IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 4 June 2024, accepted 9 July 2024, date of publication 18 July 2024, date of current version 5 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3430352

RESEARCH ARTICLE

Human-Aware Trajectory Optimization for Enhancing D* Algorithm for Autonomous Robot Navigation

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This work was supported by Korean Ministry of Land, Infrastructure and Transport (MOLIT) as "Innovative Talent Education Program for Smart City." The work of Min Je Choi was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea under Grant NRF-RS-2023-00276836. The work of Seung Jae Lee was supported by Korea Agency for Infrastructure Technology Advancement (KAIA) Grant funded by the Ministry of Land, Infrastructure and Transport under Grant RS-2024-00409428.

ABSTRACT This research focuses on modifying the D* algorithm for path optimization of autonomous robots moving on sidewalks. The existing D* algorithm is designed to make the autonomous robots recognize and avoid obstacles. However, in real-world pedestrian settings, observations indicate that passersby on sidewalks tend to notice robots and avoid them themselves. By analyzing people's trajectory data collected through lidar sensors, this study identified the average distance and angle of avoidance at which people start to avoid autonomous robots. Based on this, we proposed a modified D* algorithm that allows the robot to maintain the existing optimal path when people are willing to maneuver around while adopting an avoidance path only when they are not. Experimental results showed that the autonomous robot using the modified D* algorithm outperformed the conventional method regarding driving efficiency and time. This research is expected to contribute to optimizing autonomous robots' walking paths by enabling efficient driving even under limited battery capacity.

INDEX TERMS D* algorithm, autonomous mobile robot, trajectory analysis, path planning.

I. INTRODUCTION

In recent years, autonomous driving technology has emerged as a high-profile area of innovation around the world [1]. It is redefining the nature of transportation and contributing to improving road safety, enhancing driver comfort, and optimizing traffic management systems [2]. This development of technology has been driven by large companies such as Google, Tesla, and Hyundai. These companies are primarily focused on autonomous vehicles for road use. These advances are not just limited to cars on the road but are expanding into many aspects of everyday life [3]. Recent trends emphasize a pedestrian-centric environment, leading to research in walkability assessment, mobility modes, and pedestrian environment evaluations [4], [5], [6]. In particular, the emergence of autonomous robots that use pedestrian paths is opening new possibilities in areas as diverse as public safety, delivery services, and personal transportation. Since these autonomous robots operate in spaces where people are mainly active, it is necessary to apply an autonomous driving algorithm different from cars on the road. Unlike autonomous vehicles on the road, which follow established traffic rules and predictable routes, autonomous robots on sidewalks face a much more dynamic and unpredictable environment. Pedestrian paths lack certain rules or directions and are characterized by various irregular movements and paths, and frequently changing obstacles. To operate effectively in these environments, autonomous robots must constantly be aware of their surroundings and react quickly to determine the best path to take [7], [8]. As for the traffic method on the road, rules exist by traffic lights, CCTV, and safety signs, as presented in Fig. 1.

The associate editor coordinating the review of this manuscript and approving it for publication was Razi Iqbal.

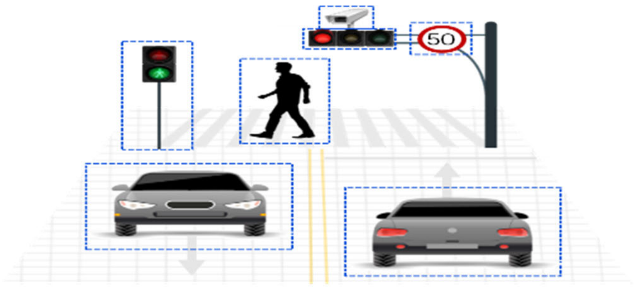


FIGURE 1. Traffic method on the road.

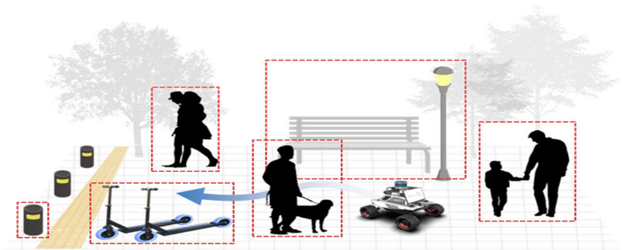


FIGURE 2. Traffic method on the pedestrian path.

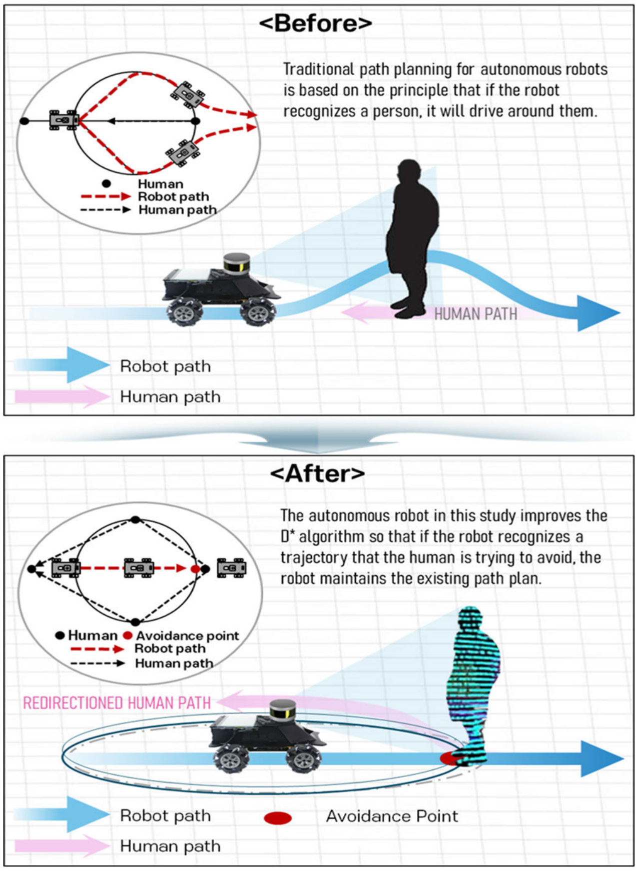


FIGURE 3. Autonomous robot's path method (Before, After).

As Fig. 2, the traffic method on the pedestrian paths is different from the road, and there is no regulation or regularity, so people can see that they pass in two directions. Additionally, pedestrian paths should be considered periodic obstacles, similar to trees, chairs, and personal mobility (PM).

This research focuses on the problem of path optimization for autonomous robots that use pedestrian paths. Fig. 3 presents the method of path determination of an autonomous robot before the traditional driving method and after the new method using the modified D* algorithm, developed in this study. This research proposes a novel approach to improve the robots' path-determination algorithm by considering the interaction between robots and pedestrians. Since pedestrians generally tend to recognize and avoid autonomous robots, this research modified the existing D* algorithm to predict human behavior patterns so that autonomous robots can react efficiently. The modified algorithm allows the robots to recognize pedestrians' avoidance intentions through sensors and only change course when necessary. This reduces the energy consumption of autonomous robots and improves their operation efficiency. In general, the power source of a robot is driven by receiving it from the battery, so its operating time is limited, and must be charged regularly [9]. In addition, energy efficiency is an important consideration as the size of a robot is often limited due to the width characteristics of the pedestrian paths, and the battery capacity is determined according to the size of the robot. Efficient battery management is a critical factor in determining the operating time and range of autonomous robots, while optimal routing algorithms can ensure safe efficient movement and minimize energy consumption.

This study reviewed previous studies on path planning, path cost, and trajectory utilization of autonomous robots, and collected and analyzed pedestrian trajectory data using sensor technology. The robot recognized the human movement path through the sensor and converted it into a trajectory. Based on the converted trajectory data, the robot modifies the route in real-time, detects pedestrians during autonomous movement on the walkway, and develops an efficient route planning methodology by determining whether to avoid the trajectory. This took a more generalized approach by calculating the average distance while considering that the distance perceived by pedestrians varies from individual to individual. Research has been conducted on minimizing path costs and improving the energy efficiency of autonomous robots using the modified D* algorithm. Fig. 4 presents the research flow, and the contribution of this research is to improve the energy efficiency of the D* algorithm by analyzing human trajectories.

The paper is structured as follows. Section II provides a detailed review of related literature in the field. Section III describes the whole process of extracting human trajectory data, the autonomous robot hardware for the experiment, and the modified D* algorithm that incorporates the avoidance points. Section IV describes the experimental part and the experimental results reflecting the original D* algorithm and

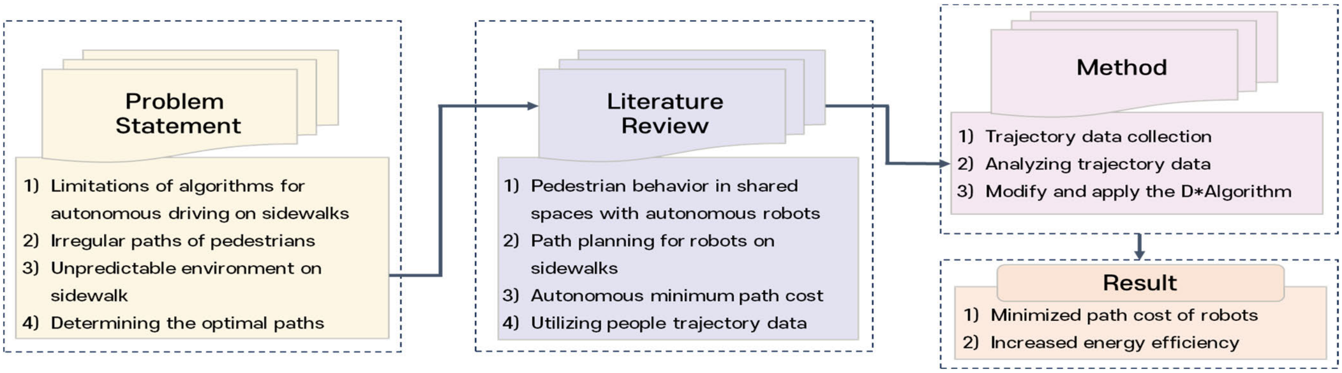


FIGURE 4. Research flow.

the modified D* algorithm. Finally, Section V summarizes the research results, discusses the contributions of this work and future research directions, and concludes the paper.

II. RELATED WORK

A. PEDESTRIAN BEHAVIOR IN SHARED SPACES WITH AUTONOMOUS VEHICLES

Various studies are being conducted worldwide, to promote pedestrian efficiency with the integration of autonomous robots, including research on mobility hubs [10], [11]. With the introduction of Autonomous Vehicles (AVs) into pedestrian shared spaces, the interaction with humans is becoming increasingly important. While the technology and necessity of AVs are designed for pedestrians, the interaction between AVs and pedestrians in shared spaces has only recently been studied. More research into the AVs' perception and following behavior of pedestrians will help advance AV navigation technology [12]. Shared spaces can be sidewalks, parking lots, roads, intersections, and more. As the shared space concept becomes increasingly popular in urban planning, AVs will need to deal with potentially large numbers of pedestrians and negotiate their passage [13]. A VR facility called "LargeSpace" has been developed to investigate pedestrian behavior when interacting with AVs in shared spaces [14]. Natasha Merat et al. have provided an overview of mathematical and computational modeling techniques used to understand how AV and pedestrian behavior can be cooperative and effective [15]. Most people have already interacted with cars in shared spaces and on roads. Based on this experience, pedestrians bring their existing knowledge, expectations, and habits about cars to interacting with AVs in shared spaces. Furthermore, AVs need to predict pedestrians' short-term behavior and respect social norms of crowd navigation. A social norm is a definition of appropriate behavior that expresses a notion of what people tend to do [16]. In the context of crowd navigation, a social norm might be about respecting a minimum personal distance or not moving erratically. AVs have some of the attributes of robots and perform autonomy, by using sensors, pedestrian trajectory prediction, etc. Many experiments use unmanned vehicles [17] or mobile robot prototypes to study pedestrian responses to AVs [18].

B. PLANNING A ROBOT'S PATH ON A PEDESTRIAN PATH

Unlike roads, pedestrian paths have no rules and traffic flows in both directions. Many experiments and solutions are needed for robots to drive automatically on pedestrian paths. According to Masahiro Shiomi et al, the traditional approach in robotics is to treat pedestrians as moving obstacles and ensure collision-free movement in the presence of moving obstacles [19]. Recent research provides collision-free behavior and movement for robots by planning the path of the robot so as not to violate the walkability of the pedestrian's space. Kitazawa et al. investigated pedestrians' gaze patterns to determine the size and shape of their information processing space (IPS) [20]. Pedestrians pay much more attention to the ground surface to detect immediate environmental hazards than to fixate on obstacles. David et al. applied a real-time deep learning-based method to the problem of human-aware robot navigation. The methodology was applied through training on images captured by cameras, and it presents a deep learning-based approach for integrating pedestrian detection into robot navigation problems [21]. Similarly, there are studies on how future commercialized robots will interact with humans on pedestrian paths. In this study, experiments were conducted using an algorithm that allows a robot to continue its course without changing its path when detecting pedestrians with proactive avoidance behaviors.

C. MINIMUM ROUTE COST FOR AUTOMATIC OPERATION ON A WALKING PATH

Recently, research has been carried out on electric vehicle batteries and different road gradients to calculate the minimum path cost, considering different weight factors [22], [23] Since the advent of mobile robots, various studies have been conducted in the field of path planning. The traditional way for robots to navigate through mobile and fixed obstacles on pedestrian paths is through avoidance. Liang et al. provided a fundamental review of the algorithms used in 3D path planning and their applications. All approaches have been classified into five categories: sampling-based algorithms, node-based optimal algorithms, mathematical model-based algorithms, biomimetic algorithms, and multi-fusion-based algorithms [24]. Among them, multi-fusion-based algorithms synthesize the strengths of multiple algorithms to achieve global optima and minimum cost. It is an algorithm that can achieve multiple objectives simultaneously and has demonstrated good environmental performance when combined with different methods. Ayawli et al. [25] used the Voronoi Diagram and Computer Geometry Technique to present a new path algorithm for robots in complex and dynamic environments. An intelligent replanning algorithm was devised that classifies moving obstacles based on their location, speed, distance, and direction of movement, to determine the level of threat they pose to the robots' responses to different obstacles. The VD-CGT method is an efficient method that avoids unnecessary calculations, which is advantageous for identifying moving obstacles with collision risk. The short re-planning time enables safe and fast route navigation. Wang [26] elaborated the basic principle of the A* algorithm, divided the robot path planning area using a grid method, and employed the MATLAB simulation platform to generate a two-dimensional path for the robot. Most of the mobile robot research is carried out in a grid method and uses grid maps. Jung et al. proposed a collision avoidance driving control algorithm for mobile robots, which is possible when the robot uses the D* algorithm and fuzzy rules for global and local path planning movement. By describing human behavior, they proposed a collision avoidance driving algorithm using the robot's action command when there is a risk of collision with moving obstacles and a cost area in the direction of travel, and route modification [27]. The above papers suggest that the shortest and least-cost paths for robot driving can be designed in different ways. Previous studies have been conducted on various path algorithms to minimize the path cost for robots [28], [29], [30]. Based on these studies, this research adds conditions to the path algorithm to minimize the path cost and presents a method to improve the battery efficiency of robots.

D. HUMAN TRACK UTILIZATION METHOD

Researchers are actively working on improving the safety and convenience of pedestrians. According to Mehdi et al. the analysis of trajectory data was used to calculate the average change in direction and speed from the perspective of the pedestrian's distance and angle [31]. Also, The features of pedestrians' pre-avoidance decision-making behaviors were analyzed and used to understand the underlying dynamics of crowd behavior [32]. Bennewitz et al. applied the EM algorithm to the trajectories recorded by laser distance sensors to cluster a set of movement patterns, and introduced a method for automatically inducing HMMs and updating them using JPDAF based on distance data and vision information [33]. Glas et al. developed a system to track the location and body orientation of many people simultaneously using a network of laser rangefinders [34]. Berclaz et al. achieved reliable multi-person tracking by using heuristic methods to rank individuals and process their trajectories over a long sequence if they are not confused with each other. It provided accurate position estimates by applying metrics to find the optimal trajectory across multiple frames [35]. Heath and Guibas presented a distributed vision-based technique for tracking people with a network of multiple stereo camera sensors in complex and dynamic environments [36]. Sighencea et al. reviewed the latest deep learning-based solutions to predict pedestrian trajectories, along with the sensors and processing methodologies used. Through this, they addressed the available datasets, performance metrics used in the evaluation process, and the practical application areas [37]. Sun et al. proposed a novel approach to predict pedestrian trajectories for autonomous mobile service robots using rangefinder sensors to learn and predict 3DOF pose trajectories [38]. A multi-object localization method was presented by fusing Lidar and camera data. The point cloud data was clustered to obtain a compact representation in 3D space and asynchronously fused to present cutting-edge and distinct technology through detection, localization, and tracking [39]. Recently, more experiments have been conducted in subway stations to predict pedestrian attributes and individual trajectories using CCTV. Lidar sensors and Deep Neural Network (DNN) algorithms were used to predict pedestrian attributes and individual trajectories [40]. This study aims to improve the driving efficiency of robots by collecting and analyzing human trajectory data using sensors.

III. METHODOLOGY

This study adopts the conceptual framework for 3D object detection used by Zhou and Tuzel [41], [41]. It exploits a methodology for collecting and analyzing trajectory data of pedestrians using Lidar and Camera sensors. The total methodology of this study is depicted in Fig. 5. A camera was used to detect people, and based on the detected people, sensor fusion was used to determine the location of the people and their distance from the robot. The data was collected in the form of RGB and PCD (Point Cloud Data). To improve the complexity and sparseness of the PCD, VoxelNet model, a 3D deep learning technology, was used to extract human trajectory data using ROS (Robot Operating System) and CloudCompare. In addition, the existing optimal path algorithm, the D* algorithm, was modified to average the avoidance points to reduce the unnecessary movement path of the robot, and a study was conducted to determine the efficient path when the pedestrian avoids first. In Table 1 is the Notation of this paper.

A. DATA COLLECTION AND ANALYSIS

This study utilized autonomous robots for collecting and analyzing trajectory data. Fig. 6 is a Scout Mini image with a different drive type. Scout Mini can be equipped with additional components such as a camera, LiDAR, GPS, IMU,

TABLE 1. Notations used in this paper.

$\{a_i^{pos}\}$	Positive anchor	t_i	Predicted trajectory
$\{a_j^{Neg}\}$	Negative anchor	t_i^*	Actual trajectory
L	Loss Function	d	Distance between robot and pedestrian
α, β	The weight of each term	$\lvert\theta\rvert$	Relative direction of movement of the robot and pedestrian
N_{pos}	The number of times the real object was detected in the image	$D_{threshold}$	Distance threshold to determine avoidance intent
L_{cls}	Classification loss	$\theta_{threshold}$	Angle threshold to determine avoidance intent
p_i^{pos}	Model prediction probability for positive samples	P_{avoid}	Behavior that a person avoids when certain conditions are satisfied
N_{neg}	Number of times the true object was not detected in the image	$C_{exist}(n)$	Cost function of the original D* algorithm
p_j^{neg}	Model prediction probability for negative samples	C_{avoid}	Additional cost for pedestrian avoidance
$\mathrm{L_{traj}}$	Trajectory Regression Loss		

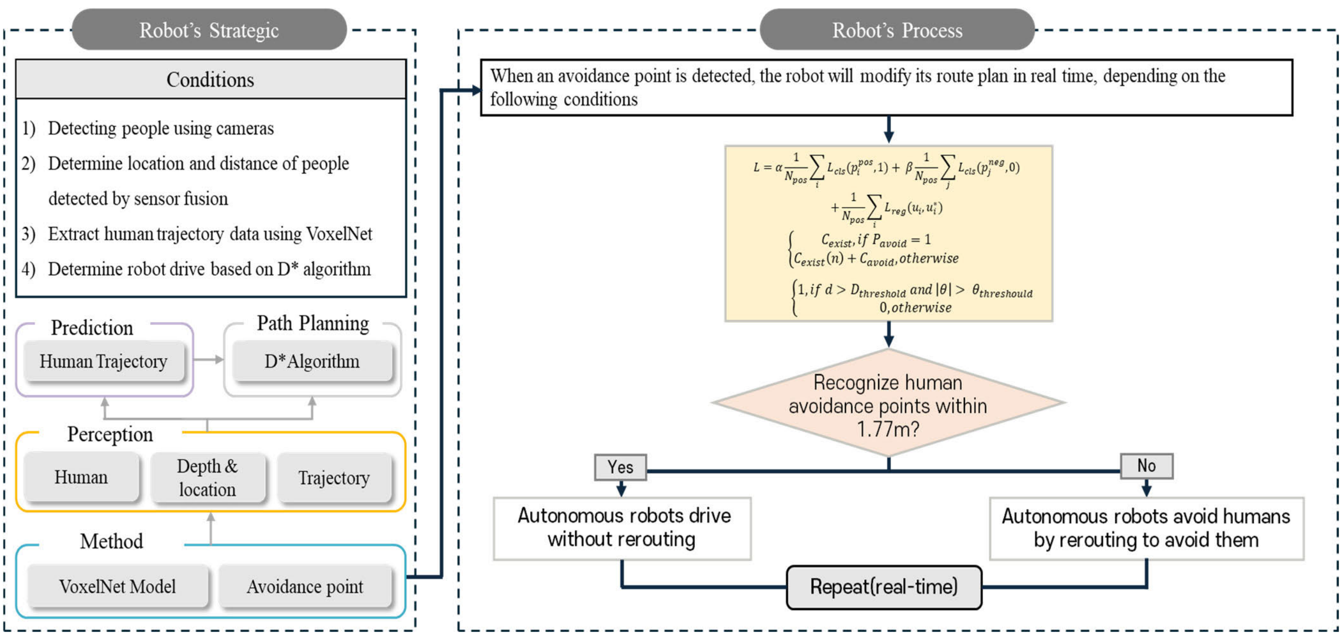


FIGURE 5. Method process.

etc. In this experiment, the Velodyne VLP-16 LiDAR was used as seen in Fig. 7 and the Realsense D435i depth camera as seen in Fig. 8. Table 2 lists the components of the Scout Mini, Table 3 lists the technical specifications of the VLP-16 LiDAR and Table 4 lists the technical specifications of the D435i depth camera.

The VLP-16 lidar, pictured in Fig. 7, collected the pedestrian trajectory data in 3D point cloud data (PCD) format. The collection of trajectory data was conducted in pedestrian environments, with the robot's mounting Lidar and camera sensors collecting data within their detection range. The robot image in Fig. 9 illustrates the customized Scout Mini used for collecting trajectory data. The mounted sensors included Lidar, Depth Camera, RTK-GPS, and IMU (Table 5).

The trajectory data was collected using both LiDAR and camera sensors simultaneously. Fig. 10 shows data fusion to extract human trajectory data, matching spatial and time series data on the same axis. A represents PCD collected

FIGURE 6. AGILE-X scout mini.

FIGURE 7. Velodyne's VLP-16 lidar.

FIGURE 8. Intel's realsense depth camera(D435i).

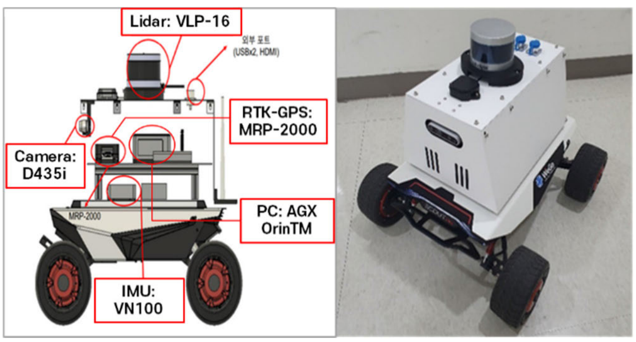


FIGURE 9. Customizing scout mini robot.

TABLE 2. Components of scout Mini(Robot).

Hardware	Specification
Size	627 x 550 x 252 mm
Mode of Operation	4wheel drive, Differential Drive Model
Wheelbase	452mm
Battery Operating Temperature	-20 ~ 60°
charging Time	2hour
Minimum Ground Clearance	107mm
Minimum Turning Radius	0m
Battery Voltage	24V / 15Ah
Max Velocity	10km/h
Communication Environment	Standard CAN / RS232

TABLE 3. Technical specifications of VLP-16(Lidar).

Hardware	Specification
Channel	16 Channel
Measuring Range	100m
Accuracy	Max $\pm$ 3cm
Field of View(Vertical)	+ 15.0° ~ -15.0°
Field of View(Horizontal)	360°
Field of View	2.0°
Rotation Speed	5Hz ~ 20Hz

with LiDAR, while B represents RGB data collected with a depth camera. The data collected by each sensor was fused to extract human trajectories; the LiDAR detected the position of individuals, and the camera verified the accuracy of the targets detected by the LiDAR.

The point cloud raw data is characterized by numerous points stored without any specific order, making it difficult to identify the geometric characteristics of trajectories and the interactions between points. Therefore, to analyze the raw PCD, the Cloud Compare software was used to quantify the PCD collected every second. The objects' shapes and the interactions between points, were quantified and visualized in Table 6, where each PCD's (x, y, z) coordinates, names, and point counts were quantified for upcoming analysis.

A 3D object recognition model was used to analyze the 3D PCD. As seen in Fig. 10(A), 3D PCD is unstructured data, consisting of many randomly distributed data points in space, which requires significant computing time to process. To effectively solve this issue, the data was preprocessed into a voxelization format of normalized data, which was then

FIGURE 10. Merging PCD and image data to exact human trajectory.

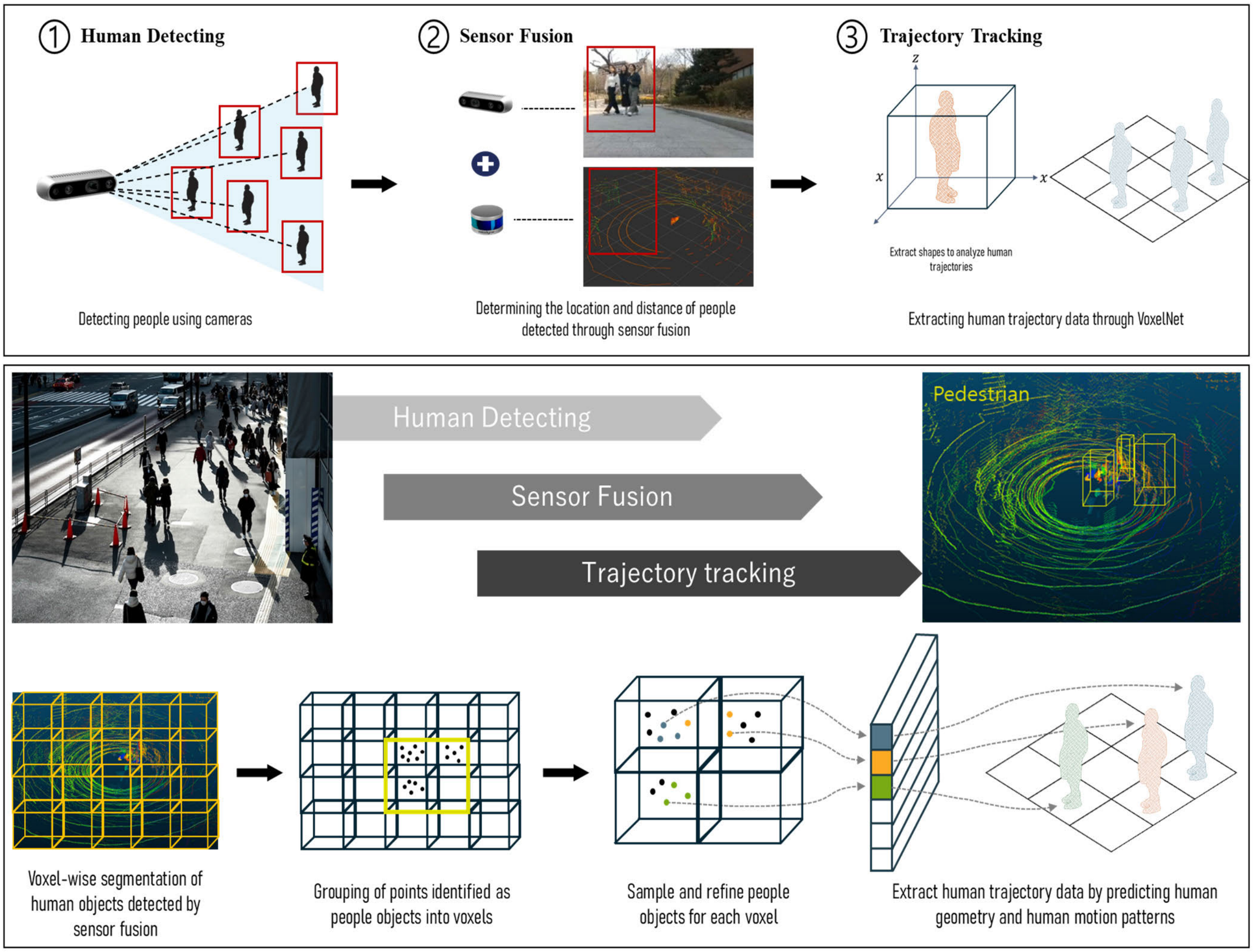


FIGURE 11. Process for extracting people trajectory data.

converted into a Sparse 4D tensor for data analysis via GPU computations.

Fig. 11 represents the process of extracting human trajectory data. After detecting a person using a camera, the data

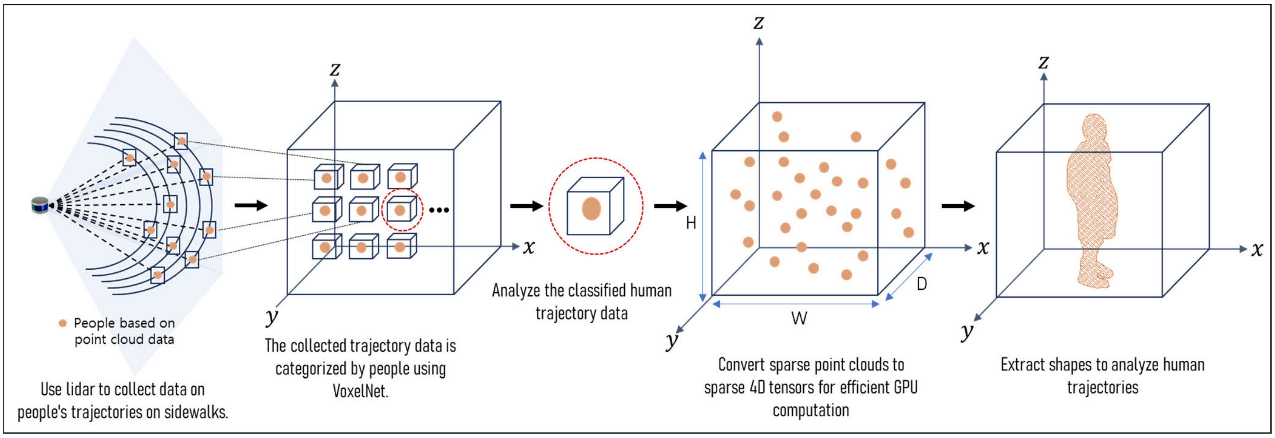


FIGURE 12. VoxelNet process for extracting people's trajectory data based on point cloud data.

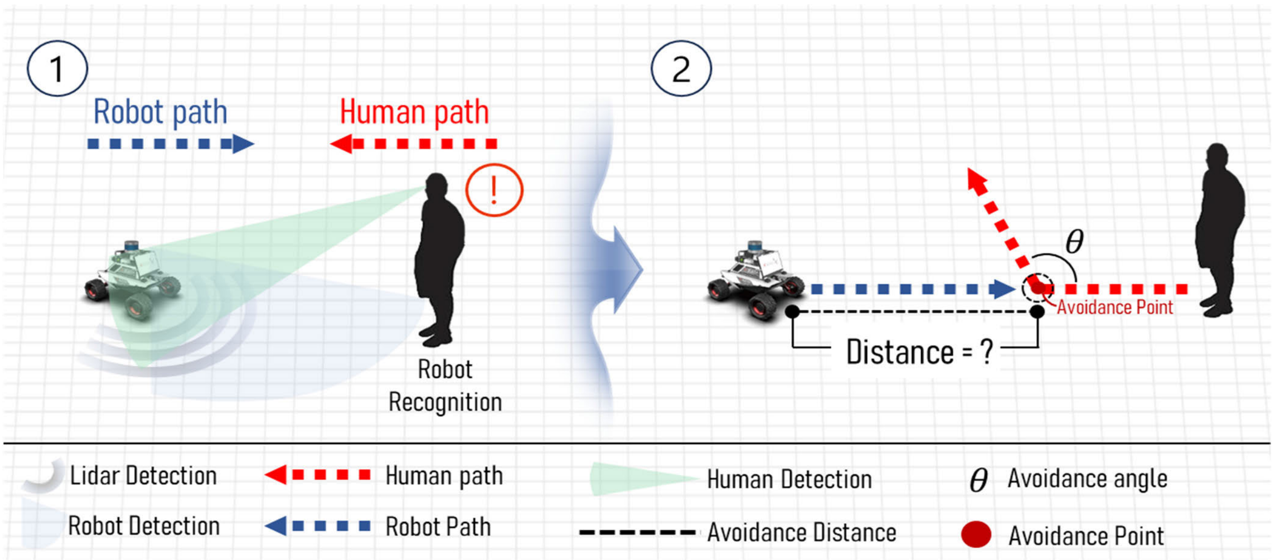


FIGURE 13. A conceptual diagram of the robot recognizing human avoidance points and driving.

was matched with the same spatial orientation and time series to identify the location of the person and the distance to the robot using sensor fusion based on the detected human. The trajectory data was then extracted using the VoxelNet model. The trajectory data was collected on a voxel-by-voxel basis and grouped points identified as human objects. The human trajectory data was extracted by sampling and refining the human objects for each voxel to predict the human shape and movement pattern.

Fig. 12 demonstrates the process of breaking down the 3D data into uniformly sized cubic voxels to organize the data structure. This approach significantly reduces the computational time required for analyzing trajectory data and enables its interpretation through a deep learning network.

$$L = \alpha \frac{1}{N_{pos}} \sum_{i} L_{cls}\left(p_i^{pos}, 1\right) + \beta \frac{1}{N_{neg}} \sum_{j} L_{cls}\left(p_j^{neg}, 0\right) + \frac{1}{N_{pos}} \sum_{i} L_{traj}\left(t_i, t_i^*\right) \quad (1)$$

TABLE 4. Technical specifications of D435i(Camera).

Hardware	Specification
Frame Resolution	1920 x 1080
Sensor FOV(H x V)	69° x 42°
Frame Rate	30fps
Sensor resolution	2MP
Sensor Technology	Rolling Shutter

This study enhanced the accuracy of trajectory prediction by modifying the loss function to reflect the detailed features

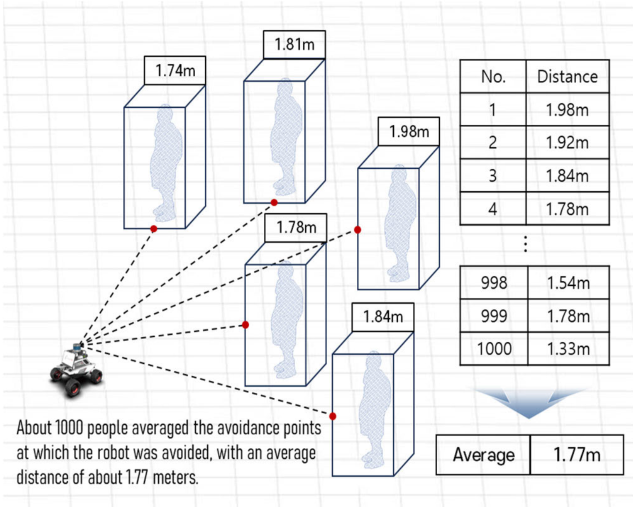


FIGURE 14. Finding the average avoidance point.

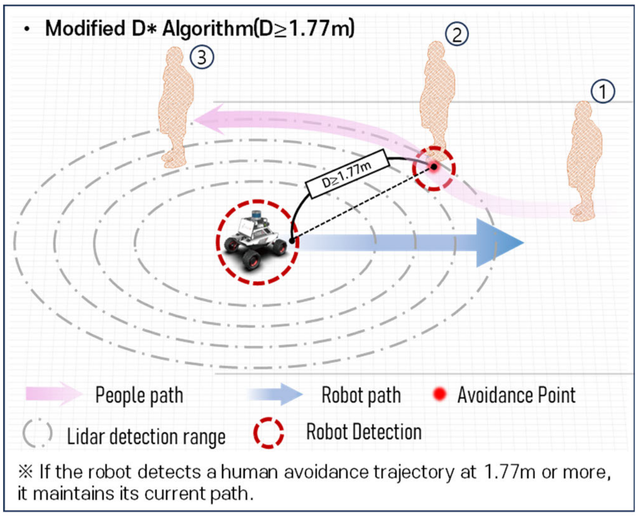


FIGURE 15. Modified D* algorithm driving behavior (D≥1.77m).

TABLE 5. Customized sensor components.

Hardware	Name
Lidar	VLP-16
Camera	Depth D435i
RTK-GPS	MRP-2000
IMU	VN100
PC	NVIDIA Jetson AGX OrinTM

of PCD. Positive anchors $\{a_i^{pos}\}_{i=1,2,3,\ldots N_{pos}}$, and negative anchors, $\left\{a_j^{Neg}\right\}_{i=1,2,3,\ldots N_{neg}}$, were utilized to define the center, location, length, width, height, and rotation of the 3D box,

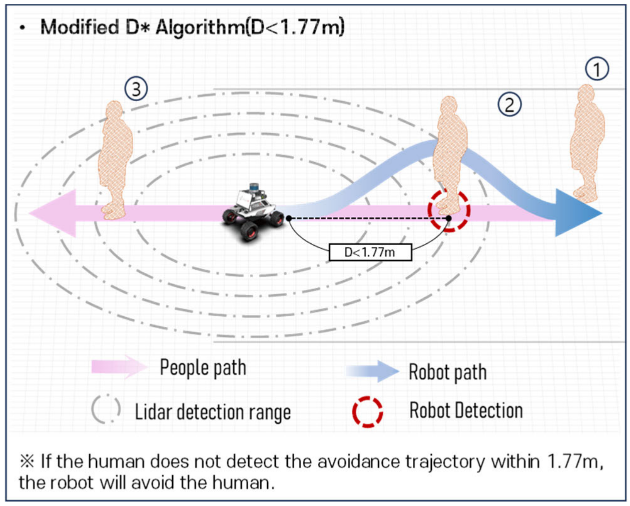


FIGURE 16. Modified D* algorithm driving behavior (D<1.77m).

and the loss function was modified. The loss function calculates the sum of classification losses for positive anchors and negative anchors, in addition to the trajectory regression loss. L_{cls} represents the classification loss, and L_{traj} represents the trajectory regression loss. t_i means the predicted trajectory, and t_i^* means the actual trajectory. α and β are weights adjusting each term in the loss function. The voxel-based trajectory regression loss is designed to precisely estimate pedestrian trajectories, contributing to robotic path planning. The loss function, which directly estimates the 3D direction of the box and uniformly normalizes x and y, is defined as in (1).

Fig. 13 presents an image of a robot detecting and navigating a pedestrian's avoidance point. An avoidance point is where pedestrians recognize robots and alter their path to avoid potential intersections or collisions. This study measured the precise location and distance at which pedestrians change their trajectory upon detecting robots. Specifically, the points where pedestrians follow straight paths, detect robots, and alter their direction were analyzed, and the changes in angle at these points were measured to determine an average.

To evaluate pedestrian perception and avoidance behavior in a real-world setting, trajectory data was collected from approximately 1,000 pedestrians on a school walkway. This measured the distance to the point at which the pedestrian recognized the robot and avoided it. Fig. 14 analyzes the average distance of the avoidance points based on the collected trajectory data, and the average distance of the avoidance points is approximately 1.77m.

B. MODIFICATION OF D ALGORITHM INCORPORATING AVOIDANCE POINTS*

In this study, the D* algorithm was used to perform path planning based on global and local plans. The D* algorithm establishes a global path plan first and then detects obstacles

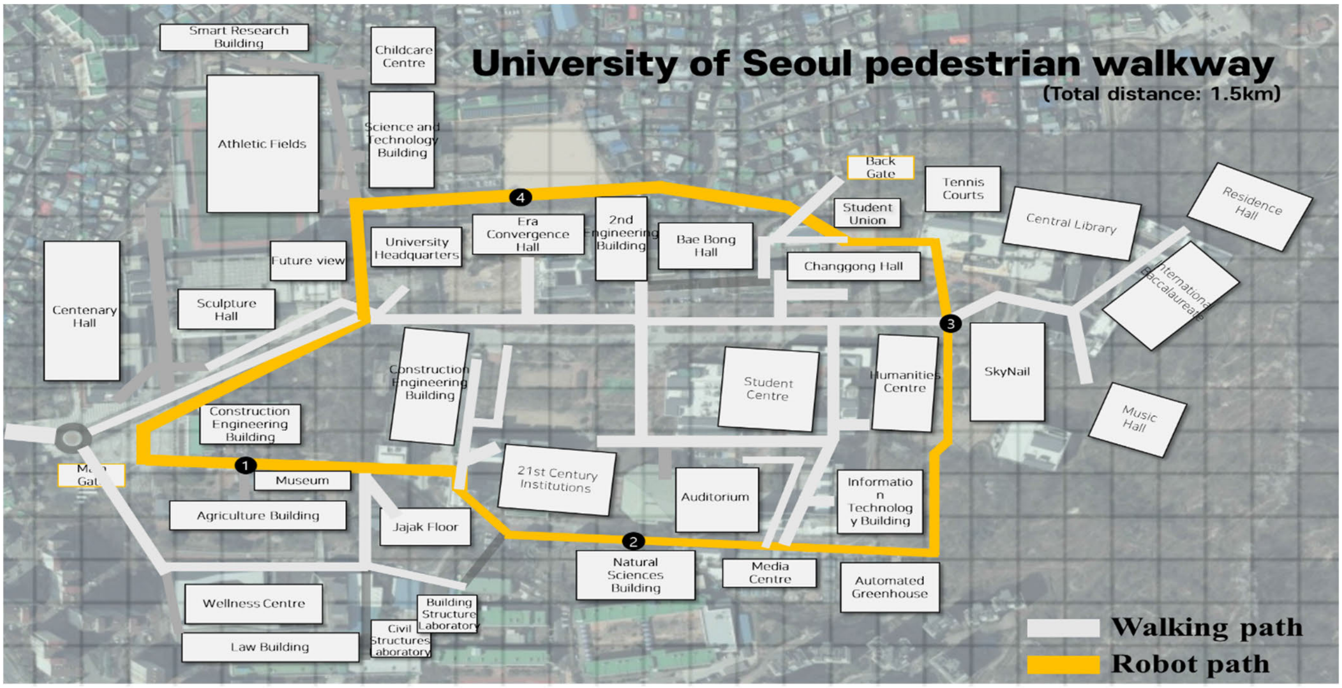


FIGURE 17. Test section for autonomous walkway robot path algorithm (University of Seoul).

FIGURE 18. Surrounding pedestrian environment for trajectory data collection.

in real-time while performing local avoidance actions as designed. While the D* algorithm typically performs local avoidance for all obstacles, this study proposed using the derived average pedestrian avoidance point to inform local planning.

Fig. 15 and Fig. 16 present the navigation methods of a robot using a modified D* algorithm, categorized by the detection distance of the avoidance points. According to the average avoidance point determined in Fig. 14, if the pedestrian's avoidance point is detected beyond 1.77 meters, the robot does not avoid the person, but instead uses an efficient navigation method, as seen in Fig. 15. Fig. 16 presents that if a pedestrian's avoidance point is detected within 1.77 meters, the robot navigates by avoiding the person to ensure the pedestrian's safety. To analyze pedestrian avoidance intentions, the distance between the pedestrian and the robot and the pedestrian's movement direction was used to study avoidance intentions.

The formula expressing this is presented in (2). D represents the distance between the robot and the pedestrian, while θ represents the avoidance angle relative to the robot's and pedestrian's movement directions. $D_{threshold}$ is the distance threshold for judging avoidance intentions, and $\theta_{threshould}$ is the angle threshold. According to previous conditions, if the robot detects a human avoidance point, condition 1 is executed and the robot drives the existing path. If it does not detect a human avoidance point, condition 0 is executed and the robot drives around the human first.

$$\begin{cases} 1, & \mathit{if}\ D > D_{threshold}\ \mathit{and}\ |\theta| > \theta_{threshould} \\ 0, & \mathit{otherwise} \end{cases} \tag{2}$$

TABLE 6. Quantify point cloud data collected in seconds (Part of the point cloud data collected).

Name	Points	Mean X	Mean Y	Mean Z
1680064359	25883	0.30863	2.5283	0.632269
1680064359	25988	0.22579	2.57587	0.631924
1680064359	25974	0.18551	2.6373	0.656801
1680064360	25814	0.21301	2.60483	0.653401
1680064359	25837	0.25939	2.64584	0.66405
1680064360	26001	0.09919	2.64867	0.656135
1680064360	26035	0.15916	2.69861	0.665131
1680064360	25944	0.13527	2.71637	0.65281
1680064360	25741	0.37542	2.43885	0.635302

TABLE 7. Experimental results of the traditional vs. modified D* algorithm.

	Monday		Tuesday		Wednesday		Thursday		Friday	
	D*[1]	MD*[2]	D*	MD*	D*	MD*	D*	MD*	D*	MD*
Driving Distance (Unit: km)	1.81	1.75	1.85	1.77	1.77	1.72	1.88	1.81	1.82	1.76
Driving Velocity (Unit: km/h)	6.16	6.41	6.13	6.44	6.22	6.44	6.13	6.39	6.12	6.38
Driving Time (Unit: min)	17.62	16.37	18.16	16.52	17.13	16.04	18.42	17.04	17.88	16.53
Number of People (Unit: person)	186	197	171	200	191	182	183	176	170	191

[1] D*: D*Algorithm(General D* Algorithm)
[2] MD*: Modified D* Algorithm

The cost function for the path planning and modification phases is revised as given in (3). $C_{exist}\ (n)$represents the modified cost function, where $C_{exist}\ (n)$ is the cost function of the traditional D* algorithm, and C_{avoid} represents the additional cost due to pedestrian avoidance.

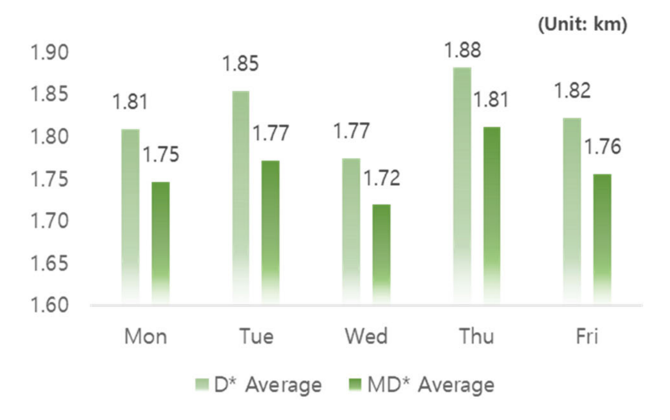
$$\begin{cases} C_{exist}\ (n)\,, & if\ P_{avoid} = 1 \\ C_{exist}\ (n) + C_{avoid}\,, & otherwise \end{cases} \tag{3}$$

IV. RESULT

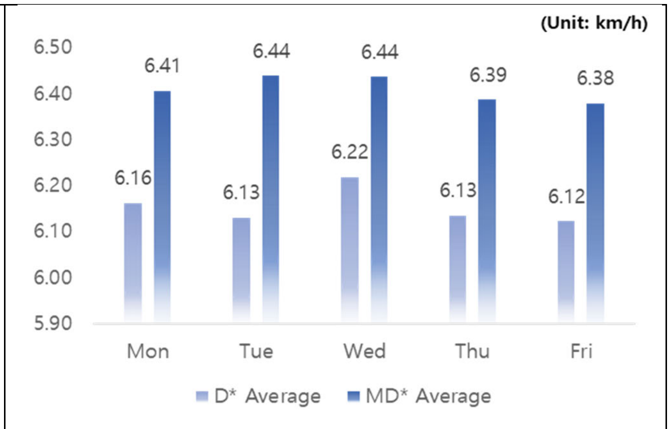
Experiments were conducted to compare the efficiency of the traditional D* algorithm and the modified D* algorithm in terms of the robot's travel distance, speed, and time. Fig. 17 presents the pedestrian path test section for the experiment, which is a 1.5 km section of the pedestrian path at the University of Seoul. Fig. 18 displays an RGB image of the surroundings of the experimental pedestrian path, with an average width of 4.05 meters.

The experiment defined the unmodified D* algorithm as the control condition and the modified D* algorithm as the experimental condition. The study was conducted over 10 weekdays, divided into 5 days under the control and 5 days under the experimental conditions. The results of the experiment tested the robot's total travel distance, speed, travel time, and number of people encountered on each weekday,

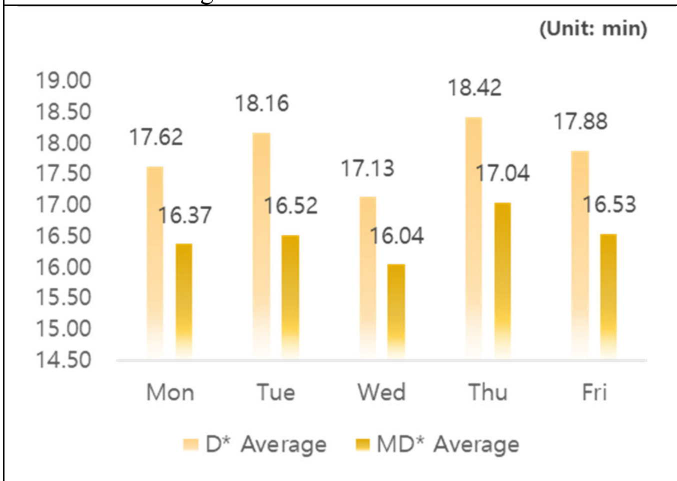
TABLE 8. Analyze the results of the D* algorithm and modified D* algorithms.



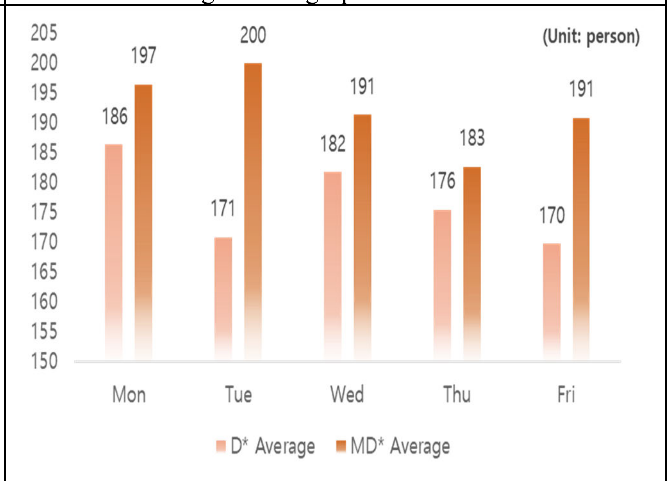
Average Travel Distance of the Robot



Average Driving Speed of the Robot



Average Travel Time of the Robot



Number of People Encountered by the Robot

TABLE 9. Efficiency of the modified D* algorithm compared to the traditional D* algorithm.

	People avoid	Distance travelled	Driving Speed	Driving time efficiency
Analysis results	76.89%	-3.66%	4.16%	-7.52%

10 times per day, and Table 7 presents the average values of each test per weekday.

The analysis revealed that the modified D* algorithm was more efficient than the traditional D* algorithm. Despite the autonomous robot covering shorter distances with the modified algorithm, it encountered more people, and there was a decrease in travel time and an increase in average speed compared to the traditional algorithm. Table 8 presents the analytical results of the experiment, calculated as averages. Table 9 analyzes how much efficiency increased in the modified D* algorithm compared to the traditional algorithm. When the modified algorithm was applied, about 76% of the encounters resulted in people avoiding the robot first, indicating that many people would move out of the robot's way upon seeing it. Also, the total travel distance of the robot decreased by an average of 3.66%, and the average speed increased by 4.16%. This suggests that the modified D* algorithm selects more efficient paths and enables faster travel. In addition, the travel time efficiency improved by 7.52%, and although the robot encountered on average 4.83% more pedestrians, it performed better with the modified D* algorithm. These results indicate that autonomous robots on pedestrian paths can minimize path costs and enhance battery and energy efficiency.

V. CONCLUSION

This study focuses on improving the D$*$ algorithm for the path planning of autonomous robots. Based on experimental results, incorporating dynamic pedestrian avoidance behavior patterns improved the safety and efficiency of robots' path planning. The modified D∗ algorithm extended robots' operating range in complex pedestrian environments and calculated the optimal average distance of avoidance points within a predefined detection range by analyzing human trajectory data. By applying avoidance points, the robot can travel to its destination with the minimum path cost according to the given environmental conditions, thereby reducing travel time and enhancing energy efficiency. This can also contribute to reduced power consumption and longer battery life for the robots. Future developments could refine the algorithm by adding conditions such as areas with high pedestrian density and damaged walkways. In addition, advancements in point cloud data processing technology are needed for commercialization, focusing on improving data processing speed and efficiency. These improvements are expected to make autonomous robot path planning safer and more efficient.

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