Regular Paper

Pedestrian Cooperative Autonomous Mobility
-Path Planning Adapted to Pedestrian Face Direction-

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Abstract - Autonomous mobility in mixed traffic environments with pedestrians need functions to avoid contact with pedestrians. In this study, path planning method adapted to pedestrian face direction was developed. For pedestrians who are aware of mobility (forward facing walking), small avoidance path is generated. For pedestrians who are unaware of mobility (downward facing walking), such as those who are walking on their smartphones, large avoidance path is generated. Subjective evaluation experiments were conducted on four items: distance, speed, smoothness of avoidance, and reliability. The subjective evaluation results showed that the evaluations improved for all items except speed, both for forward and downward walking. In particular, for downward facing pedestrians the evaluation of the distance was considerably improved. In addition, objective evaluation indicators corresponding to the subjective evaluations were examined.

Keywords: Autonomous Mobility, Pedestrian behavior prediction, Yolo

1 INTRODUCTION

In recent years, the practical application of autonomous mobility has been progressing worldwide in areas such as office building security and package delivery. Autonomous mobility moves in mixed traffic environments with pedestrians need a path planning function that avoids contact with pedestrians. When humans pass each other, they unconsciously make eye contact with each other and anticipate the other's movements to ensure smooth movement. Therefore, we are working on the realization of autonomous mobility that enables this type of behavior.

DWA (Dynamic Window Approach) [1] and RRT (Rapidly exploring random tree) [2] have been widely used as static obstacle avoidance methods for mobile mobility. The problem with these previous studies was that dynamic obstacles such as pedestrians could not be avoided because they were not considered.

For dynamic obstacle avoidance, pedestrian prediction using the Kalman filter [3], pedestrian prediction and avoidance using the potential method [4], and the application of ORCA (Optimal Reciprocal Collision Avoidance) to the prediction and avoidance of multiple pedestrians [5] have been studied.

One of the problems for previous studies is avoidance for pedestrians walking on their smartphones. It is difficult for mobility to avoid pedestrians walking while gazing at their smartphones. This is because their walking path is unstable and behavior prediction is difficult. Also, pedestrians walking on their smartphones may be surprised when mobility suddenly appears in their field of vision when they pass by at close range while they are gazing at their smartphones. To solve the problem, a method of warning by sound can be considered. Although pedestrians may notice mobility with sound warnings, this method causes mobility to impede pedestrians' walking, and frequent warning sounds can make pedestrians uncomfortable. Especially when autonomous mobility increases in the future, it is unlikely that autonomous mobility will always be prioritized over pedestrians. As another means, a method of large avoidance can be considered. Although the method could avoid the pedestrian safely, such large avoidance would be excessive for pedestrians walking forward. If excessive avoidance is always performed, there is a high possibility that it will take a long time to arrive at the destination or the route cannot be generated and the mobility cannot move. Pedestrians appear to avoid other pedestrians according to their characteristics.

Therefore, in this study, a method to adjust the amount of avoidance according to the face direction was attempted. After predicting the pedestrian's behavior, the risk of collision is reduced by avoiding a small amount when the pedestrian's face is in front of the vehicle and a large amount when the face is facing downwards. Despite avoiding pedestrians using this method, if a collision is unavoidable, the mobility stops. This avoidance strategy is similar to that used by humans every day.

2 PEDESTRIAN BEHAVIOUR EXPERIMENTS

Pedestrian trajectory measurement experiments were conducted to see how pedestrians avoid each other.

The experiment was conducted on 12 subjects. Each subjects were asked to walk at a natural speed and pass opposite pedestrians. The starting position was completely face each other and the walking distance was 10 m.

An example of pedestrian trajectory against a forward-facing pedestrian is shown in Fig. 1. And an example of pedestrian trajectory against a downward-facing pedestrian is shown in Fig. 2.

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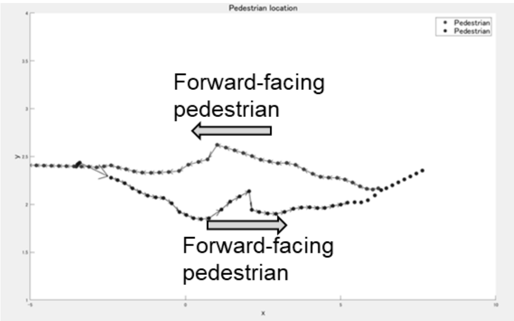

Figure 1: An example of pedestrian trajectory against a forward-facing pedestrian.

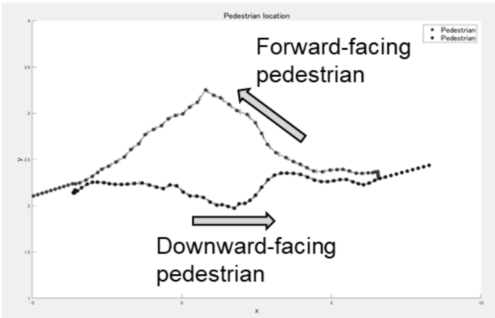

Figure 2: An example of pedestrian trajectory against a downward-facing pedestrian.

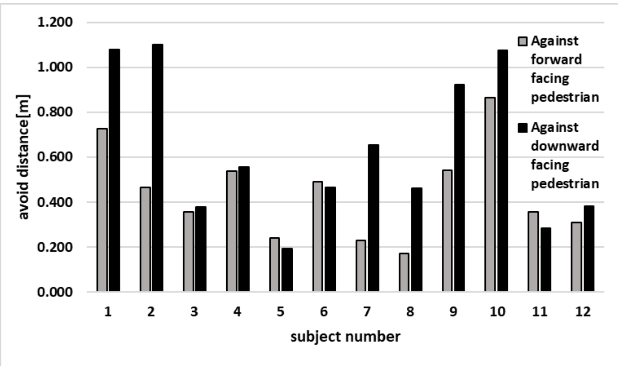

Figure 3: The avoidance distance result.

The amount of avoidance against forward-facing pedestrians and the amount of avoidance against downward-facing pedestrians were compared. The amount of avoidance is shown in Fig. 3.

Significant difference tests were conducted paired t-test with a significance level of 0.01 and a null hypothesis of 'no difference in mean values between the two groups. The two groups are the amount of avoidance against forward-facing pedestrians and the amount of avoidance against downward-facing pedestrians. The results of the significance difference test showed a p-value of 0.0077, with a significance level of 1%. This shows that pedestrians, on average, largely avoid other pedestrians who are downward-facing pedestrian. Therefore, in this research, an attempt was made to realize such human behavior in autonomous mobility.

3 METHOD

To safely avoid a downward-facing pedestrian, the face direction of the pedestrian is recognized by face direction recognition. Next, if the result of the face direction is a downward-facing pedestrian, a large avoidance path is generated. We considered these two requirements for pedestrian avoidance.

The method is based on the following procedure.

Step1 Measurement of pedestrian position using 3D LiDAR, pedestrian detection, tracking, and pedestrian behavior prediction.

Step2 Pedestrian face direction detection by image recognition .

Step3 Collision risk area calculation based on the pedestrian behavior prediction and pedestrian face direction detection results.

Step4 Pedestrian avoidance route generation.

A schematic diagram of the proposed algorithm is shown below (Fig. 4).

As in previous studies [3], 3D LiDAR information and a Kalman filter were used for pedestrian recognition and pedestrian behavior prediction.

3.1 System Configuration

The autonomous mobility used in this experiment is shown in Fig. 5. It was equipped with a camera for face direction detection of pedestrians and an omnidirectional laser sensor for self-localization and obstacle detection. Data obtained from these onboard devices is processed and controlled by a compact computer DH310 (Shuttle) and a Jetson Xavier NX (NVIDIA) (Table. 1).

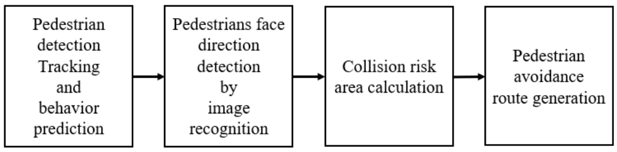

Figure 4: Method of pedestrian cooperative path planning.

Figure 5: Mobility.

Table 1: System Configuration.

Camera	C920n web camera (Logicool)
LiDAR	VLP-16 (Velodyne)
Computers	DH310 (Shutlle)
	Jetson Xavier NX (NVIDIA)

3.2 Face Recognition

To estimate whether pedestrians are aware of autonomous mobility or not, this study assumes that pedestrians whose faces are forward-facing are aware of autonomous mobility and those whose faces are downward-facing are not aware. Pedestrian face direction recognition was performed using deep learning with Yolo [6]. An example of recognition is shown in Fig. 6. First, 300 images were taken of each pedestrian with a forward face and a downward face. Next, 4000 epochs of deep learning by Yolo were performed using the collected images. The recognition rate of forwarding-facing was about 99% and that of downward-facing was about 77% (Table. 2).

3.3 Path Planning

Route generation was performed by RRT* [7] based on the occupancy grid map.

Based on the results of pedestrian face direction recognition and pedestrian behavior prediction, collision risk areas were defined on the occupancy grid map used in route generation (Fig. 7). For pedestrian behavior prediction, the walking speed of the tracked pedestrian was calculated using a Kalman filter, and the predicted position was calculated based on the calculated walking speed.

The width of the collision risk area is the same as the width of the body when avoiding a forward-facing pedestrian (hereinafter referred to as 'small avoidance'), and is wider when avoiding a downward-facing pedestrian (hereinafter referred to as 'large avoidance') so that a safe distance is maintained between the pedestrian and the collision risk area. The collision risk area was treated like an obstacle in the route generation.

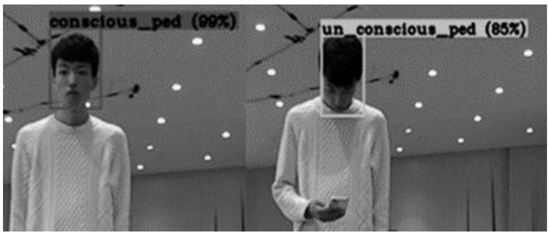

Figure 6: Recognized example of face direction.

Table 2: Recognition result of face direction.

		Recognition result	
		Forward	Downward
Human behavior	Forward	99%	1%
	Downward	23%	77%

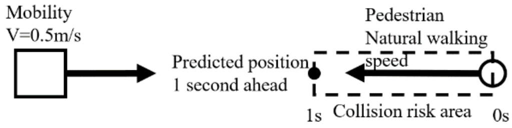

Figure 7: Collision risk area.

4 EXPERIMENS AND RESULTS

Using the proposed path planning algorithm, a subjective evaluation experiment on pedestrian avoidance was conducted in a laboratory. A course was created as shown in Fig. 8, and the autonomous mobility was moved at a translational velocity of 0.5 m/s. Pedestrians were instructed to walk at their natural walking speed and evaluate whether the autonomous mobility could avoid pedestrians.

4.1 Path Planning Results

The path planning results are shown below. For comparison, similar experiments were conducted under path planning without behavior prediction. Three types of path planning were used: without behavior prediction (Fig. 9), small avoidance (Fig. 10), and large avoidance (Fig. 11). The bold lines are the selected paths and the branches are the candidate paths. It was confirmed that the system generated a largely avoidable path for downward-facing pedestrians compared to forward-facing pedestrians.

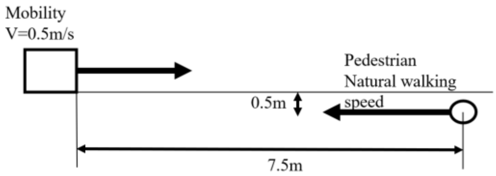

Figure 8: Layout of pedestrian avoidance experiment.

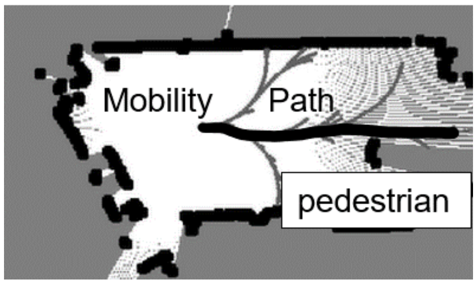

Figure 9: Path planning example of without behavior prediction path planning. The bold line represents the selected path and the branch line represent candidate path.

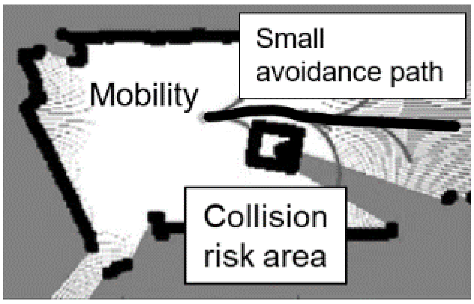

Figure 10: Path planning example of small avoidance cooperative path planning. The bold line represents the selected path and the branch lines represent candidate path. The square represents the collision risk area.

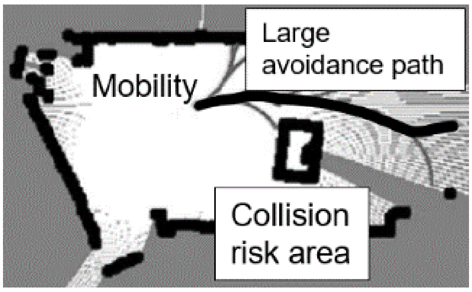

Figure 11: Path planning example of large avoidance cooperative path planning. The bold line represents the selected path and the branch lines represent candidate path. The square represents the collision risk area.

Figs 12, 13, and 14 show the trajectory examples for without behavior prediction, small avoidance, and large avoidance, respectively.

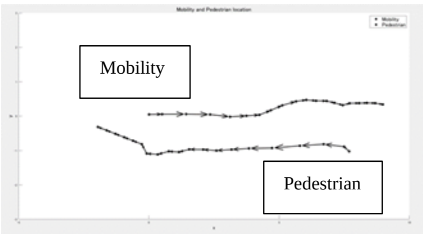

Figure 12: Trajectory example of without behavior prediction path planning.

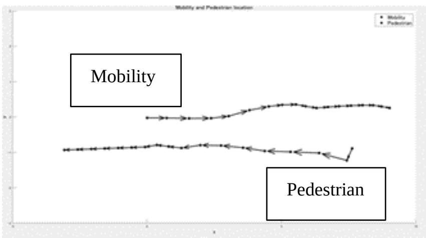

Figure 13: Trajectory example of small avoidance cooperative path planning.

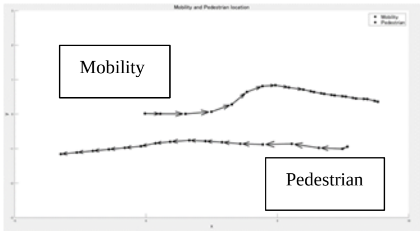

Figure 14: Trajectory example of large avoidance cooperative path planning.

The paths also showed that large avoidance was avoided to a greater extent than small avoidance and that the timing of avoidance was delayed without the collision risk area.

4.2 Subjective Evaluation Results

Subjective evaluation of pedestrian avoidance performance was carried out on nine subjects. In the experiment with 12 subjects in Chapter 2, it was shown that there was a significant difference between the trajectories of avoidance against forward-facing pedestrians and those against downward-facing pedestrians. Therefore, a more detailed experiment on avoidance with mobility was conducted with nine subjects. Two trials of each condition were made to each subject. Experiments were carried out based on the approval of the Human Ethics Review Committee of Kanagawa institute of technology.

Subjective evaluation was performed with 4 evaluation items. They are "distance from the autonomous mobility when passing by", "speed of the mobility when passing by", "smoothness of passing by (avoidance performance)", and "reliability when passing by". These items were evaluated in five levels, with the following ratings: 'good', 'a little good', 'undecided', 'a little bad', and 'bad'.

Subjective evaluation results are as follows (Figs. 15 and 16). In the case of forward-facing pedestrians, the evaluation of all items improved in comparison without behavior prediction and small avoidance. In the case of downward-facing pedestrians, the evaluation values of all items improved in comparison without behavior prediction and large avoidance. Especially, in the case of downward-facing pedestrians, the evaluation of distance was considerably improved. No change was observed in the evaluation of speed, partly because the vehicles were driven at the same speed in all three conditions.

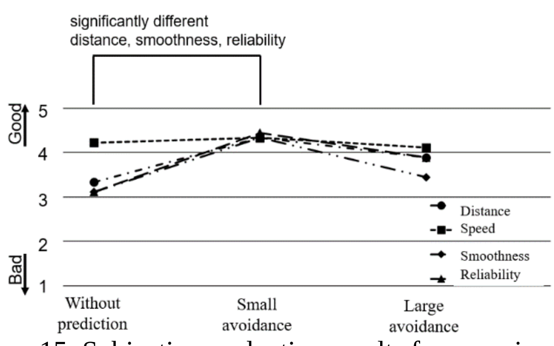

Figure 15: Subjective evaluation results for conscious pedestrians.

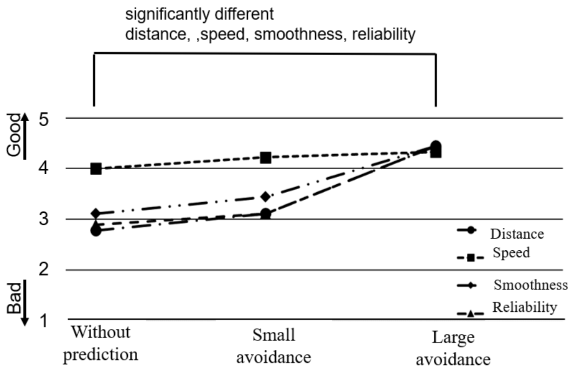

Figure 16: Subjective evaluation result.

Significant difference tests were conducted paired t-test with a significance level of 0.05 and a null hypothesis of 'no difference in mean values between the two groups. In this study, method of successive categories was used to convert subjective evaluation results from ordinal scale to interval scales. Without behavior prediction and small avoidance were compared for forward-facing pedestrians, and without behavior prediction and large avoidance were compared for downward-facing pedestrians. The p-values for each item are shown below (Tables 3 and 4).

5 PHYSICAL INDICATORS

5.1 Objective Evaluation Results

The physical quantities corresponding to the four evaluation items “distance”, “speed”, “smoothness”, and “reliability”, which were considered to be related to passing each other, were examined.

First, we considered the item of "distance" when passing each other. In this study, the nearest neighbor distance at the time of passing was used as the distance perceived by the subjects. As an example, the distance was 0.83 m in the case of without behavior prediction, 1.05 m in the case of small avoidance and 1.45 m in the case of large avoidance.

Table 3: Result of significance test for forward facing pedestrian (* p<0.05).

item	P-value
Distance	0.043* significantly different
Speed	0.173
Smoothness	0.057 significantly different
Reliability	0.025* significantly different

Table 4: Result of significance test for downward facing pedestrian (* p<0.05, ** p<0.01).

item	P-value
Distance	0.004** significantly different
Speed	0.041* significantly different
Smoothness	0.017* significantly different
Reliability	0.005** significantly different

Next, "speed" was examined. Relative speed and absolute speed can be considered as index candidates. In this study, the speed perceived by the pedestrian is considered as the relative speed of the mobility. The pedestrian was asked to walk at natural walking speed in all three conditions and the translational velocity of the mobility was constant for all three conditions. As an example, the relative velocity was 0.87 m/s in the case of without behavior prediction, 1.01 m/s in the case of small avoidance, and 0.93 m/s in the case of large avoidance.

“Smoothness” was further considered. The turning angular velocity ω during the avoidance is used as an indicator. The point where the angular velocity became 0.1 rad/s or bigger was defined as the avoidance start, and the angular velocity until it became less than 0.1 was averaged. In the case of without behavior prediction, no avoidance is performed, therefore the average value of the turning angular velocity reached to the nearest distance is used. As an example, the average value of the turning angular velocity during avoidance was 0.00 rad/s is for the without behavior prediction, 0.14 rad/s for small avoidance, and 0.29 rad/s for large avoidance.

5.2 Indicator for Reliability

A physical quantity that correspond to the "reliability" when passing each other was examined.

Time to collision (TTC) is a physical index used in the Autonomous Emergency Braking (AEB) installed in vehicles. This indicator represents the time until collision with the leading vehicle if the current relative speed of the leading vehicle to the ego vehicle is maintained. Let x_e, v_e, be the front end position and velocity of the ego vehicle and x_l, v_l be the rear end position and velocity of the leading vehicle in the world coordinate system. In this case, the relative distance d_x and the relative velocity v_x of the leading vehicle relative to the ego vehicle are $x_l - x_e$, $v_l - v_e$ (Fig. 17). Therefore, if the value of TTC is t_x, the following equation is obtained (1).

$$t_x = -\frac{d_x}{v_x} = -\frac{x_l - x_e}{v_l - v_e} \tag{1}$$

In a previous study [8], it was shown that most people drive with a TTC of 4 seconds or longer. Therefore, TTC may be used as an indicator of reliability. In this study, a physical quantity by expanding the TTC to two dimensions (2D TTC) was investigated. In addition, pedestrians are assumed to be in constant velocity linear motion and mobility is assumed to have constant translational and rotational velocity.

The method for calculating 2D TTC is as follows. It was assumed that the pedestrian would move linearly at a constant velocity and the mobility would move at a constant translational velocity and a constant angular velocity. The coordinate transformation from the world coordinate system to the mobility coordinate system is performed. The positions and velocities of the autonomous mobility and pedestrian in the world coordinate system are shown in the Fig. 18. The position and speed of the mobility are $(x_e(t), y_e(t))$ and

$(v_{ex}(t), v_{ey}(t))$, and the predicted position and the predicted speed of the pedestrian are $(x_p(t), y_p(t))$ and (v_{px}, v_{py}). The distance from the center of gravity of the vehicle to the front center of the vehicle is h. The position and velocity of the pedestrian in the world coordinate system are transformed into the mobility coordinate system with reference to the mobility's center of gravity. In this case, the relative position $(x_r(t), y_r(t))$ and relative velocity $(v_{rx}(t), v_{ry}(t))$ of the pedestrian relative to the vehicle front of the mobility are $(x_p(t) - (x_e(t) + h), y_p(t) - y_e(t))$ and $(v_{px} - v_{ex}(t), v_{py} - v_{ey}(t))$ (Fig. 19).

The path distance d_p is defined as the Equation (2). The path distance represents the distance from the current location to the collision point. $t_{collision}$ represents the predicted time when the collision would occur.

$$d_p(t) = \int_t^{t_{collision}} \sqrt{v_{rx}(t)^2 + v_{ry}(t)^2} dt \tag{2}$$

In addition, the absolute value of the relative velocity is given by equation(3).

$$v_r(t) = \sqrt{v_{rx}(t)^2 + v_{ry}(t)^2} \tag{3}$$

Therefore, if the value of the 2D TTC is t_c, it follows that equation(4).

$$t_c(t) = \frac{d_{p(t)}}{v_r(t)} \tag{4}$$

The value of the 2D TTC in the case of no collision is defined as infinite.

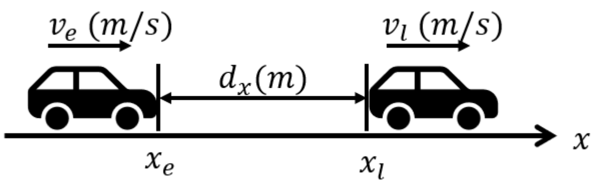

Figure 17:TTC outline figure.

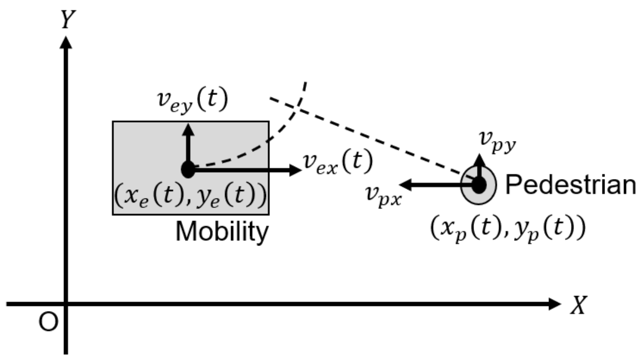

Figure 18:World coordinate system.

The 2D TTC was calculated for three conditions: without behavior prediction, small avoidance, and large avoidance. The mobility, pedestrian position and 2D TTC values during the calculation using MATLAB are shown (Figs 20, 21, and 22).

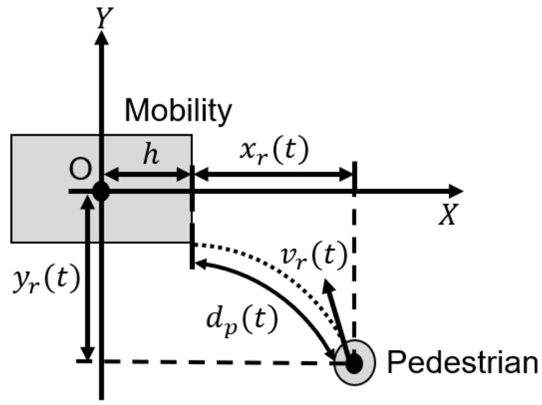

Figure 19: Mobility coordinate system.

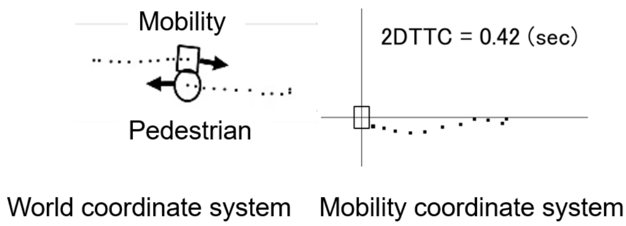

Figure 20: Without behavior prediction 2DTTC calculation diagram.

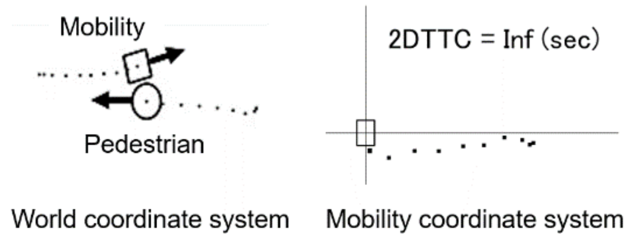

Figure 21: Small avoidance 2DTTC calculation diagram.

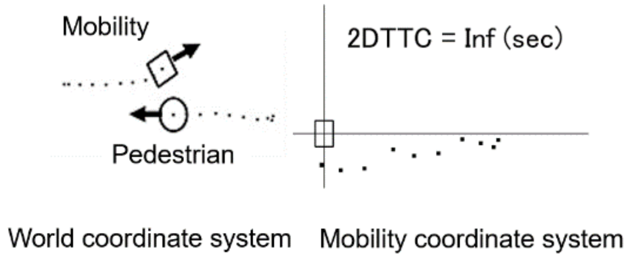

Figure 22: Large avoidance 2DTTC calculation diagram.

5.3 Example of Physical Indicators

An example of physical indicators value during forward-facing pedestrians is shown in the figure in chronological order (Fig. 23).

5.4 Relationship Between Subjective Evaluation and Physical Indicators.

The results for the subjective and objective evaluation values are shown in Figs 24, 25, 26, and 27.

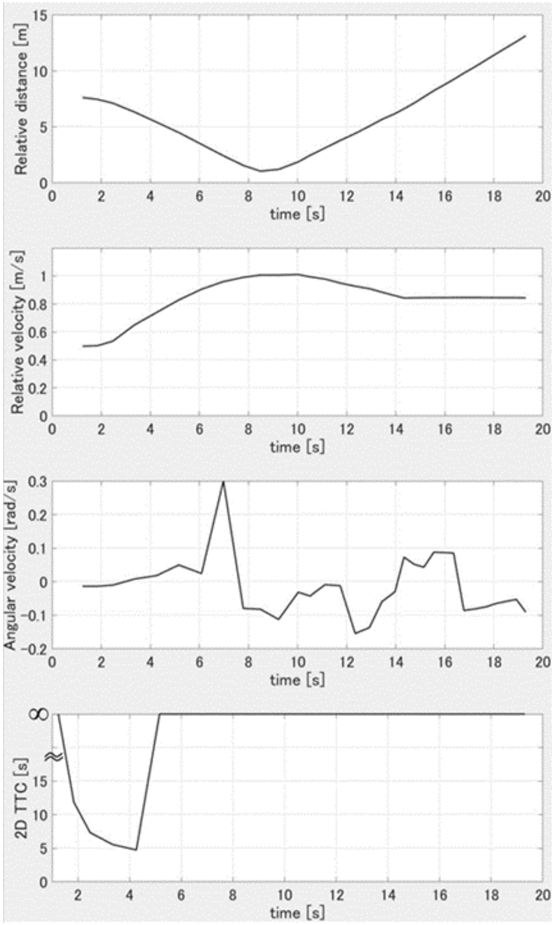

Figure 23: Example of physical indicators.

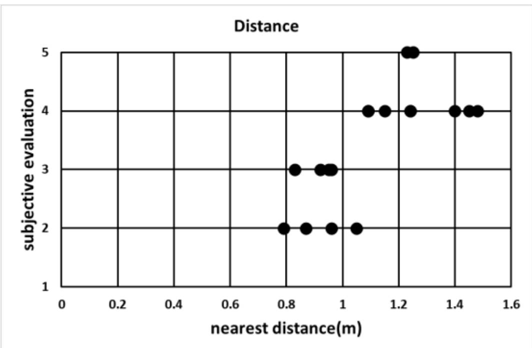

Figure 24: Relationships between distance and subjective evaluation.

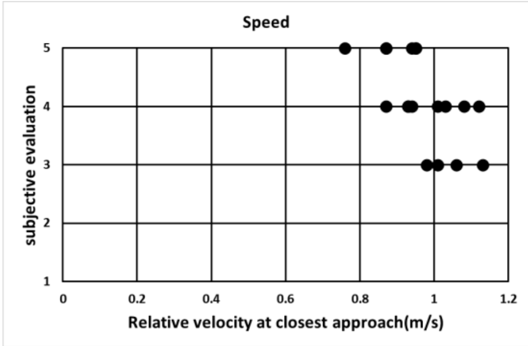

Figure 25: Relationships between speed and subjective evaluation.

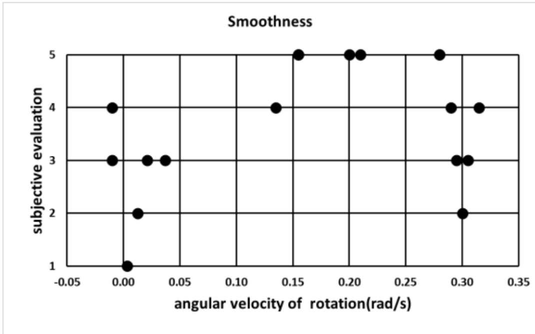

Figure 26: Relationships between smoothness and subjective evaluation.

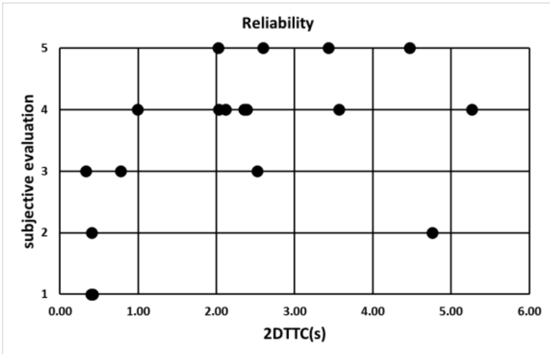

Figure 27: Relationships between reliability and subjective evaluation.

As for distance, the subjective evaluation value improves as the value of the closest neighbor distance increase.

For speed, the subjective evaluation value improves as the value of the relative speed at the closest approach decrease.

Regarding smoothness, the subjective evaluation value improves as the angular velocity of the turn increase.

The subjective evaluation value of the reliability worsens when the 2D TTC value is less than one second, while the subjective evaluation value improves when the 2D TTC value is two seconds or more.

6 DISCUSSION

6.1 The Results of the Subjective Evaluation.

Both forward and downward-facing pedestrians improved the subjective evaluation results for all items except speed. Speed was highly rated in all three conditions, with no significant differences observed. It is considered that this is because the mobility moved at a constant speed under all experimental conditions.

In the subjective evaluation of forward-facing pedestrians, the evaluation of large avoidance was slightly worse than that of small avoidance. Several subjects commented on the poor smoothness of large avoidance, such as "I felt poor smoothness" and "If I were a human, I would feel un-comfortable as if I were being large avoided". From this result, it seems that small avoidance is appropriate for for-ward-facing pedestrians.

Significant differences in distance and reliability were found for forward-facing walking. This result is thought to be due to the fact that the mobility without prediction (no collision risk area) pass pedestrians at a close distance, while those with a collision risk area maintain a certain distance while avoiding pedestrians.

In downward-facing walking, significant differences were observed in all items except speed. In forward-facing walking, the presence of mobility can be confirmed early on in the effective field of view, whereas in downward-facing walking, the effective field of view is narrower than in forward-facing walking because walking is done while gazing at the smartphone [9], and the pedestrian only confirms the presence of the mobility when it enters the peripheral field of view just before passing by. Therefore, the evaluation of distance, the reliability and smoothness decreased, whereas with the collision risk area, the reliability also improved because the robot maintains a maximum safe distance and makes a larger avoidance compared to forward-facing walking.

6.2 The Results of the Objective Evaluation.

With regard to the relationships graph for smoothness (Fig. 26), the subjective evaluation value largely changes at the small turning angle speed value. These conditions are path without behavior prediction and no avoidance is performed. Further studies are needed on these characteristics.

With regard to the relationships graph for the reliability (Fig. 27), there is an outlier where the subjective evaluation worsens despite the high 2DTTC value, but this is thought to be influenced by one subject's opinion that he felt nothing in particular about the reliability because he avoided the area a little himself. Overall, the subjective evaluation largely changes as the value of 2DTTC increased.

7 CONCLUSION

In this study, we proposed a path planning algorithm that adapts to the face direction of pedestrians and safely avoids pedestrians who are walking while on their smartphones.

Our subjective evaluation results suggest that there are relationships between the evaluation values and the physical indicators.

This method would enable the operation of advanced collaboration between pedestrians and autonomous mobility on campus.

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