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RELATIONSHIP BETWEEN THE ACCURACY OF MODELS FOR JUDGING CAR SICKNESS BASED ON LINE-OF-SIGHT FEATURES AND ROAD ATTRIBUTES

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Abstract. *In previous research, we examined whether it was possible to determine if people would suffer from car sickness based only on the movement of the line of sight. The results of our work indicate that it is possible. However, in the previous research, this finding was only verified by the line-of-sight movement while driving on a straight road, so it is necessary to verify that this finding still holds for other types of less straight roads. Therefore, in this research, we verified the findings using three types of roads, including straight roads. We added line-of-sight movement while driving in cities and residential areas. As a result, the model constructed using the line-of-sight movement while driving on a straight road achieved the highest accuracy, with a correct answer rate of 82.9%. In contrast, the model constructed based on the line-of-sight movement while driving in the city was the lowest with a correct answer rate of 58.1%. Therefore, we revealed that the nature of the road has a significant influence on judgment accuracy when determining if people will suffer from car sickness based only on the movement of the line of sight.*
Keywords: Motion sickness, Line-of-sight trend, Random forest, Road attributes

1. Introduction.

Technology in various fields continues to advance rapidly. One such area is the automobile, which has long been used as a means of transportation for people. In recent years, the development of self-driving cars has attracted considerable attention. Self-driving cars are expected to have various roles, such as reducing stress caused by driving, realizing a safe society by reducing traffic accidents, and maintaining infrastructure in depopulated and aging areas. In recent years, the focus on realizing a carbon-free society has increased [1], due to the aggravation of environmental problems [2]; hybrid vehicles (that are fueled by both gasoline and electricity) and electric vehicles (EVs), that do not use gasoline, have received increasing attention, and demand is expected to grow in the future [3]. Research and development on car performance are actively being carried out. In contrast, there are challenges when conducting research on riding comfort and comfort of the vehicle interior environment, as human subjectivity is greatly involved. Motion sickness is one such condition. Dizio and Lackner [4], Webb and Griffin [5], Griffin and Newman [6], and Manning and Stewart [7] explained that motion sickness is caused by inconsistency between organs. The sensory organs depend on the individual, and some people are affected, even with a slight vibration. In contrast, many people experience motion sickness only when they are riding without driving and not even when they are driving by themselves. In addition, it is possible that the number of people affected in this way will increase in parallel with the realization of self-driving cars. Various factors can

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be considered for this phenomenon; however, among them, the line-of-sight movement is considered to be one of the main factors in the same in-vehicle environment. Thus, it may be possible to reduce motion sickness by changing the line-of-sight movement. Therefore, the goal of this research is to develop a system that presents line-of-sight trends to eliminate motion sickness in easy-to-understand language and to suit the individual. However, motion sickness by some causes cannot be eliminated because there are many causes of motion sickness other than line of sight. However, it is expected to be useful in that it is possible to eliminate car sickness from only the line of sight.

Three steps were required to realize this system: "1) Build a high-precision model that automatically judges if people will suffer from car sickness based on the line of sight", "2) Develop a system that presents line-of-sight trends in easy-to-understand sentences to eliminate motion sickness", and "3) Build a system that incorporates these steps". In previous research [8], using random forest method, we construct a model that automatically judges if people will get car sick based on the movement of the line of sight. In addition, the performance evaluation of the model reflected an accuracy level of approximately 80% for the test data. In previous research [8], a model was created from the line-of-sight trends acquired by movies while riding, as this approach is both simple and safe. Moreover, a video of a straight road was used to acquire the line-of-sight movement. The line-of-sight movement is assumed to differ depending on the attributes of the road on which the vehicle is driving. Therefore, the results of previous research are extremely limited and the model requires verification if it is effective on all roads. In this research, we reconstruct models using three types of roads, with different attributes, to conduct a basic verification. In addition, we performed an accuracy evaluation, using test data, for performance verification. Finally, based on the results of the accuracy evaluation, we reveal the types of roads that our car sickness prediction model can be applied to. In addition, we consider the limits and possibilities of automatic car sickness judgment based only on line-of-sight trends. In this research, a model was created using the line-of-sight movements acquired by filming whilst riding in a car, owing to high safety levels and the simplicity of the system, as confirmed in previous research [8].

Finally, we discuss the difference between existing studies and this study. Several studies have been conducted that attempt to determine some state from the line-of-sight movement (such as determining game proficiency [9], estimating consumer behavior patterns [10], and deriving keys to improve marine operations [11]). However, these studies do not analyze the relationship between motion sickness and gaze trends. In addition, there are many previous studies on car sickness (such as the relationship between car sickness and gender [12], relationship between brain waves and car sickness [13], and relationship between vibration and car sickness [14]). The mechanism of car sickness is the focus of the majority of these studies. However, there are insufficient studies mentioning the specific methods to improve car sickness. As mentioned above, although there are numerous studies related to the line-of-sight movement and car sickness, studies that automatically predict whether people will experience car sickness, as well as studies on the development of a system that provides feedback on how the line-of-sight movement can be improved to prevent car sickness, are insufficient. For these reasons, this study may be considered as novel.

The remainder of the paper is as follows. In Section 2, we describe the overall system, which is the ultimate goal of this research, and the position of the paper within the system. Section 3 provides an overview of the experiment. In Section 4, the outline, results, and discussion of the analysis are explained. Section 5 summarizes our study and discusses the future scope of research.

2. **Overview of the Final Conceptual System.** Figure 1 shows the final conceptual system of this study. This system is premised on showing users, wearing an eye-mark recorder, a video footage that was taken during a car journey. It is more suitable, for the purpose of this system, to actually measure the line-of-sight movement while riding in a car, but the video is used owing to high safety levels and the simplicity of the system. The eye mark recorder was EMR-9 [15], developed by Nac Image Technology, Inc., Japan. This is an off-the-shelf system that outputs XY coordinates of where the user is looking at and there are numerous other cases where this technology has been used in previous research (e.g., Kawaguchi et al. [9], Hori et al. [16], Takada and Miyao [17]). The origin is at the upper left of the display, and the X coordinate value increases as it goes to the right, and the Y coordinate value increases as it goes down. As shown in the left of Figure 2, the subject's point of view is output as XY coordinates. In this study, the subject's point of view was represented by 5400 XY coordinates because the sampling frequency of eye mark recorder was 60 Hz and the measurement time was 90 s. The XY coordinate

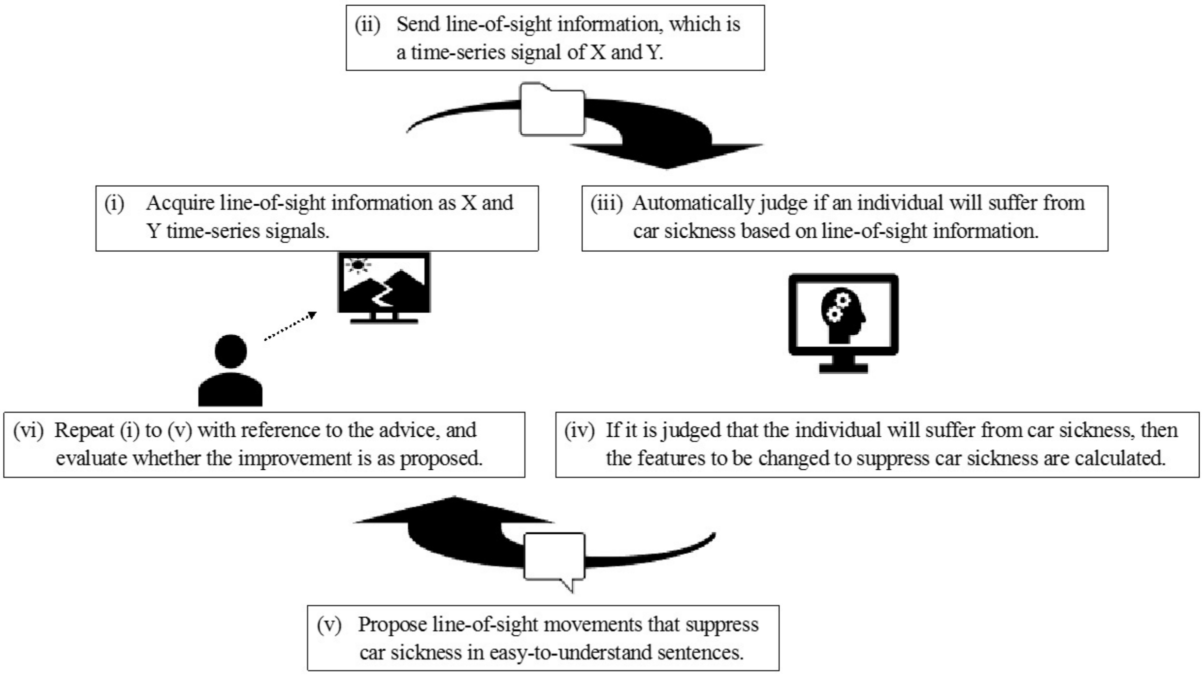
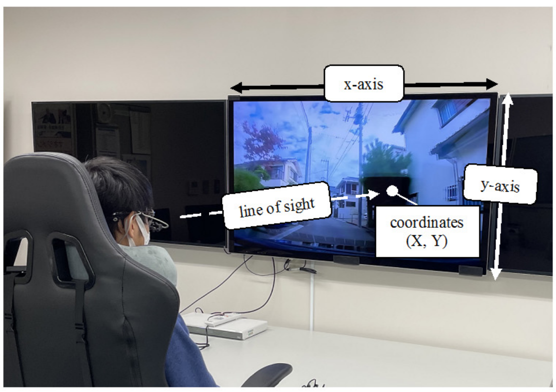
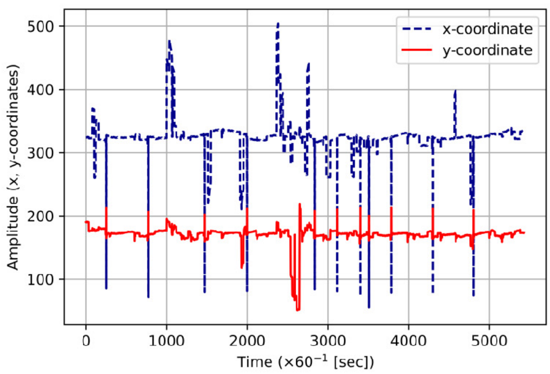


FIGURE 1. The system proposed to improve car sickness



Scene of measuring eye tracking data



Line-of-sight trends acquired as time-series signals

FIGURE 2. Acquisition method and structure of eye tracking data

data measured in this manner as shown in the right of Figure 2 is a time-series signal. The vertical axis indicates amplitude of XY coordinate, and the horizontal axis indicates unit time (1/60 s). In addition, viewing point data, estimated from the XY coordinate values of the right eye and the left eye, were measured. By summarizing the data obtained, in the shape of the signal, the linguistic information for eliminating car sickness is fed back to the user.

Procedure (i): The user, wearing the eye mark recorder, is shown the video taken while riding the car, and the eye tracking data is measured.

Procedure (ii): Transfer the measured eye-tracking data to the analysis computer.

Procedure (iii): Judge if the individual will suffer from car sickness based on the transferred eye-tracking data.

Procedure (iv): If people are judged to have car sickness, calculate the features of line-of-sight that should be changed numerically to prevent the car sickness.

Procedure (v): Convert the line-of-sight trend that should be improved to an easy-to-understand sentence.

Procedure (vi): The user who receives the feedback information changes the line-of-sight based on the feedback and repeats the procedure from (i).

By repeating the above procedure, we aim to improve car sickness step-by-step. In addition, the main targets of this system are people who suffer from car sickness only when they are not driving by themselves. Therefore, this system is built in an experimental environment, not from the driver's point of view, but assuming that the inside of the car is driven by another person.

This is the final concept. To this point, we have conducted study to judge if people will suffer from car sickness based on the movement of the line of sight in previous research [8]. This corresponds to "procedure (iii)". In a previous study [8], we constructed a random forest model that automatically judges if people will get car sick using video footage of a straight road, corresponding to road B. In addition, we suggested the possibility of determining if people will get car sick based only on the movement of the line-of-sight. The accuracy evaluation of the constructed model indicated an achieved accuracy of approximately 80% on the test data. However, the line-of-sight trend is assumed to differ depending on the attributes of the road.

Therefore, it is necessary to verify if car sickness can be automatically judged based only on the line-of-sight trend, even on roads other than straight roads. Therefore, in this research, we reconstruct the models using video footage taken whilst driving on three types of roads with different attributes, including straight roads. From the judgment accuracy of these models for the test data during performance evaluation, we reveal the types of roads that can be assessed using our model and approach. However, it cannot conclusively reveal the types of roads that it can be applied to because there are innumerable types of roads.

Finally, we discuss the system's usefulness in the context of reducing car sickness. Some studies have been conducted to improve car sickness. There have been studies that focused on various aspects such as postural activity during the ride as the cause of car sickness [18,19], clarifying the relationship between behavior during the ride (such as watching videos) and car sickness [20], and quantifying motion sickness based on the acceleration data of the head during the ride [21]. These studies are critical in reducing car sickness. However, they do not refer to the line-of-sight movement in a running vehicle, which is the focus of this study. In addition, there are previous studies on the relationship between sickness and line-of-sight trends [22,23]. However, while these studies focused on video sickness such as virtual reality, there are few studies focusing on car sickness. Therefore, we consider it a novel system. In addition, we believe that the system is practical in terms of the physical burden on the user because this system only requires a single element of data, that is, eye-tracking data.

3. **Experiment.** The subjects consisted of 37 healthy men and women (28 men, 9 women, aged 21.86 ± 1.21 years), and a questionnaire on car sickness was conducted, as shown in Table 1. In this questionnaire, those who corresponded to (1) to (3) were those deemed to be prone to car sickness, and those who corresponded to (4) to (6) were defined as those who were not prone. As a result, 17 people were prone to car sickness (label: 1), and 20 people were not prone (label: 0).

TABLE 1. Questionnaire on car sickness

Choices	Meaning
(1)	I always get car sickness.
(2)	I get car sickness frequently.
(3)	I get car sickness sometimes.
(4)	I have been car sick a few times.
(5)	I have been car sick at least once.
(6)	I have never been car sick.

The implementation period of the experiment was 40 days from September 21 to October 30, 2020. Left of Figure 2 shows the state of the experiment. In this experiment, the line-of-sight movement was measured using the video footage taken while riding in a car due to high levels of safety and the simplicity of the system. In the experiment, subjects were seated in a chair and wore an eye mark recorder (EMR-9, Nac Image Technology [15]) with a sampling frequency of 60 Hz. The line-of-sight movement was measured while watching the videos projected onto a liquid crystal display (55 inch) located approximately 140 to 145 cm away from the seated position. The height of the chair was adjusted so that the position of the viewpoint was parallel to the center of the display. To prevent a decrease in the calibration accuracy of the eye mark recorder because of the head movement during the test, a firm high-resilience neck pillow was attached.

Subjects in the above condition were asked to watch video footage taken while riding a car. Figure 3 shows the video frames used in the experiment. Road A, which is a

FIGURE 3. Experimental videos A, B, C (All 90 s in duration)

mostly straight road in a city, and features a gentle curve with many oncoming vehicles and pedestrians. The video of Road A features two stops due to traffic lights; roads in the city have heavy traffic and so signals are installed at regular intervals. Road B, which is a straight road, runs in the center lane of a wide three-lane road, so overtaking vehicles are shown multiple times, but pedestrians are not. In addition, Road B does not feature oncoming vehicles because there is a median strip where trees have been planted. Road B does not feature stops due to traffic light that are installed at greater intervals on this type of road. Road C, which is a residential area, has many crossroads and T-junctions. Road C features stops at points where right and left turns are made (five stops in total). These movies were taken by installing a camera (HERO9 Black, GoPro [24]) on the dashboard of cars and filming the landscape of the actual driving scenery. From the landscape of the actual driving scenery, three patterns of movies (each 90 s in duration) were created with different scenes. The subjects were asked to watch a video twice in the order of roads A, B, C. As the number of subjects was 37, the number of available data was 74.

The content of the questionnaire, conducted before the experiment, does not include a question on if an individual felt sick by watching the footage of roads A, B, and C, but only asks car sickness in general. Therefore, caution must be taken, for the purpose of this research, to not analyze video sickness (i.e., if you get sick by watching video).

4. Automatic Judgment of Car Sickness Based on Line-of-Sight Information.

4.1. **Features and judgment model used for analysis.** The time-series signal consists of a large amount of numerical information. Therefore, it is desirable to convert it into a value that expresses the characteristics of the signal before analysis. Such values are called features, and statistics such as mean, variance, skewness, and kurtosis are often used as features of time series signals (e.g., Omae et al. [25]). Therefore, these features are adopted in this study. In addition, we considered that the line-of-sight movement distance was important in the case of line-of-sight movement data, so we also adopted the average line-of-sight movement distance, which is the line-of-sight movement distance per unit time (1/60 s). Table 2 lists all the features that were finally adopted.

Table 2. Adopted features

Feature	Labels	Meaning
f_1	Mean(X)	Average value of X signal
f_2	Mean(Y)	Average value of Y signal
f_3	Var(X)	Dispersion of X signal
f_4	Var(Y)	Dispersion of Y signal
f_5	Skew(X)	Skewness of X signal
f_6	Skew(Y)	Skewness of Y signal
f_7	Kurt(X)	Kurtosis of X signal
f_8	Kurt(Y)	Kurtosis of Y signal
f_9	Dist	Average viewpoint movement distance

Subsequently, we discuss analytical methods of this study. The purpose of this study is to verify whether it is possible to automatically determine if people would suffer from car sickness based solely on the movement of the line of sight, even if the road is not straight. Therefore, in this study, we used the same random forest model as in the previous study [8].

4.2. **Data preprocessing.** The error values that occurred when blinking or when looking outside the display during the experiment were removed by substituting them with the time-series signal average value of the subject. Subsequently, min-max normalization was carried out for scale adjustment of each feature quantity, with the minimum and maximum values of each feature adjusted to 0 and 1. In this experiment, data were measured twice for one subject, and the first and second data were used as teaching and test data, respectively, because the number of subjects was small. However, when a new third-party subject is tested using the random forest model constructed in this study, it is possible that the generalization ability may decrease. This is because both data teaching and testing are collected from the same subjects. Normally, test data should be collected from an unknown third person, so we plan to acquire new third-person data and verify it again as part of future work.

4.3. **Chance level measurement.** In this research, the chance level is measured by randomly determining if an individual is car sick from the data of 37 cases corresponding to the test data. However, we calculated the correct answer rate of 100 patterns using the random number seed ranging from 0 to 99 and determined the chance level as the interval given by the average value and standard deviation. By the value of the chance level depending on the random number, the result is not stable.

As a result of implementing this procedure, the average percentage of correct answers at the chance level was 50.11%, and the standard deviation was 8.89%. Therefore, if the correct answer rate of the model construction in this research exceeds the average correct answer rate of 50.11% of the chance level, it can be judged that the model has some tendency and possibly indicates some new findings.

4.4. **Random forest condition setting.** This section describes the setting of various variables in a random forest. First, we set the minimum number of leaf node samples to one to induce overtraining in individual decision trees. Next, we considered the number of features, selected from all the features that are used when determining the branch at each decision tree. In general, the square root value of the number of all features is recommended [26]. The total number of features in this study was nine, as shown in Table 2. Therefore, we selected three evenly spaced values including square roots such as 3, 6, and 9. Finally, in this study, the number of decision trees included in one random forest was set in a wide range of intervals, such as 10, 100, 500, and 1000, from the viewpoint of both judgment accuracy and judgment time. In this study, we created 100 models by changing the seeds of random numbers, as we did in previous studies [8].

In addition, we performed resampling using the bootstrap method when constructing individual decision trees. Therefore, the same subject may be duplicated in the resampled dataset.

4.5. **Results and discussion.** We constructed a random forest based on the conditions described in Section 4.4. Table 3 shows the percentage of correct answers when the test data for performance verification were input to the constructed model. These values are the average values of the correct answer rate, standard deviation, maximum value, and minimum value, and are derived from the judgment results of all 100 random forests.

First, we describe the results for road A. The highest average accuracy was 58.1%, and it was measured by adopting the random forest using the following parameters (the number of randomly selected features: 9, the number of decision trees: 1000). This result was not considered to be highly accurate because it was not much different from the average correct answer rate of the chance level (50.11%). Therefore, it is difficult to judge if people who will suffer from car sickness is correctly determined by the model based on

Table 3. Correct answer rate of judgment model

Video type	Number of features randomly selected	Number of decision trees	Average accuracy	Standard deviation	Max accuracy	Min accuracy
A	3	10	55.9%	5.2%	67.6%	43.2%
A	3	100	56.6%	2.4%	62.2%	51.4%
A	3	500	56.4%	1.4%	59.5%	54.1%
A	3	1000	56.4%	1.1%	59.5%	54.1%
A	6	10	56.0%	5.3%	70.3%	43.2%
A	6	100	56.8%	2.3%	62.2%	51.4%
A	6	500	57.3%	1.4%	59.5%	54.1%
A	6	1000	57.3%	1.2%	59.5%	54.1%
A	9	10	55.3%	5.2%	67.6%	45.9%
A	9	100	55.9%	2.6%	59.5%	48.6%
A	9	500	57.5%	1.8%	59.5%	54.1%
A	9	1000	58.1%	1.7%	59.5%	54.1%
B	3	10	65.4%	6.4%	78.4%	48.6%
B	3	100	75.7%	4.6%	91.9%	62.2%
B	3	500	79.9%	4.0%	89.2%	70.3%
B	3	1000	80.5%	3.2%	89.2%	73.0%
B	6	10	67.0%	6.1%	83.8%	51.4%
B	6	100	77.4%	4.2%	89.2%	67.6%
B	6	500	81.5%	3.6%	89.2%	73.0%
B	6	1000	82.9%	2.7%	89.2%	75.7%
B	9	10	67.1%	5.1%	78.4%	48.6%
B	9	100	78.4%	4.0%	89.2%	67.6%
B	9	500	80.7%	2.9%	89.2%	73.0%
B	9	1000	81.6%	1.8%	83.8%	75.7%
C	3	10	64.7%	5.4%	75.7%	48.6%
C	3	100	66.8%	3.5%	75.7%	56.8%
C	3	500	66.8%	2.9%	75.7%	59.5%
C	3	1000	66.5%	2.4%	73.0%	62.2%
C	6	10	65.4%	5.9%	86.5%	48.6%
C	6	100	65.2%	3.7%	75.7%	56.8%
C	6	500	64.3%	2.8%	70.3%	59.5%
C	6	1000	63.0%	2.6%	70.3%	56.8%
C	9	10	65.5%	5.6%	78.4%	51.4%
C	9	100	65.0%	3.8%	78.4%	56.8%
C	9	500	63.5%	2.5%	70.3%	56.8%
C	9	1000	63.3%	2.4%	70.3%	56.8%

the movement of the line-of-sight while driving on Road A assuming in the city. Second, we explain the results for Road B. In the case of this road, high accuracy levels were achieved. The highest average accuracy was 82.9%, and it was measured by the random forest using the following parameters (the number of randomly selected features: 6, the number of decision trees: 1000). This result indicates that many models of the random forests that adopted the described conditions can recognize car sickness labels with an accuracy of approximately 80%. According to this result, it is possible to judge if people will suffer from car sickness based on the movement of the line-of-sight while driving on Road B, (i.e., a straight road). Finally, we describe the results for Road C. The highest average accuracy is 66.8%, which is 16.69% higher than the chance level of 50.11%, which is measured by the random forest with the following parameters (the number of randomly selected features: 3 and the number of decision trees to compose: 100 or 500). From this result, although there is information for identifying car sickness in the line-of-sight movement while driving on Road C (assuming a residential area), it may be difficult to judge with high accuracy if people will get car sick based on the movement of the line of sight.

In this research, the accuracies of Roads A and C were not high. However, we consider that making strong conclusions is difficult because this result indicates the tendency of the accuracies of the models proposed by this research, which is just a case study. The judgment accuracy may improve if we adopt new line-of-sight features that are not adopted in this research.

To obtain the overall judgment accuracy excluding the effect of the variable settings of the random forest, we calculated the average of "Average accuracy" in Table 3 by each video A, B and C shown in Figure 3. The results are shown in Figure 4. According to the bar chart in Figure 4, Road B, which is assumed to be a straight road, has the highest accuracy when compared to the other road attributes. Road B is followed by Road C, assuming a residential area, and Road A, assuming in the city. In the mentioned order, the accuracy of the judgment decreases by about 10% in each value. This result indicates that judgment accuracy varies depending on the road attributes. Therefore, it is necessary to verify why the accuracy of the judgment changes depending on the road attribute. Hence, we list the characteristics of the road attributes assumed in this study and consider the cause of the effect on the model's decision accuracy.

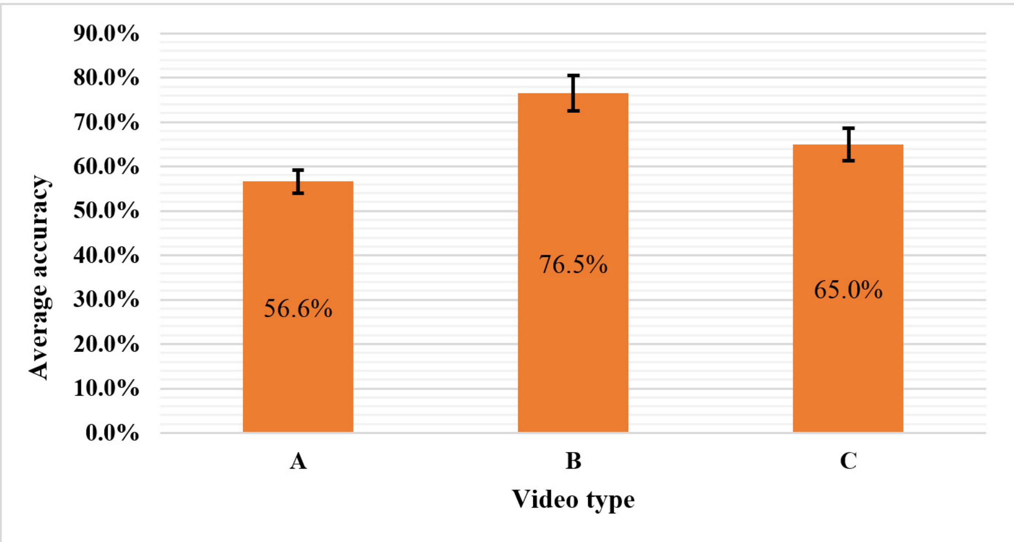


Figure 4. Average accuracies of judgment models

First, we focus on the objects existing in the three types of roads used in this study. The objects existing on Road B, which is a straight road and achieves the highest judgment accuracy among all of the road types adopted in this research, are only overtaking vehicles. Next, the objects existing on Road C, which is road in a residential area and has the second highest judgment accuracy, are buildings (e.g., houses) and pedestrians. In addition to overtaking vehicles, buildings, and pedestrians, oncoming vehicles also exist on Road A (which is road in a city based and has the lowest judgment accuracy). Therefore, when comparing the judgment accuracies of the models for predicting car sickness on Roads A, B, and C from the viewpoint of objects that exist on these roads, it is considered that the road type with the fewest objects may lead to a difference in the line-of-sight movement between people who would get car sickness or do not.

Next, we considered the relationship between the number of stops and judgment accuracy for road attributes. Road B does not feature any stops and is wide compared to other road attributes, and the signal installation interval is wide. In contrast, on Road A, there are many pedestrians and pedestrian signals that exist at frequent intervals. Therefore, waiting for a signal is observed multiple times. Road C also features stops when making a right or left turn. Focusing on the stop, the model of the straight road, that does not feature stops, has higher judgment accuracy than the other two road types, so it is thought that the line-of-sight movement when driving has an impact on car sickness more than the line-of-sight movement when the vehicle is stopped. However, this result may be observed only in the scenes used in this experiment. Therefore, it will be necessary to reexamine other roads that were not used in this research in the future.

Finally, we discuss the usefulness of results obtained in this study. Most of the existing studies that have been conducted to improve car sickness [19,20,21,27] focus on the behavior of the subjects during the ride. Therefore, the road attributes used in the experiments are frequently of a single pattern. However, human behavior during the ride is assumed to differ depending on the outside environment of the vehicle. Therefore, in this study, we focused on the line-of-sight movement during the ride and investigated about the road attributes that lead to a difference between the gaze movement of those who will suffer from car sickness and those who will not. As a result, new findings on the relationship between car sickness and the environment outside the vehicle were obtained. In this regard, the study is considered to be novel and useful.

As mentioned above, we revealed that road attributes have a significant influence on the judgment accuracy in judging if people will get car sick based only on the movement of the line of sight. However, this research is focused on simulated experiments because the line of sight movement was measured by using the video while riding in a car. Although it is appropriate from the viewpoint of safety, it is insufficient from the viewpoint of acquiring data. Therefore, it is unclear if the results obtained conform, even when actually getting the subject in a car and acquiring the line of sight movement. From this point of view, this research has a strong meaning in basic research. In the future, we would like to consider obtaining line-of-sight data by actually getting the subject in the car, while taking the safety of the participants into account. In addition, the number of subjects and gender ratio in this study are insufficient; therefore, the results in this study show only one trend. In future studies, we would like to verify again about the results of this study using more data without any bias in the gender ratio.

5. **Conclusions.** In this research, we revealed the types of road attributes that can be used to judge if people would suffer from car sickness based only on the movement of the line-of-sight. We measured the line-of-sight movements using three types of movies with different road attributes while riding in a car, due to safety and simplicity. Based on previous research [8], we constructed an automatic car sickness judgment model for each road type from the measured line-of-sight movement and evaluated the accuracy of each model. As a result, we observed a difference in the correct answer rate of approximately 25% between the straight road model, with the highest accuracy of 82.9%, and the model for the road in the city, with the lowest accuracy of 58.1%. From this result, it was revealed that the road attribute has a big influence on the judgment accuracy in judging if people

will get car sick based only on the movement of the line of sight. In addition, only one type of road obtained a correct answer rate of over 80% in this study. Thus, the automatic judgment of car sickness based only on the line of sight may be effective only in limited situations. However, the features used in this research are very biased because they all are time domain features. Therefore, it is necessary to consider if an accuracy higher than that achieved in this research can be obtained by adopting line-of-sight features other than the time domain. Specifically, we would like to consider the adoption of new features such as time to follow the gaze object (building, oncoming vehicle, etc.) with the eyes, and features such as power band, energy, and frequency domain entropy, which are features other than the time domain. In addition, we would like to examine if the accuracy can be improved by reconstructing the model using the deep learning method, which was used in existing studies that proposed a new analysis method based on image processing [28] and realized the state judgment from the time-series signals [29]. In future, we aim to build a system that provides feedback on how to improve the line-of-sight movement for people who will get car sickness, complete the entire system shown in Section 2, and verify its effectiveness.

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