A Combined Approach to Mobile Robot Navigation Using CCTV

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***Abstract*— This paper proposes a navigation framework utilizing external CCTV cameras for a mobile robot to overcome the limitations of its embedded sensors. The framework includes a global path planner based on observed human behavior and a deep reinforcement learning network to learn optimal navigation guided by the global path. The experiments showed efficient navigation with low collisions in complex and crowded indoor environments.**

I. INTRODUCTION

Recently, many service robots have been operating indoors in crowded environments. Navigation in such an environment is challenging due to the wideness and complexity of the working space with unpredictable human intentions. However, sensors mounted on the robot, such as LiDAR or RGB-D cameras, provide only information about a limited local area. As a result, the robot cannot know about invisible areas outside the sensor range or due to occlusion, leading to a decrease in navigation performance.

In this study, we propose using CCTV as an external source to overcome the problem of robot navigation based on limited local sensor information. Closed-circuit television (CCTV) is the most widely installed and affordable source of information in the indoor environment. Robots can gain rich information from CCTV for navigation without visiting unknown areas outside of their limited local sensors.

We propose how CCTV information can be applied to navigation to overcome the limited local sensor capabilities of the robot (Fig. 1). This work introduces a framework that detects people from CCTVs and uses the detection results for path planning. We also utilize the generated global path in a deep reinforcement learning based navigation, for the robot avoids dangerous areas of blind spots in advance, e.g., congestion or blockage.

II. MAIN APPROACH

We propose a navigation method that considers the observed human behavior in an indoor environment with CCTV. First, we model the information about human behavior observed in an individual space. We generate a global path through the fused individual space and a static map. Then, we combine the global path with a reinforcement learning network to learn the navigation policy.

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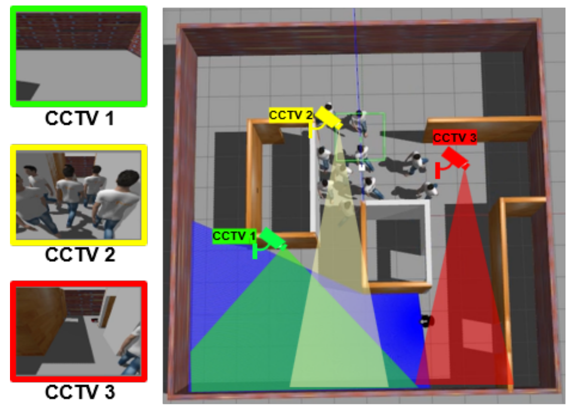

Fig. 1. Our navigation framework complements a robot's limited local sensing capabilities (blue-colored region) with information (other-colored regions) from an external source (CCTV) in a crowded and complex environment. Our framework calculates a global path that proactively avoids crowds or blockage based on the observed human movements. The robot can reach the goal safely and robustly by utilizing the path.

Human identification via CCTV. We use a widely used deep learning based human detection method called YOLO [1] to detect humans within the CCTV's view. This network represents a human detection result as a bounding box consisting of X, Y center, width, and height in the local image frame. To use the detection results for robot navigation, we use a homography to convert the local coordinates of people into global coordinates.

Global path planner based on human movement. Our method integrates the human detection results, i.e., human movements, with the geometry information of static objects for global path planning. A global occupancy map, m_o, represents static objects using a fixed resolution grid map of the environment. Furthermore, an individual space map m_h is modeled as an occupiable area based on the observed behavioral characteristics of pedestrians. To concern the dynamic behavior of pedestrians, we model a dynamic individual space as a 2D asymmetric Gaussian distribution from [2].

We propose the A* algorithm with a new heuristic function, H_{IS}, to consider individual space in path planning. H_{IS} costs how the individual space generated by the observed human movement affects the robot's path planning. Large crowds or people walking toward the robot in areas where the robot cannot detect are hazards that should be avoided in advance. To quantify the risk as a navigation cost, the

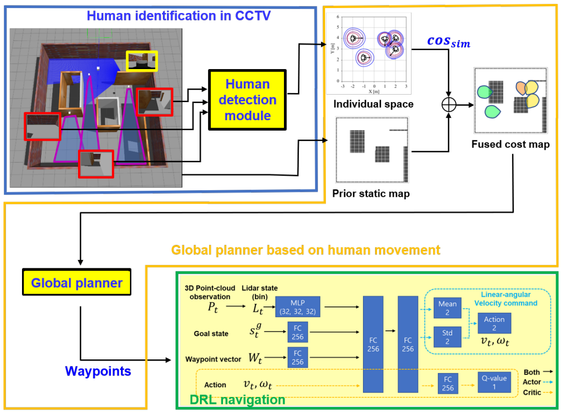

Fig. 2. Main components of our proposed navigation framework. The proposed global planner builds a fused cost map considering the observed human behavior with a static map and calculates a global path. The DRL network uses the global path as input to learning navigation policy to reach the goal.

heuristic cost at point i, $H_{IS}(i)$, is calculated as follows:

$$H_{IS}(i) = \begin{cases} \gamma \frac{1-\cos_{sim}}{2} & \text{if } i \in m_h \\ 0 & \text{else,} \end{cases} \tag{1}$$

$\cos_{sim}$ is a novel term that embodies the state of the robot and the behavioral characteristics of the pedestrian as a cost. We calculate the cosine similarity between the robot's normal vector to the goal and the relative human velocity to get $\cos_{sim}$ to represent the similarity between the robot's intention to reach the goal and the human motion.

Deep reinforcement learning navigation Our framework adopts a deep reinforcement learning network to learn a navigation policy that considers the global path generated and avoids dynamic obstacles. As input to the SAC algorithm [3], we feed the LiDAR sensor measurement, L_t, the goal state, s_t^g, the robot action, $[v_t, \omega_t]$, and the sampled waypoints, W_t, to reference the global path. Then the network outputs linear and angular velocities.

III. EXPERIMENT AND ANALYSIS

We test our method on a machine with a 3.80GHz Intel i7-10700 CPU and 32GB RAM. We used a combination of two simulators, Gazebo[1] and PedSim[2], to simulate environments embedded in CCTV and human movement. The experiment utilized a crowded environment as shown in Fig. 1, where the floor map and the installation configuration of the CCTV in the indoor environment were implemented by referring to [4]. To evaluate the effectiveness of our work using the global path as a guide, we compared it with the local planner based on deep reinforcement learning that only uses information from the LiDAR sensor on board [5].

Tab. I shows the quantitative result of the methods tested. Our method showed better navigation performance than the local sensor-based DRL method. The success rate increased

[1]https://gazebosim.org/home
[2]https://github.com/srl-freiburg/pedsim_ros

TABLE I
QUANTITATIVE RESULT IN THE PROBLEM SCENARIO

	Naive DRL [5]	Our Approach
Success rate	0.49	**0.74**
Average travel length	136.7	**127.34**
Average travel time	200.08	**195.81**

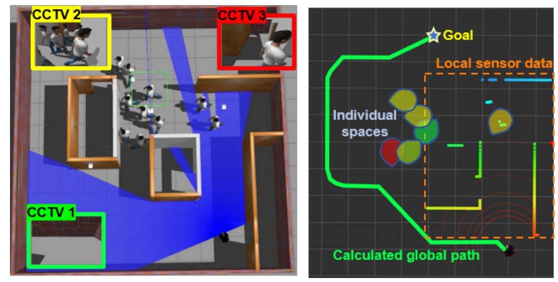

Fig. 3. An example of using our method to navigate a crowded environment is demonstrated. CCTV 2 detects the congested situation in the center of the environment, which cannot be observed by the robot's local LiDAR sensor (orange dashed line). The proposed global planner then generates a safe bypass global path (solid green line) by modeling individual space based on the observed human movement. The robot then utilizes this global path to arrive at the goal.

because the robot followed a global path to avoid dense crowds outside the sensor range. Fig. 3 shows the path of a robot following a global path generated to avoid an observed congested area. This result shows the benefits of our approach that compensates for the limited local sensing capabilities of the robot by utilizing a global path from the partial information obtained through CCTV.

IV. CONCLUSION AND FUTURE WORK

In this paper, we have introduced a framework for mobile robot navigation using information from an external CCTV to compensate for the limitation of the local sensor in an indoor environment. Based on the observed pedestrian movements, the robot can calculate a global path that proactively avoids congested areas, resulting in a more successful and efficient navigation task.

In future work, we would like to handle various types of environment and estimate the future motion flow of humans to support better planning.

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