driver's head tilt reduces motion sickness. Furthermore, Kuiper *et al.* [8] explored the role of anticipation in motion sickness by comparing three conditions varying in motion predictability. Then they assessed the effect of anticipation on subsequent illness ratings using a within-subjects design, which underlines the importance of an individual's anticipation to motion in motion sickness.

In addition, Newman *et al.* [9] found that motion sickness largely depends on the visual scene, and horizontal acceleration with a frequency lower than 0.1Hz will lead to motion sickness, while Kuiper *et al.* [10] found that in the lateral sinusoidal motion, average motion sickness on an 11-point scale was 2.21 + /- 1.97 for 0.2 Hz and 1.93 + /- 1.94 for 0.35 Hz. Rinaldi *et al.* [11] evaluated the results by using the Lilliefors test and discussed the influence of lateral acceleration and angular acceleration on the symptoms and level of motion sickness of people. Saruchi *et al.* [12], [13] proposed an inner-loop lateral control strategy which utilized head roll angle to generate corrective wheel angle to reduce the lateral acceleration, and a time delay neural network (TDNN) was utilized to model the correlation of the occupant's head movement and lateral acceleration. However, they don't pay attention to the motion of buses except for lateral vection (Vection refers to various cognitive factors that can influence self-motion perception in virtual reality), such as vertical and longitudinal vection, which could cause discomfort to passengers. The traditional test methods are limited by the passengers not being able to evaluate the discomfort by different symptoms, which leads to the inability to analyze the impact of vehicle motion parameters quantitatively accurately on passenger comfort. In our test, the subjects can evaluate the discomfort combined with specific symptoms, which can accurately analyze the relationship between vehicle motion parameters and passenger discomfort.

Some authors evaluated the passenger comfort by the adoption of embedded systems or IMU. By integrating subjective measurements of driving style with objective measurements of longitudinal and transversal accelerations collected by intelligent transportation system tools, Barabino *et al.* [14] established a comfort scale in a real operational environment as a tool to regulate driver behavior, i.e., each driver would be able to recognize when passengers experience conditions of discomfort and acts to improve comfort. Lin et.al [15] proposed a novel Comfort Measuring System (CMS) for public transportation systems. Then, it mashed up the sensed data with the authorized data of the public transportation system and provided a detailed comfort statistic as a value-added service. Coni *et al.* [16] analyzed the correlation between some geometric and cinematics road parameters that may affect the comfort and the different passenger's judgments on the three acceleration components by age classes and hourly day. The results generally show weak correlations between the selected parameters and passenger judgments. To relate vehicle motion with the comfort of the actual experience, some scholars studied by using questionnaires as well as verbal ratings. In Turner and Griffin's study [17]–[19], self-report data about motion sickness were limited to overall symptom ratings obtained from questionnaires, which were administered only once, near the end of each journey. Barabino *et al.* [14] evaluated the passenger comfort related to vehicle motion event, but the vertical component of the acceleration was disregarded, since subjective evaluations were not performed.

By means of the spatial oscillatory model of the intercity bus IK-301 with ten degrees of freedom, Sekulic et.al [20], [21] assessed oscillatory comfort in the driver and passengers according to the 1997 ISO 2631-1 standard, as well as the allowable vibration exposure time in drivers for the reduced comfort criterion. On the basis, they found that the most comfortable oscillatory zone is in the middle part of the bus, whereas the least comfortable oscillatory zone is on the rear bus overhang. Maternini and Cadei [22] proposed and gave an initial validation of a comfort scale, putting into relation a specific comfort index with the dynamic effects on standing bus passengers and with certain road characteristics. They found a correlation between these indexes and the dynamic effects felt by bus passengers. By adopting a set of independent measures, the jerk algorithm was developed by Castellanos and Fruett [23] to determine the Comfort Index with Acceleration Threshold Detection (CIATD). According to the speed, acceleration, and other operating characteristics of the vehicle, a relatively mature embedded system combined with the CIATD index was established. However, they provided only qualitatively analysis of these subjective report data, without independent variables or inferential statistical tests. That is, their study was observational, rather than experimental.

Through the above literature review, we can find that most of the studies considering passenger comfort, whether it is the lateral movement or the longitudinal motion of the vehicle, take vehicle acceleration and jerk as discomfort or motion sickness indicators. However, when setting the index threshold, the difference in the symptoms of different passengers to vehicle motion parameters is not considered. Based on the above research, we accurately record the passenger's feeling through the actual driving test, use the smartphone with MEMS to collect the data of the vehicle's six degrees of freedom (6-df) acceleration and angular velocity, and conduct discriminant analysis and research on the characteristics of passenger comfort and motion sickness. Motion sickness discussed in the present article primarily refers to a serious type of discomfort. It is helpful to answer the following questions: 1. Which vehicle motion parameters change significantly causing passenger discomfort? 2. What are the thresholds of the characteristic that affect passenger discomfort? 3. Can the vehicle motion parameters predict the DMS?

TABLE 1. Characteristics of the vehicle employed.

Configuration parameters	Basic information
Announcement model	XMQ6115AYD5C
Purpose	Bus for passengers/tourist /group
Seating capacity	49
Body length/ width/ height	11500mm/2550mm/3670mm
Vehicle mass	12000kg
Swept volume	8424ml
Body structure	Unibody
Maximum speed	100km/h

The rest of this article is structured as follows. Section 2 describes the scenarios, materials, implementation processes, and data processing methods of the test. Section 3 analyzes the characteristic variables and establishes a prediction model for the DMS. The results are discussed in section 4 and the findings of this study are drawn from section 5.

II. METHODS AND MATERIALS

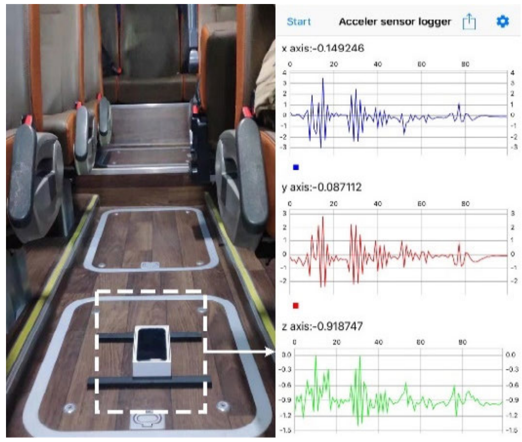
A. PARTICIPANTS

The volunteers were recruited online and offline in Chang'an University. A total of 22 volunteers were recruited (mean age 26.1 years, SD = 7.03; 5 women). To better complete the test, participants were required to be in a healthy physical state, and they did not have a history of acute heart disease and other diseases that were not suitable for the test. Participants were also required to not take alcohol and other neurogenic drugs that affect the physiological conditions within 48 hours before the test, and they should sign the informed agreement before the test to show that they clearly understand the content and purpose of the test.

The test vehicle was driven by professional drivers. To ensure safety during the test, the driver was required to hold a valid A1 level license for at least 3 years and drive at least 9000 km per year. More importantly, there was no record of major accidents or drunk driving during work. The driver was not aware of the study as well as the purpose of the test. The scheme of the test had been approved in advance by the ethics committee of Chang'an University.

B. DEVICE

To eliminate the influence of uncertain factors such as weather and accidents in the test and avoid excessive travel times, the Jinlong XMQ6115AYD5C bus (as shown in Table 1) was used in the test, and a smartphone (iPhone 7, Figure 1a) was installed at the vehicle center of gravity, which can collect location (GPS) and motion data of the vehicle. The 3-axis coordinate system of the smartphone was aligned with the 3-axis coordinate system of the vehicle to maintain consistency with the vehicle's movement. The application software (Acceler log, Figure 1b) of the smartphone was used to call the built-in MEMS sensor (InvenSense 773C) to collect 6-df motion data of the vehicle. During the test, the motion data of the vehicle were recorded at a frequency of 100 Hz,



(a) (b)

FIGURE 1. The fixed location of the IOS smart device (a) and the operation interface of Acceler log (b).

FIGURE 2. UFM (User's feedback module).

including linear acceleration (lateral, longitudinal, and vertical) and angular velocity (roll, pitch, and yaw). The change of motion data indicates the state of vehicle movement.

The user's feedback module (UFM, Figure 2) was used to mark the timestamp of the device that the passenger pressed during the test, which was made based on the programed K60 single-chip microcomputer, which was then welded to a circuit board, as depicted in Figure 2. The four keys (KEY1\KEY2\KEY3\KEY4) of the UFM represent different types of discomforts and motion sickness. During the test, the events recorded by UFM are synchronized with the acquisition time of motion data. All recorded data will be saved as a.csv file that can be used for offline analysis.

C. TEST PROGRAM

A route in Xi'an, China (Figure 3) was chosen for a real driving test. The total length of the route is 28.5km, including urban expressway and main roads, with a speed limit of 60 km/h −80 km/h (Table 2). The tests were conducted during peak traffic hours. Before the test, participants completed a questionnaire about their travel history to assess their initial symptom level and make sure they were familiar with the symptoms of motion sickness.

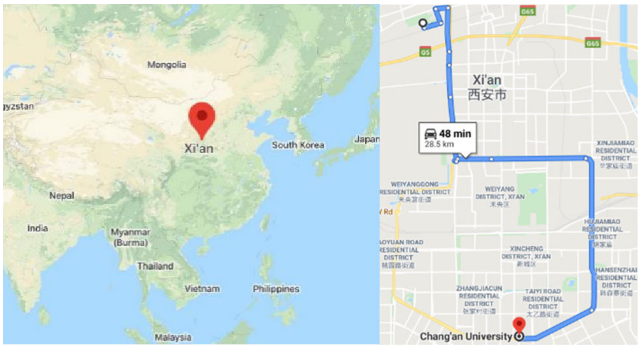


FIGURE 3. Route of real driving test (28.5km, 48min of driving).

TABLE 2. Detailed information of the test route.

#	Name	Length	Type
1	Mingyuan Rd	0.84 km	Approach
2	Shangyun Rd	1.3 km	Approach
3	1st Caotan Rd	1.2 km	Main
4	Side Rd of Airport Expressway	1.4 km	Main
5	Zhuhong Rd	4.9 km	Arterial
6	West section of 2nd Ring North Rd	6.1 km	Arterial
7	2nd Ring East Rd	2.2 km	Expressway
8	Jinhua Tunnel	0.397 km	Arterial
9	2nd Ring East Rd	3.9 km	Expressway
10	2nd Ring South Rd	3.6 km	Expressway
11	Side Rd of Second Ring South Rd	1.4 km	Main
12	Jingye Rd	1.3 km	Approach

TABLE 3. Standard of discomfort.

Causes of discomfort	Symptoms	Test 1	Test 2
Sharp acceleration	Leaning back and back-pushing sensation in sitting posture, having strong feeling of vehicle acceleration	KEY1	KEY1
Sharp deceleration	Leaning forward and being pulled by the seat belt in sitting position, having strong feeling of braking	KEY1	KEY2
Sharp turning / lane changing	Body tilting and the balance is broken, barely maintaining the stability, having strong feeling of direction changes	KEY1	KEY3
Environmental factor	Uncomfortable feeling due to abnormal smell (gasoline, etc), noise (vehicle whistle, etc), dazzling light, abnormal temperature/ humidity	KEY1	–
Sharp acceleration/ deceleration/ turning/ lane changing	Nausea, lethargy, dizziness and headache, increased saliva, cold sweating, pale complexion	KEY4	KEY4

All participants in each test were divided into 3 groups, and each with 2 participants. They were distributed in the front, middle and rear areas of the vehicle. Each member of the group was required to press the corresponding button (KEY1\KEY2\KEY3\KEY4) on the UFM according to the standard in Table 3 when he or she feels discomfort caused by the vehicle's motion. Participants were trained uniformly before the test to ensure familiarity with the standards and operations.

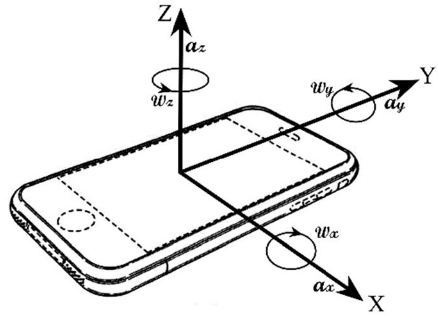


FIGURE 4. Datum coordinate system.

In Test 1, participants were allowed to press KEY1 and KEY4 on the UFM. KEY1 corresponds to "uncomfortable feelings" and KEY4 corresponds to "MS attack/end". If participants feel any discomfort to the body, they will press KEY1. If participants feel that motion sickness occurs or disappears, they will press KEY4.

In Test 2, participants were allowed to press KEY1, KEY2, KEY3, and KEY4 on the UFM. KEY1 corresponds to "discomfort due to rapid acceleration". KEY2 corresponds to "discomfort due to rapid deceleration". KEY3 corresponds to "discomfort due to vehicle diversion or turning". KEY4 corresponds to "onset/end of motion sickness". Participants need to classify the discomfort caused by vehicle movement and press the corresponding button accurately and timely, which is different from Test 1.

We set the Test 1 (north to south) as the controlled trial of Test 2 (return, south to north). More specifically, under the condition of the same test route, period, vehicle, participants, we found that the proportion of discomfort caused by environmental factors is very small (8.8%) in Test 1, which means that the discomfort caused by environmental factors had very limited influence on the discomfort caused by vehicle movement.

Participants were free to talk to each other during the test. They were required to follow local regulations and fasten their seat belts. If participants feel unwell and cannot proceed with the test, the test should be stopped. At the end of the test run, the data were exported and checked to confirm the synchronization and validity of the time.

D. DATA PROCESSING

This study establishes a datum coordinate system based on ISO 2631-1 [24], with the vehicle horizontally to the right as the X-axis positive direction, the vehicle forward direction as the Y-axis positive direction, and the vehicle vertical upward direction as the Z-axis positive direction (Figure 4).

The function of the acceleration/angular velocity sensor is to measure the acceleration and angular velocity of an object along the axis. In practical applications, the moving status of the object can be determined, and it has high dynamic characteristics. The basic calibration of the acceleration/angular velocity sensor found that its output has a floating of 1%

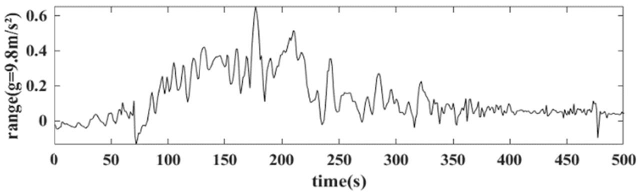


FIGURE 5. Acceleration of X-axis unfiltered.

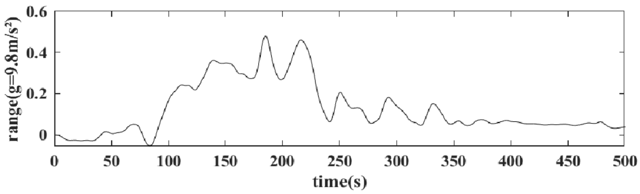


FIGURE 6. Acceleration of X-axis filtering.

(fixed error), and we used a digital filter to eliminate the fixed error.

It cannot be ignored that continuous testing for a long time will raise the temperature of the sensor and cause zero drift, which will affect the accuracy of data collection. Besides, the random noise generated by the engine vibration of the vehicle also has a large impact on the accuracy of the sensor. Therefore, we use the global threshold denoising based on wavelet analysis to filter the data. Continuous Wavelet Transformation (CWT) is a multi-scale, low-entropy signal analysis method with strong recognition capabilities in both time and frequency domains. The function is as follows:

$$CWT\,(s,\tau) = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{\infty} f\,(t) * \exp - \left[\frac{i\omega_0\,(t-\tau)}{s} + \frac{(t-\tau)^2}{2s^2}\right] dt \tag{1}$$

where s represents the scale of the wavelet function; τ represents the translation of the wavelet function; $f\,(t)$ represents the original input signal; ω_0 represents the centre frequency; t represents the time; i is a constant, taking 1, 2..., n.

By transforming the original signal data to the wavelength domain, the small wave coefficient with random noise was suppressed as the subject. The signal was reconstructed by using the processed wave coefficient to obtain the signal after suppressing random noise. Part of the data before and after filtering is shown in Figure 5 and Figure 6.

III. RESULTS

A total of 157 key-presses were recorded. According to different causes of passenger's discomfort, 52 key-presses due to sharp acceleration (KEY1), 62 key-presses due to sharp deceleration (KEY2), and 23 key-presses due to sharp turning/ lane changing (KEY3). 20 events of passenger motion sickness (KEY4) were recorded. We extract the 6-df acceleration and angular velocity data fragments within the first 3s of each key-press, and after removing 5% of the maximum and minimum at both ends of the 3s data segment, the average of the rest is taken as the sample value. Table 4 provides some records of raw data collected.

TABLE 4. Some records of raw data collected.

Time	a_X	a_Y	…	ω_Z	Type of the button
14:40:59.937	0.1438	-0.1328	…	0.1103	KEY2
14:40:59.946	0.1409	-0.1324	…	0.1120	
…	…	…	…	…	…
15:03:52.008	0.0347	-0.0414	…	-0.0084	KEY4
15:03:52.017	0.0349	-0.0441	…	-0.0086	
…	…	…	…	…	…
15:04:03.997	0.1012	-0.0560	…	0.0880	KEY4

FIGURE 7. Bivariate Pearson correlations between 6-df variables (The size of circle represents the correlation coefficient of two variables, corresponding to the number displayed in the circle.)

A. DISCRIMINANT ANALYSIS

We take the passenger's discomfort (determined by the type of key) as the observation variable and take the acceleration and angular velocity of each axis of the vehicle as the influencing factors. Based on Table 1, the variable corresponding to pressing KEY1 is determined as the positive longitudinal acceleration (a_{y+}), and the variable corresponding to pressing KEY2 is determined as the negative longitudinal axis acceleration (a_{y-}).

However, the variable corresponding to KEY3 cannot be simply determined as linear acceleration or angular velocity. Therefore, Pearson correlation analysis was performed on the collected 6-df motion data (Figure 7). The results show that the X-axis acceleration a_x has a strong correlation with Y-axis acceleration (a_y) and angular velocity (ω_y) ($|\,r\,| > 0.9$), and there is a strong correlation between a_y and ω_y ($|\,r\,| > 0.8$).

To prevent the redundancy of variables, we analyzed an ANOVA of other motion variables without considering a_y and ω_y to determine the variables that have the most significant effect on the press of KEY3. The results of ANOVA show that a_x, F (44,45) = 108.142, $p < 0.001$, and ω_z, F (44,45) = 39.006, $p < 0.001$, have a significant effect on the press of KEY3. Therefore, we choose a_x and ω_z as the variable corresponding to the press of KEY3.

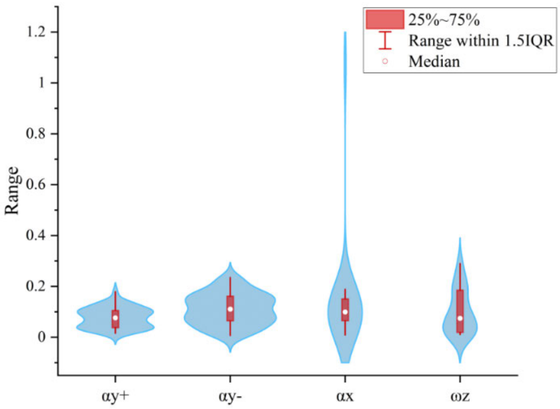


FIGURE 8. **Distribution of the variables.**

The data are statistically analyzed based on the above variables (a_{y+} and a_{y-} in the state of acceleration/deceleration, a_x and ω_z in the state of turning/ lane changing), as shown in Figure 8.

By the distribution of the variables (Figure 8), there is an outlier (1.0722g) in a_x in the state of turning/ lane changing. The distribution of the three acceleration variables, with a maximum of no more than 0.0862g (a_x), is more concentrated than that of ω_z. After cutting 5% data of the maximum and minimum ends, the average value of a_{y-} (0.1749g) is the largest, while that of a_{y+} (0.0323g) is the least, i.e. the passenger's sensitivity at acceleration is significantly higher than at deceleration.

B. DISCOMFORT LEVEL EVALUATION

Based on discriminant analysis, we introduce a method of predicting the level of passenger discomfort which compares the type of discomfort perceived on board by the passengers with the instantaneous accelerations recorded by smartphone. Eboli *et al.* [24] developed a related method, in which using subjective and objective data to define the level of bus comfort. However, they did not define independent variables for different motion states, and did not take the effect of angular velocity into consideration.

Specifically, as we stated above, we create a cumulative frequency graph using SPSS (Version: IBM SPSS Statistics 26.0) for variables ($a_{y+}, a_{y-}, a_x, \omega_z$), which related to different motion states. The graph reflects the functional relationship between variables and cumulative frequency, as reported in Figures 9 and 10.

The relationship between cumulative frequency and linear acceleration is shown in Figure 9, where there are two concentrated distribution intervals of a_{y+} and a_{y-} in the vehicle acceleration and deceleration state. After the last distribution interval ($a_{y+} = 0.11$g, $a_{y-} = 0.18$g), the proportion of passenger's discomfort events in both states has reached more than 80%. In other words, at least 80% of the passengers in this state are uncomfortable and associated with α_y (−0.18g, 0.11g).

The cumulative frequency in the state of turning/lane changing is shown in Figure 10, 96% of the discomfort

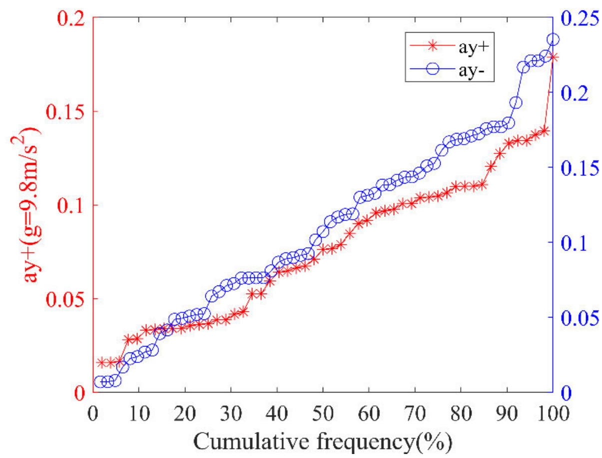


FIGURE 9. **Cumulative frequency of α_y.**

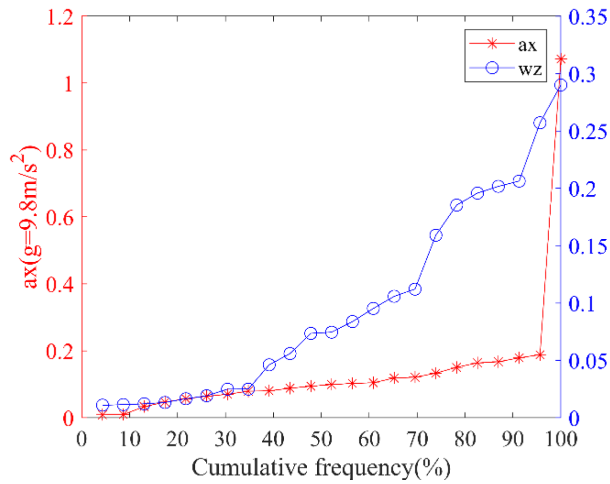


FIGURE 10. **Cumulative frequency of α_x /ω_z.**

events occur in the interval (0.08g-0.2g). The curve of ω_z has two large jump intervals, (0.046rad/s-0.112rad/s) and (0.159rad/s-0.206rad/s). At an angular velocity of 0.206rad/s, the proportion of discomfort events reaches 90%.

Based on the above analysis of the data, we can conclude that the threshold of $a_{y+}, a_{y-}, a_x, \omega_z$ is: 0.11g, 0.18g, 0.2g, and 0.206rad/s, which could be adopted for indicating a limit situation distinguishing between a low and a high level of discomfort on board linked to the driving behavior (Sharp acceleration/ deceleration/ turning/ lane changing). More specifically, if for a certain ride, the value of the above motion variable is higher than the threshold value, we can conclude that the level of discomfort onboard is bad; on the contrary, if the value of the above motion variable is lower than the threshold value, the level of discomfort is good.

C. PREDICTION OF PASSENGER MOTION SICKNESS DURATION

To determine the factors influencing the DMS, a Pearson correlation analysis was carried out with the 6-df acceleration

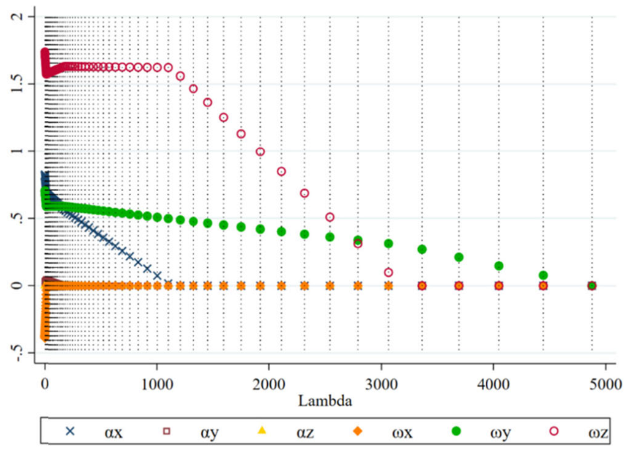


FIGURE 11. The coefficient regression path of the model.

TABLE 5. Prediction model coefficient for the DMS.

X	Coefficient	P	Model Indexes	Value
$N(a_x)$	0.667	<0.01	R^2	0.983
$N(\omega_y)$	0.606	<0.01	F	220.88
$N(\omega_z)$	1.632	<0.01	P	<0.001

and angular velocity variation amplitude $A(i)$, stability $D(i)$, and the number of direction change $N(i)$ as independent variables ($i = a_x, a_y, a_z, \omega_x, \omega_y, \omega_z$). The results show that there is no significant correlation between the DMS and $A(i)$ ($r < 0.4$, $p > 0.001$). In addition, there is no significant correlation between DMS and $D(i)$ ($r < 0.3$, $p > 0.01$). However, there was a strong correlation between DMS and $N(i)$ ($r > 0.8$, $p < 0.01$), which could be expressed by a quantitative model.

Since the sample we have is limited, it is likely to be insufficient if we want to estimate too many coefficients with limited information, so it is necessary to filter the variables to improve the estimation. We performed Lasso regression with $N(i)$ as the independent variables and DMS as the dependent variable to identify the suitable predictor. Lasso regression was implemented via Stata SE 15 (64-bit). The coefficient regression path of the model is shown in Figure 11.

After obtaining the regression model, we performed a K-fold cross-validation (K = 10) of the model using the dataset to obtain the parameter, Lambda (187.950), which minimizes the mean square prediction error (MSPE) of the model.

As shown in Table 5, the regression model finally identified $N(a_x)$, $N(\omega_y)$, and $N(\omega_z)$ as significant predictors with $P < 0.01$, yielding the following prediction model for the DMS:

$$T = 0.666N(a_x) + 0.606N(\omega_y) + 1.632N(\omega_z) - 15.219 \tag{2}$$

where T represents the DMS (s), $N(a_x)$ represents the direction mutation number of X-axis positive acceleration per unit time, $N(\omega_y)$ is the number of direction change of Y-axis axial angular velocity per unit time, and $N(\omega_z)$ is the number of direction change of Z-axis axial angular velocity per unit time. The weight of different coefficients in the model reflects that $N(\omega_y)$ has the greatest impact on the DMS. By this model, 79.8% of the original cases are correctly predicted (the error is less than 10%).

IV. DISCUSSION

As in many previous studies [17]–[19], drastic changes in space for passengers are the direct causes of discomfort and motion sickness. Therefore, understanding how to monitor the discomfort and determine the DMS plays an important role in improving passenger comfort. We investigate the association between 6-df acceleration, angular velocity, and the discomfort and DMS of passengers during the driving of buses, so as to propose a possible method or tool to determine the threshold of discomfort and the DMS.

Through 18 round-trip tests of 22 passengers on a commuter bus, it is shown that acceleration, deceleration, lateral movement, and change of forwarding direction of the vehicle will cause discomfort and symptoms of motion sickness significantly. It verifies the Hoberock's conclusion that only vertical, roll, and pitch vibrations are considered in human riding comfort analysis [25].

Thresholds for $a_{y+}, a_{y-}, a_x, \omega_z$ are obtained. The threshold of vehicle lateral acceleration is 1.96 + / −1.96, which is consistent with the acceleration threshold (1.9 3 + /- 1.94) obtained by Kuiper [10]. Compared with the results obtained by Barabino *et al.* [14] (2.12 + /-2.12), the threshold is smaller, which may be due to different route conditions and traffic management measures. It is not difficult to conclude that passengers are most sensitive to the deceleration of the vehicle. We speculate that due to the high speed of the expressway when the vehicle encounters a change of lane in front of the vehicle, a sharp break, etc., the head of the passenger cannot hold a fixed position (by leaning against the back of the chair) as when the vehicle is decelerating, which is consistent with the statement of Willem that relevant factors accelerate the sensitivity of body balance organs called vestibular [3].

Further, by incorporating the relevant statistics of vehicle motion variables into Pearson correlation analysis, the number of direction changes $N(i)$ of 6-df acceleration and angular velocity are clearly screened out. Then a quantitative regression model is proposed to describe the relationship between the changes of the above variables and the DMS of he or her. The results show that it is feasible to predict the DMS by the $N(a_x)$, $N(\omega_y)$, $N(\omega_z)$. Specifically, the analysis proves that frequent acceleration caused by accelerating or braking and angular changes caused by turning lanes both increase the DMS, whereas the direction change of vehicle yaw angular velocity has the greatest impact on the DMS. Motion sickness is highly likely to occur when sudden changes in vehicle lateral acceleration, yaw, and roll angular velocity are at a certain level, which is consistent with the conclusion of Turner and Griffin [17], [18].

In data analysis using ANOVA, it is found that when the vehicle is in a turning or lane changing state, the lateral acceleration and yaw angular velocity of the vehicle has a significant impact on the passenger's comfort, i.e., compared with other driving status, passengers in turning or lane changing state are more likely to experience discomfort, which is consistent with the conclusion of Saruchi et al [12], [13].

Further analysis shows that the length of time between the start of the test and the discomfort occurs for the first time is significantly correlated with the DMS ($r = 0.583$, $p < 0.001$, $N = 20$), i.e. earlier discomfort the passenger experience in the test means a greater probability of longer DMS further indicate more conflicts between the direction of motion perceived by the sensory organs and the predicted movements of the central nervous system, which leads to more severe motion sickness [3]. Correlation analysis also excluded the association between the DMS and the frequency of discomfort ($r = 0.322$, $p > 0.01$). Therefore, motion sickness monitoring and evaluation method could be used to remind the risk of motion sickness and encourage more rest [23].

Generally speaking, this study has some methodological limitations:

a. Since the age range of the 22 participants in this study is 17-55 years old, it cannot represent the general situation of older or younger age groups, which will have a certain impact on the determination of variable threshold;

b. The process of the test is affected by the subjective and random factors of passengers, and it is not further controlled by the traffic flow, road traffic control measures, and other factors.

c. Since the passenger comfort is a crucial facet of service quality, some key indicators of service quality, such as personal space in vehicle as well as the ambient conditions, should also be considered [26]. In future research, comprehensive consideration of the above variables should be focused on to get a more extensive application.

V. CONCLUSION

In this study, we validated a new way to obtain real-time data on passenger's discomfort combined with specific symptoms and motion sickness associated with discrete changes in vehicle motion. The results show that our method is sensitive to discomfort and motion sickness, and these are related to discrete changes in the vehicle's 6-df acceleration and angular velocity.

In the context of road congestion and the strategy of ''Public transport priority'', the development of large-capacity vehicles such as buses is in line with today's trends, and the broader application based on this study can improve the service and passenger comfort, which can prevent motion sickness more efficiently and help to provide a potential theoretical basis for policymakers to improve the adjustment of the driving strategies and path trajectory of city buses.

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