

Efficient Navigation in Crowded Environments for Autonomous Electric Wheelchairs Using Human Flow Activity Trend and Most Frequent Direction

Takuya Kojima *, Mihoko Niitsuma *, *Member, IEEE*

Abstract— Human flow data is being acquired and utilized in various situations. In this paper, we propose a navigation system for autonomous electric wheelchairs that makes use of usage trends in the driving environment obtained from human flow data. This system is expected to generate globally optimal paths and plan highly effective driving strategies. As a result, the navigation system may reduce the physical and mental burden on the user and harmonize with the surrounding pedestrians. In particular, this paper verifies through simulation experiments the usefulness of the system that takes into account environmental usage information, such as stay history, transit history, and most frequent travel directions.

I. INTRODUCTION

Human flow data has been applied across various domains, including retail for sales optimization, transportation system enhancement, and disaster prevention and crime reduction in communities [1-2]. Similarly, this data holds potential for improving the performance of autonomous electric wheelchairs. Utilizing human flow data enhances navigation and ensures smoother operation in dynamic environments.

Several navigation systems for autonomous electric wheelchairs have been developed. These include systems based on artificial potential fields [3], systems that predict the movement of dynamic obstacles [4-7], and systems that follow pedestrians moving in the same direction as the wheelchair [8]. Most of these systems rely on reactive navigation, utilizing data from onboard sensors and focusing on local range planning.

However, these approaches face significant limitations. First, they are not capable of detecting obstacles located in the blind spots of the sensors. Second, even if new sensors are added to reduce blind spots or data from other robots is utilized, the path may still become suboptimal due to the unpredictable movement of dynamic obstacles. In essence, reactive systems only respond to what is immediately detected and may fail to account for future changes in the environment. As a result, these paths might be locally optimal but not globally efficient.

Research on navigation for mobile robots in environments with pedestrians has been proposed [9]. These navigation systems focus on obstacle avoidance but rarely incorporate past travel histories or congestion patterns for path planning that fosters coexistence between humans and robots in shared environments. This study focuses on this point and aim to develop a navigation system that harmonizes pedestrians.

For instance, automatic electric wheelchairs have been introduced at airports [10-11]. Although human flow data at airports often shows patterns, such as congestion near gates at certain times, current systems do not incorporate this data, leading to inefficiencies. This omission often results in the wheelchair navigating into congested areas, causing delays or inconvenience to surrounding pedestrians.

To address these challenges, this paper proposes a navigation system for autonomous electric wheelchairs that uses human flow data to proactively predict obstacle behavior and plan efficient driving strategies. By doing so, the system can preemptively avoid congested areas and optimize travel paths based on the movement trends within the environment.

This approach is expected to offer several benefits. First, it will enable the wheelchair to avoid high-traffic areas in advance. Second, it will allow the system to plan paths that align with the space's usage patterns. Third, it will generate globally optimal paths, reducing the frequency of avoidance maneuvers and minimizing speed limitations. Ultimately, these improvements are anticipated to enhance both the user's experience and the safety of surrounding pedestrians by reducing the physical and mental burden on wheelchair user associated with ride time and avoidance behaviors and by reducing the negative impact on surrounding pedestrians, such as lower walking speeds or higher crowd density caused by the wheelchair's presence.

From the above, we propose a proactive navigation method for autonomous electric wheelchairs based on human flow data. Based on human flow data, this system ensures efficiency and performs path planning that is highly effective even in congested areas and harmonizes with the trends of surrounding pedestrians. The objective is to reduce the burden on both passengers and surrounding pedestrians.

This paper reports the results of evaluating the usefulness of the system in simulation experiments. Since the experiment with the actual machine has progressed to the stage where the vehicle is driven with a passenger on board, the results of the experiment with the actual machine will be reported at another time in the future.

II. NAVIGATION FOR AUTONOMOUS ELECTRIC WHEELCHAIRS BASED ON HUMAN FLOW DATA

A. System Configuration

We use the Personal Mobility Tool (PMT) (Fig. 1) [12] as the autonomous electric wheelchair. The PMT was proposed to reduce the user's physical burden of having to keep the joystick depressed when operating the electric wheelchair. The PMT system is illustrated in Fig. 2. When the passenger tilts

*T. Kojima and M. Niitsuma are with Chuo University, Bunkyo-ku, Tokyo, 112-8551. (e-mail: niitsuma@mech.chuo-u.ac.jp)



Fig. 1 The Personal Mobility Tool (PMT) used as the autonomous electric wheelchair in this study.

the joystick in the desired direction, the PMT estimates the destination based on the costmap and performs global path planning to avoid known obstacles in the costmap and reach the destination. By acquiring real-time 3D point cloud data from the onboard sensor (VLP-16), the PMT receives speed commands that allow it to follow the global path while locally avoiding unknown obstacles.

B. Obtaining Environmental Use Information from Human Flow Data

Systems proposed in [13–15] consider dynamic obstacles in their navigation, including pedestrians, but still have challenges. They do not use the direction of movement of pedestrians, nor do they actively use historical information. However, using the direction of movement may reduce the number of evasions and harmonize with surrounding pedestrians, and using past information to determine appropriate action strategies in advance, i.e., proactive actions.

To solve these problems, the proposed system acquires human flow data using the Single 3D LiDAR-based Moving Object Extraction system (the S3L-MOE system) (Fig. 3) [16–17]. The S3L-MOE system enables the acquisition of past human flow data, such as locations where many pedestrians stayed or passed, or where a particular trend in human flow was observed. The S3L-MOE system accumulates the history of obstacles and human activities in the environment by reflecting the point clouds obtained from LIDAR sensors installed in the environment on a 10 cm square grid map. Specifically, the human activity history includes degree of activity and walking dynamics information. The former quantitatively indicates how many people stayed in or passed through a particular cell, with a larger value indicating a longer stay or a greater number of people passing through. The latter indicates the most frequent movement direction, average movement speed, average acceleration, and other dynamics in that cell. Here, when the PMT performs path planning based on environmental information, it may be more effective if it takes into account locations where pedestrians tend to stay or pass or where a particular trend in human flow is observed. Therefore, the proposed method uses degree of activity and the most frequent direction of movement.

C. Self-positioning Estimation

In this system, an environmental map is pre-constructed offline. For this purpose, Simultaneous Localization and Mapping (SLAM) is utilized, which allows for high-precision self-position estimation and environmental map construction using only the sensors mounted on the PMT. During the PMT

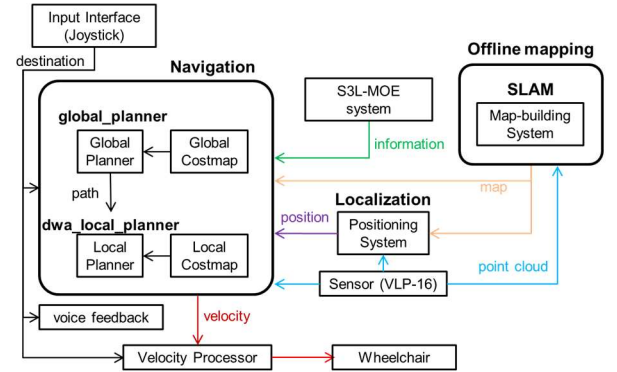
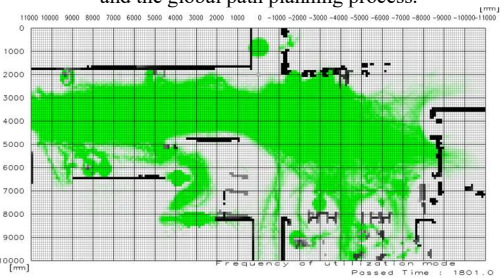
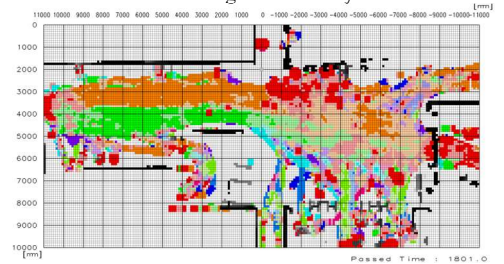


Fig. 2 The PMT system configuration, illustrating the onboard sensor and the global path planning process.



(A) Degree of activity acquired by the S3L-MOE system. Black cells represent static obstacles (e.g. walls) and green cells represent degree of activity.



(B) The most frequent direction of movement acquired by the S3L-MOE system. Black cells represent static obstacles (e.g. walls) and each color represents a mode direction based on the legend.

Fig. 3 Example of human flow information acquired by the S3L-MOE system.

operation, self-position estimation is performed online by matching the real-time point cloud data obtained from the center with the pre-constructed environmental map.

D. Path Planning

This system performs path planning based on global_planner *1 and motion planning based on dwa_local_planner *1. By integrating these, we achieve path plan.

When performing path planning and motion planning, we use a costmap that reflects obstacle information to calculate the traversable areas for the PMT and optimal paths. We define the costmap used for path planning as the Global costmap, and the costmap used for motion planning as the Local costmap. Each costmap consists of Static layer, Obstacle layer, Inflation layer, and Environment layer. The Static layer reflects known obstacles, the Obstacle layer reflects unknown obstacles in

*1 <https://github.com/ros-planning/navigation>, (accessed Sept. 10, 2024).

real-time, and the Inflation layer reflects the collision margin between the PMT and obstacles. The Environment layer is a unique layer in this proposed system that reflects environmental information obtained from the S3L-MOE system.

E. Reflection of Environmental Use Information

This paper describes a method for path modification using degree of activity and the most frequent direction of movement. This is expected to enable avoiding areas with high human presence and passing through areas where the direction of movement aligns with the flow of people. Specifically, this is achieved by reflecting the degree of activity and most frequent direction of movement as costs in the Environment layer of both the Global costmap and Local costmap. The final cost, $cost(x, y)$, to be reflected is calculated based on degree of activity and the most frequent direction of movement, but the calculation method differs depending on the current orientation of the PMT and the most frequent direction of movement in that cell. When the front of the PMT is set at $0[^\circ]$, cases where the most frequent direction of movement is $90[^\circ]$ or more, or $-90[^\circ]$ or less, are considered “different direction,” while other cases are considered “same direction.” Let $act(x, y)$ be the degree of activity obtained from the S3L-MOE system, and $vr(x, y)$ be the variation in the most frequent direction of movement. Then, the cost, $cost(x, y)$, is calculated using equation (2). Here, $vr(x, y)$ is determined by equation (3), which is calculated using the weights of each direction in the cell when determining the most frequent direction of movement in the S3L-MOE system.

Furthermore, it is possible to adjust the cost, $cost(x, y)$, in response to real-time fluctuations in congestion levels. The system used in this experiment calculates the cost, $cost(x, y)$, based on the degree of activity and the most frequent movement direction obtained from the S3L-MOE system in the past. However, since the S3L-MOE system enables congestion levels in real time, by enabling communication between the S3L-MOE system and the PMT, the cost, $cost(x, y)$, reflected in the costmap also enables it to be dynamically adjusted in real time.

$$tmpCost(x, y) = \frac{200}{1 + e^{-0.5 \cdot 10^{-5} (act(x, y) - 2 \cdot 10^6)}} \quad (1)$$

$$cost(x, y) = \begin{cases} 200 & \text{if(static obstacle)} \\ tmpCost(x, y) \cdot vr(x, y) & \text{if(different direction)} \\ tmpCost(x, y) \cdot (1 - vr(x, y))^2 & \text{if(same direction)} \end{cases} \quad (2)$$

$$vr(x, y) = \frac{(\text{Value of the most frequent direction of movement})}{(\text{Value of stay}) + \dots + (\text{Value of } top_{right})} \quad (3)$$

The highest value obtained in Equation 1 and 2 is 200 to avoid getting stuck in cells that reflect information from the human flow data. The maximum value of cost in the costmap used is 255. If the information of human flow data is reflected in a cell with a cost of 255, the cell will get stuck if a robot unintentionally enters the cell. To prevent this, the maximum cost value that reflects the information of human flow data is set to 200, which is smaller than the maximum cost value of costmap and empirically determined to be no obstacle for the robot to travel.

F. Destination Estimation by Joystick

In the proposed system, a joystick is used as the interface for inputting the destination. The method of inputting with the joystick is determined by the direction and angle it is tilted (Fig. 4).

First, the direction is estimated to determine the intended direction. The process differs depending on whether the PMT is in a stationary or moving state. When the PMT is stationary, the direction in which the joystick is tilted becomes the intended direction. When the PMT is moving, if the input direction, $\theta_{direction}$ [rad], is in the range of $\theta_{direction} < -3\pi/4$ or $3\pi/4 < \theta_{direction}$, the system stops; otherwise, the tilted direction becomes the destination direction.

Next, the distance to the destination is estimated based on the tilt angle. When the tilt angle, θ_{slope} [rad], satisfies $|\theta_{slope}| \leq 0.8$, the closest static obstacle in the direction of $\theta_{direction}$ [rad] from the current location is set as the destination. If $0.8 < |\theta_{slope}|$, the second closest static obstacle in the direction of $\theta_{direction}$ [rad] from the current location is set as the destination.

In this process, destination estimation is performed based on the environmental map that was pre-created offline.

III. EXPERIMENT

A. Experimental Conditions

To verify the effectiveness of the proposed method, we conduct simulation experiments using Unity. The environment is assumed to be the simplest situation in which there are two directions of human flow. In order to make it easy to understand the difference between the two directions of flow, one flow is generated per corridor. The distance is assumed to be the same for both paths. This environment will make clear the importance of the robot's cooperation with the surrounding pedestrians, even if the distance traveled is the same. With this in mind, an experiment is conducted in the environment shown in Fig. 5. The experiment begins by acquiring environmental usage information using the S3L-MOE system. During this process, human flow is generated based on the Pedestrian LOS, determining the number of people, maximum walking speed, and density. Pedestrian LOS is an evaluation of the service level of the walking environment on a six-level scale from A to F, using evaluation indicators such as human flow rate, walking speed, and walking density. Level A represents the situation with the fewest people, while level F represents the situation with the most people. The pedestrians constituting the flow are generated in two groups: one moving from the start point (Fig. 5, point c) to the goal point (Fig. 5, point d), i.e., from the bottom to the top of the right-side corridor in Fig. 5, and another moving from the start point (Fig. 5, point e) to the goal point (Fig. 5, point f), i.e., from the top to the bottom of the left-side corridor in Fig. 5. In this case, pedestrians move based on the social force model (SFM). The SFM used in this study calculates velocity based on repulsive forces from static obstacles, repulsive forces between pedestrians, repulsive forces from the PMT, and attractive forces towards the goal. The factors considered in the SFM have random weights for each pedestrian. This allows the system to represent individual differences among pedestrians as would be expected in the real

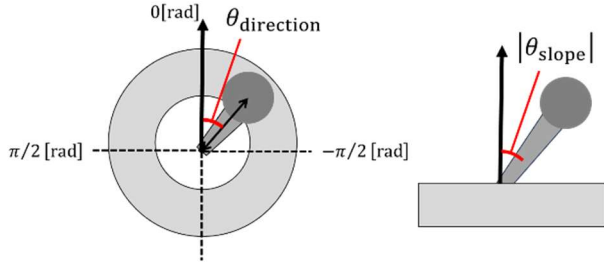


Fig. 4 Calculation of joystick direction and tilt for the PMT to estimate destination.

world. For example, it is possible to reproduce a pedestrian who has a large gravitational force toward the goal and a person who has a small repulsive force from surrounding pedestrians. In an environment where such human flow is generated (Fig. 6), we acquire activity history of human flow for LOS levels A, C, and E, each for 5 minutes. During this time, the PMT is not present in the environment.

Subsequently, the PMT performs navigation in an environment with the pedestrians, conducting five runs for each LOS level from the start point (Fig. 5, point a) to the goal point (Fig. 5, point b). This is done using both the conventional method without using pre-acquired environmental usage information, and the proposed method reflecting degree of activity and most frequent direction of movement. Pedestrians move based on the SFM described above, but with different weights and locations of appearance than when the human flow data was obtained.

The evaluation criteria include the PMT's travel time, travel distance, average speed, as well as the average pedestrian speed, occupied area per pedestrian, and distance between the PMT and pedestrians, all within a 3 m radius. The PMT-related items quantitatively evaluate the efficiency of the PMT, while the evaluation of surrounding pedestrians quantifies the behavioral changes in the crowd due to differences in the PMT's travel strategy.

B. Experimental Results and Discussion

Firstly, regarding the number of times the goal was reached, the conventional method reached the goal 5 times at level A, 5 times at level C, and 0 times at level E, whereas the proposed method reached the goal in all trials.

Next, regarding the paths, as shown in Fig. 7, while the conventional method traveled on the left side in all trials, the proposed method traveled on the left side at level A and on the right side at levels C and E. The reason why the conventional method traveled on the left side in all trials is likely because, despite the physical distance of the travel environment being similar, the map generated by the PMT's offline mapping showed a slightly shorter distance when traveling on the left side. In contrast, the proposed method traveled on the right side at levels C and E based on information about degree of activity and the most frequent direction of movement (Fig. 8), effectively riding the flow of people. At level A, it traveled on the left side due to low degree of activity (Fig. 8), similar to the principle of the conventional method. These results show that the proposed method makes it possible to avoid congestion and generate paths that follow the flow of people by taking into account the degree of activity and the most frequent direction of movement.

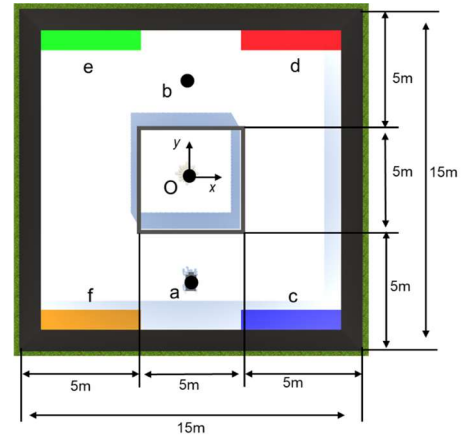
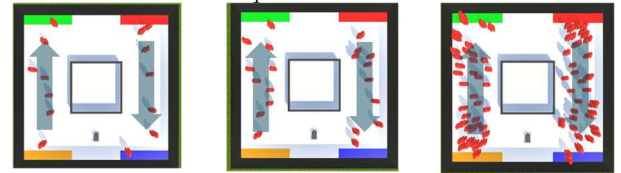
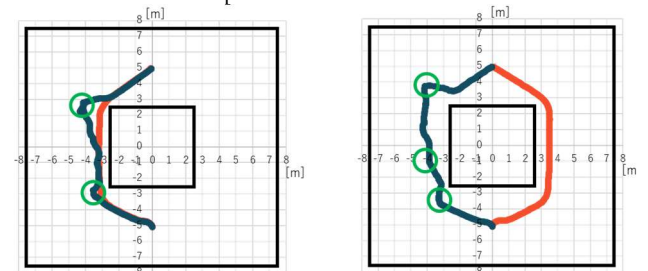


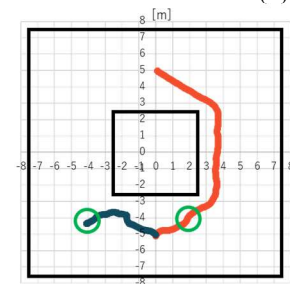
Fig. 5 The experimental environment, consisting of two corridors with human flow in opposing directions for evaluating navigation performance.



(A) Level A (B) Level C (C) Level E
Fig. 6 Pedestrian Level of Service (LOS), where red objects represent pedestrians in the environment. Levels A, C, and E illustrate varying pedestrian densities.



(A) Level A (B) Level C



(C) Level E

Fig. 7 An example of the paths the PMT traveled in the experiments. The dark blue line is the path of the conventional method and the orange line is the path of the proposed method. The green circle is the position where the PMT took evasive action. The trajectory of the conventional method for Level E is to the stuck location.

Fig. 9 shows the results of evaluations using t-tests with a 5% significance level for the evaluation items. For items related to the PMT's travel performance, such as travel time and travel distance, the proposed method showed significantly smaller values. For items related to harmony with surrounding pedestrians, such as the average occupied area per pedestrian and the average distance between the PMT and pedestrians, the proposed method showed significantly larger values.

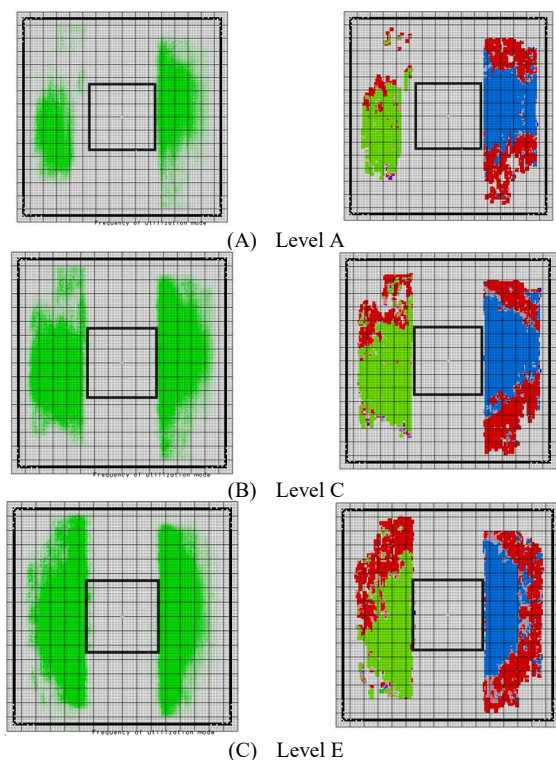


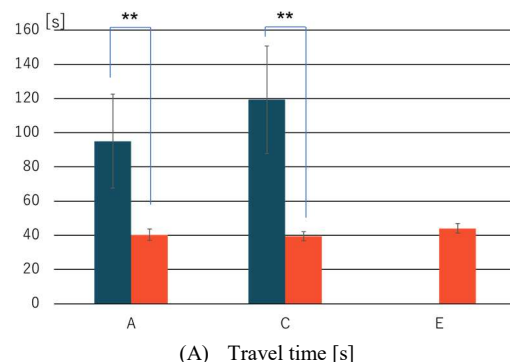
Fig. 8 Human flow information acquired by the S3L-MOE system. The left figures show the degree of activity. Black cells represent static obstacles (e.g., walls) and green cells represent the degree of activity. The right figures show the most frequent direction of movement. The black cells are static obstacles (e.g., walls) and each color represents a mode direction based on the legend.

These results suggest that the proposed method provides more space for pedestrians to change their walking paths and potentially reduces the risk of collision between the PMT and pedestrians, indicating improved safety.

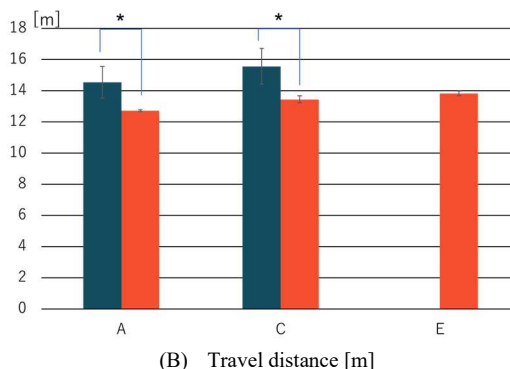
In conclusion, this proposed system suggests that when the PMT plans paths based on degree of activity and the most frequent direction of movement, it allows the PMT to improve its mobility efficiency and reduce the burden on both passengers and pedestrians.

C. Application to Real-world Environments

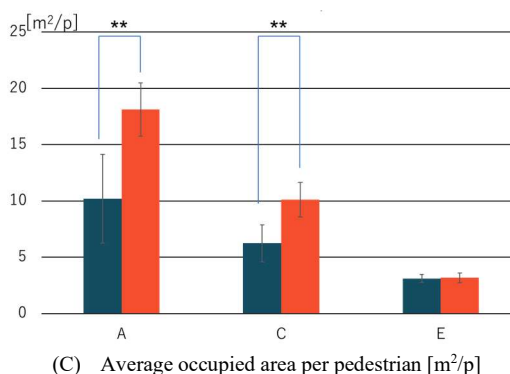
The proposed method in this paper is to be applied to real-world environments. In this paper, human flow data was acquired in a simulation environment and used for navigation to prove the concept before the experiments in the real world. When the proposed method is applied to real-world environments, human flow data should be acquired in the environments. By doing so, it is possible to obtain data, naturally including the randomness of pedestrians, in real-world environments where environmental factors influence human behavior.



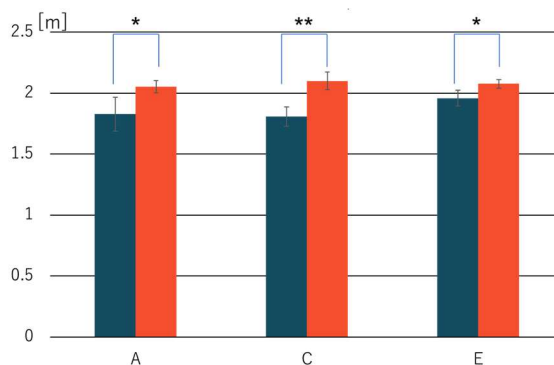
(A) Travel time [s]



(B) Travel distance [m]



(C) Average occupied area per pedestrian [m²/p]



(D) The average distance between the PMT and pedestrians [m]

Fig. 9 Results of the evaluation items of the experiment results. The dark blue bars represent the conventional method and the orange bars represent the proposed method. ** indicates that a t-test at a 5% significance level resulted in $p < 0.01$. * indicates that a t-test at a 5% significance level resulted in $0.01 < p < 0.05$. The results of the conventional method for LOS level E in figures (A) and (B) are not shown because the PMT did not reach the goal in all trials.

IV. CONCLUSION

In this paper, we proposed a navigation system for the PMT (Personal Mobility Tool) that plans paths based on degree of activity and the most frequent direction of movement, which are usage information within the PMT's operating environment. The results of simulation experiments showed that the proposed method outperformed the conventional method not only in evaluation items related to the PMT but also in evaluation items related to surrounding pedestrians. These results suggest that the proposed method enhances the PMT's performance, enabling more efficient operation. Furthermore, it suggests that the safety of surrounding pedestrians is also improved, and the PMT harmonizes with the traveling environment.

The current study does not include experiments in real-world environments. Future work will focus on collecting real-world data to validate the proposed method under more complex and unpredictable conditions.

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