Human Monitoring for Entire Area Coverage by using a Mobile Robot

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Abstract: This paper presents a mobile robot system designed for human monitoring for entire area coverage by using an omnidirectional camera without using any distance sensors. The system ensures detection and tracking of individuals while effectively maintaining detailed tracking records and managing individuals data. The robot behaviour and motion strategy is designed to define sensing areas, prioritize individuals for target selection, and navigate safely. The experimental results demonstrate that the system management performs efficiently and reliable, with the robot successfully sensing and accurately approaching all individuals within the area.

Keywords: Human Monitoring, Area Coverage, Mobile Robot, Omnidirectional Camera

1. INTRODUCTION

Detecting and tracking all the individuals in an environment with a mobile robot has been an active research area [1] due to its functionality in security and safety monitoring systems. However, this remains a challenging task particularly when individuals are far from the robot [2]. To overcome this, the robot must engage in a constant process of sensing, recognizing, and tracking individuals present in an environment. On the other hand, when multiple individuals are present, it is often difficult for the robot to determine which individuals it should interact with first [3].

To address the above mentioned challenges this papers presents a mobile robot setup configuration with an omnidirectional camera. This system ensures comprehensive monitoring of individuals within an area without using any distance sensors. Fig. 1 illustrates the concept of the developed system, showing individuals moving within a room. The circles represent the sensing range of the system. Since a single point cannot cover the entire room, multiple sensing points are used to ensure complete area coverage. With in the sensing range, the system identifies individuals, estimates their positions using panoramic images, and sends this information to the robot. Next, a priority function is proposed to decide which individuals the robot approaches first. This system aims to provide monitoring for security and management in indoor settings such as offices, malls, airports, and healthcare facilities, while ensuring comprehensive coverage and preventing suspicious activities.

To design such a system, there are technical challenges such as dealing with moving individuals, processing data of multiple individuals in real time, and ensuring complete area coverage to sense all persons. We addressed these by utilizing tracking algorithm, designed a manager module to handle individual information, and employed predetermined positions respectively. The experiments evaluate the system's management capabilities and ensure complete area coverage for sensing all individuals. The results indicate that the robot effectively senses and approaches every person within the area.

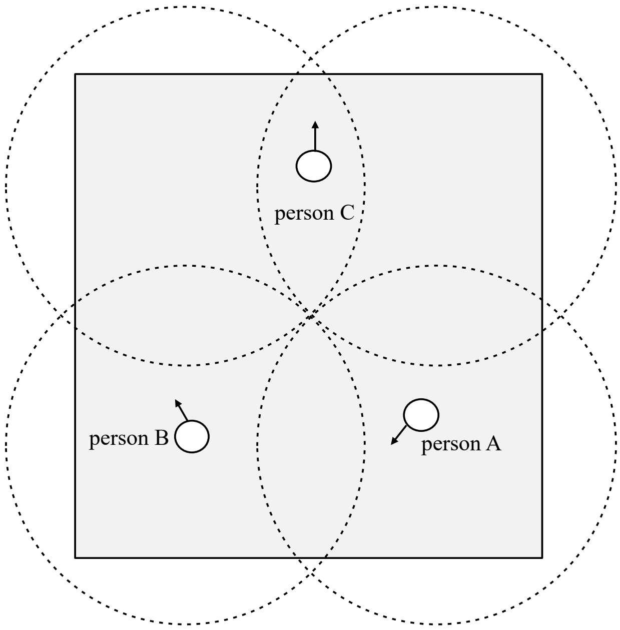

Fig. 1: System concept showing individuals in a room, with circles representing sensing ranges to ensure full area coverage.

Our main contributions to this work are:

- The system achieves full monitoring coverage without relying on traditional distance sensors, using only panoramic images. This approach reduces the system's hardware complexity and cost.
- Our designed module enables robust multi-person tracking and management, with continuous, real-time updates of tracked individuals.

† Sumiya Ejaz is the presenter of this paper.

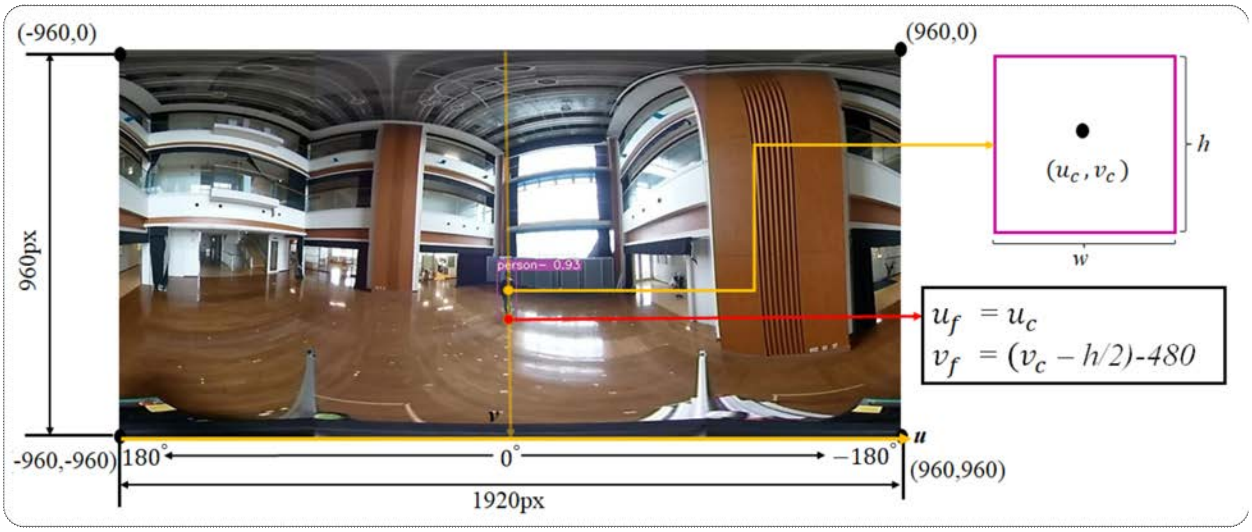

Fig. 2: Person location estimation.

2. RELATED WORK

Plenty of research has focused on enhancing people detection and tracking methods [4-7]. State-of-the-art algorithms for person detection and tracking [8-10], such as DeepSort and YOLO, have been widely utilized, and we adopted a similar approach. After detecting an object, classification techniques analyze features like face, color, and shape to identify individuals [11-12]. In previous work [13], we identified individuals based on facemask usage and applied a similar method in the proposed study.

Real-time approaches often rely on specialized hardware like stereo cameras to track individuals. For example, systems in [14] and [15] used stereo cameras on mobile robots for tracking. However, we opted for an omnidirectional camera, as it offers greater area coverage [16], making it more suitable for our tasks. Additionally, many mobile robots use distance sensors, like LiDAR, for person tracking and path planning [17-21]. While effective, these sensors can be expensive. This research demonstrates that person position estimation can be achieved without relying on costly sensors.

3. METHODOLOGY

This section outlines our method for person detection, tracking, and location estimation. It also describes the system management strategy, including the robot's behavior, path planning, and the implementation of the designed system.

The proposed robotic perception and monitoring system consists of four key components: person detection and tracking, person location estimation, multi-person ID management, and robot behavior for area monitoring. These modules work together to detect, track, and manage individuals, estimate their locations, and approach targets based on prioritization, ensuring efficient monitoring. Details of each module are provided in the following sections.

3.1. Person Detection and Tracking

For person detection, we created and utilized our own dataset of panoramic images, as described in [22]. Next, we used this dataset and trained a deep learning model YOLO, which is well-known for its speed and accuracy in object detection tasks. This allowed us to perform both person and facemask detection effectively. For tracking individuals, we used DeepSort, a robust and efficient tracking algorithm that assigns unique IDs to each detected person.

This enables the system to maintain consistent identification of individuals as they move within the camera's field of view. By combining our trained YOLO model with DeepSort, we were able to obtain detailed bounding box information, class names, and unique tracking IDs for each person. This integration allowed our system to not only detect the individuals but also to continuously track their movements, providing a comprehensive solution for monitoring and managing persons in indoor environments.

3.2. Person Location Estimation

We estimate a person's location based on their footprint. To calculate the person footprint v_f , we used bounding box information BB= (u_c, v_c,w,h) and the image centre point 480 as shown in Fig. 2. This estimation was performed by utilizing v_c (the centre of the bounding box) and the h (height of the bounding box), along with the image centre point.The footprint v_f is used to estimate person distance d while u_f is used to find the angle θ from the robot's coordinate to the destination coordinate. For more information on person position estimation, refer to [22].

It is essential for our proposed system to convert the human position into global coordinates. Knowing the position and orientation of the person with respect to the robot coordinate, it is possible to calculate the transformation matrix that translate the person position from image to global coordinate. Therefore, we also carried out a global transformation using the robot's odometry data to align the detected targets with the global coordinate frame, ensuring accurate localization and tracking.

3.3. Multi-Person ID Management

To maintain the list of tracking IDs, we designed a program that is responsible for:

3.3.1. Elimination of Multiple IDs for the Same Person

When using DeepSort, a common issue is that it can generate multiple IDs for the same person. To resolve this, we proposed a position-based merging technique to ensure each individual is assigned a unique ID and to prevent the problem of multiple IDs for the same person. This technique uses the concept of positional proximity to determine if two detected individuals are actually the same person. When a new detection occurs, we compare its position with the positions of all previously detected individuals. If the new detection is found to be within a certain distance of an existing detection, it is assumed to be the same person, and thus, not assigned a new ID. Instead, it is merged with the existing detection. The distance threshold is carefully chosen to balance between accurately identifying the same person and distinguishing between different individuals. This approach ensures that the tracking system avoids mistakenly assigning multiple IDs to the same person, thereby enhancing the accuracy and consistency of tracking.

3.3.2. Maintaining Records of Tracked Individuals

To maintain a record of whether tracked individuals have been checked or not, their unique tracking IDs are utilized. When an acknowledgment is received that a specific target person has been checked, the system adds the individual's tracking ID to the list and verifies it against the existing list of tracked IDs. If the ID is not already present, it is added, and the individual's status is updated accordingly. This method keeps a complete and current list of all tracked individuals, allowing for efficient management and monitoring in the environment.

3.4. Robot Behaviour for Entire Area Monitoring

To ensure the robot detects all individuals, we proposed a strategy by dividing the room into small portions based on the sensing radius and room dimensions, using predetermined positions to guarantee full area coverage. The robot first moves to the initial predetermined position and approaches the targets in that area. After checking all the targets in the first area, it proceeds to the second predetermined position. Alternatively, if no target is detected in the first sensing area, it directly moves to the second predetermined position and continues to approach the targets in that area until all individuals are sensed.

3.4.1. Target Person's Priority

To determine which person the robot should approach first in a given area, we designed a priority function based on specific criteria derived from the detection data. In the previous work [13], the detection results included four classes. In the current work, we used these classes to develop a priority function, resulting in two cases. The primary priority is given to case 1: individuals who are not wearing masks. If no such individuals are detected, the next priority is assigned to case 2: those who are not facing the camera. In situations where multiple individuals are classified as not wearing facemasks, the robot will prioritize the person closest to its location. This hierarchical prioritization ensures that the robot addresses the most critical and relevant cases first. Initially, the robot waits to receive target person information from the robot behaviour module. Once the information is received, it applies the priority function to select the first target. This process continues until all individuals in the area have been checked.

3.4.2. Robot Path Planning

If a person is facing the camera without a facemask, the robot must move at a distance and stop 1 meter away to avoid the collision. However, if a person is not facing the camera, the robot moves to a position where it can see the person's face to inspect their face mask. For further details on robot path planning, refer to [22].

4. IMPLEMENTATION OF THE DESIGNED SYSTEM

Fig. 3 provides a detailed implementation of the entire system, demonstrating the operation of each module.

4.1. Detector and Tracker Module

After capturing panoramic images with an omnidirectional camera, we utilize YOLO along with the DeepSort algorithm to enable real-time person detection and tracking. The process involves several key components: first, the bounding box identifies the position of detected individuals within the frame. Next, the IDs of the detected persons assign a unique ID to each individual to facilitate continuous tracking. Finally, the class names provide information about the detected persons, categorizing them as "person," "person′" (those who are not facing the camera), "mask," or "no_mask".

4.2. Manager Module

Next, we designed the manager module to handle the information from the detector and tracker. This module oversees various processes within the system based on the received data. It begins with initialization, where new detections are assigned unique IDs and their initial positions are recorded. The person location estimation component calculates the precise locations of individuals using bounding box coordinates. The module also maintains a list of assigned IDs, ensuring that each person is uniquely identified and tracked. To prevent duplication, the merging of two different IDs for the same person step combines IDs assigned to the same individual based on positional data. Finally, the module updates the list of tracked persons, continuously reflecting any changes, such as new detections, merged IDs, and the status of whether a person has been checked by the robot.

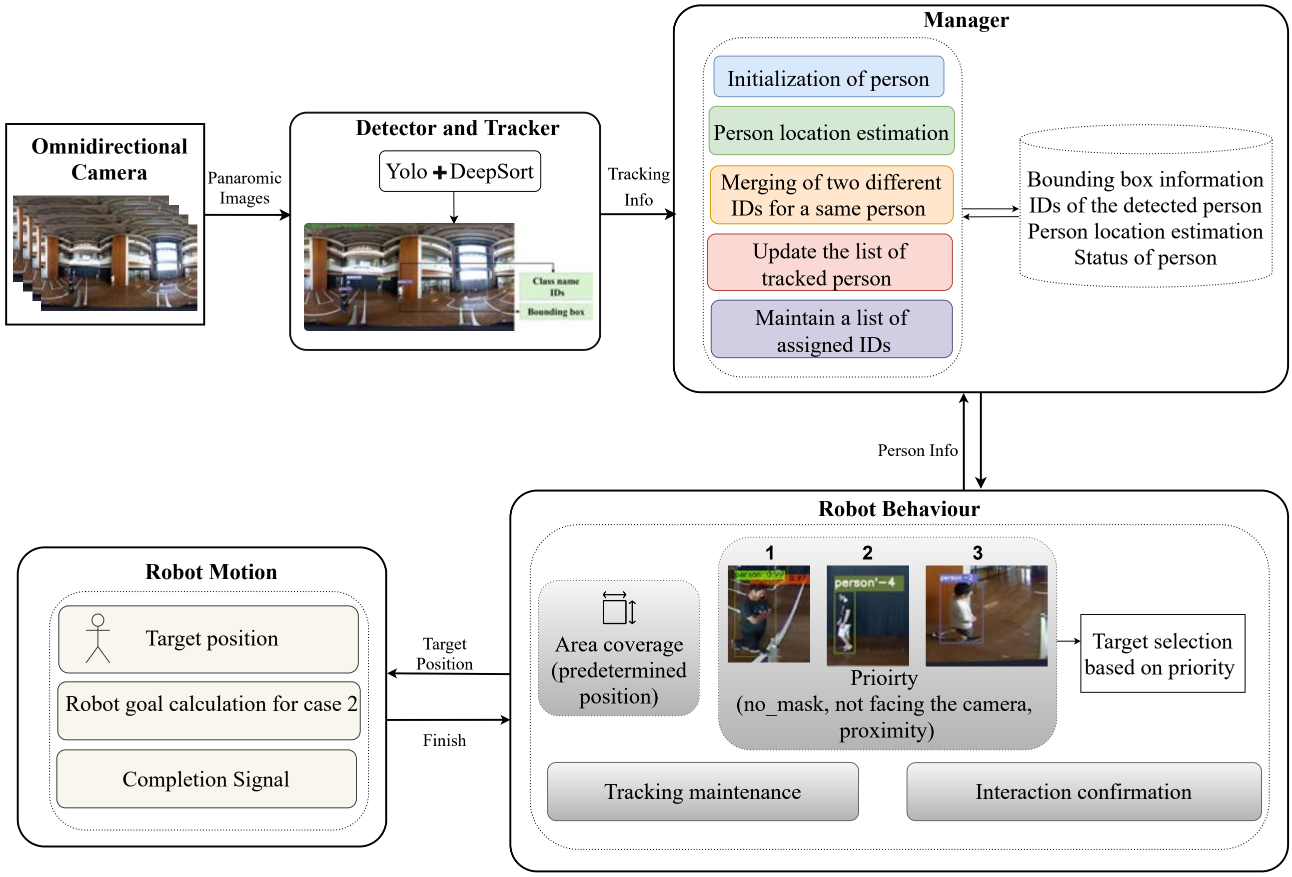

Fig. 3: Detailed implementation of the designed system, showcasing the integration of detection and tracking algorithms, the components of the manager module, and the functionalities of the robot behavior and motion modules.

4.3. Robot Behaviour Module

We designed the robot behavior module to ensure complete area coverage by using predetermined positions and prioritizing individuals based on detection results to determine which person the robot should approach first. The module begins with area coverage, utilizing predetermined positions to ensure complete coverage of the area. Next, priority management assigns priority levels to targets based on specific criteria such as whether they are wearing a mask, whether they are facing the camera, and their proximity to the robot. Furthermore, target selection based on priority allows the robot to choose which targets to approach first, based on their assigned priority. Tracking maintenance ensures that selected targets are continuously tracked, providing accurate and up-to-date information throughout the interaction. Finally, interaction confirmation verifies that interactions with target persons are completed and updates their status, ensuring the system is aware of all interactions.

4.4. Robot Motion Module

Furthermore, we developed a robot motion module tasked with executing actions and interactions to approach the targets effectively. This module relies on three key functionalities. First, it receives detailed target position information from the robot behavior module to determine the precise location of the target. Second, in scenarios where the target person is not facing the camera, the module calculates the optimal position for the robot to ensure the person's face is visible, enabling proper interaction. Finally, after completing the interaction with a target, the robot sends a completion signal to indicate that the interaction is finished, allowing the system to proceed to the next target.

By implementing this detailed and integrated approach, the designed system ensures efficient person detection, tracking, and interaction and robot senses all individuals effectively.

5. EXPERIMENTS AND RESULTS

In this section, we first describe the robot hardware setup, then show the set of designed evaluation experiments of how system is effectively managed and robot sensing all persons in entire area.

5.1. Robot Hardware

Fig. 4 shows a three-wheel robot with dimensions of 200×30 cm. The omnidirectional camera "Theta V" is mounted on the robot. The 360° image from the camera is converted into a 1920×960 panoramic image and divided into four 90° sections. Each section represents a part of

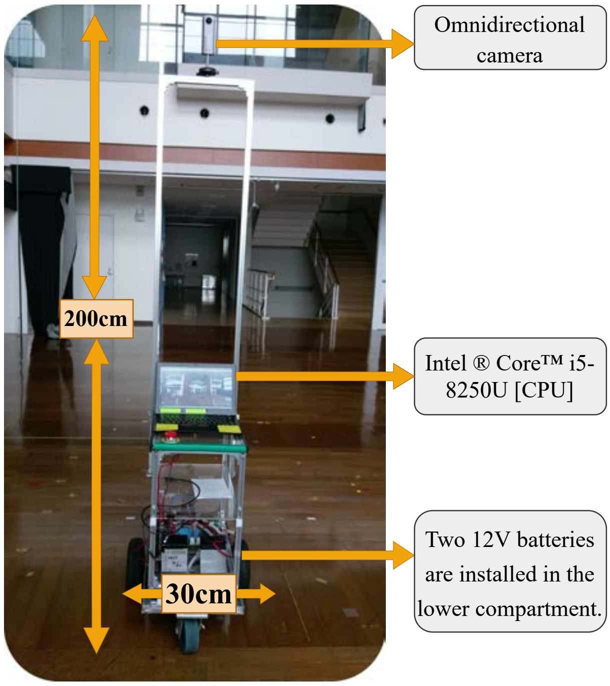

Fig. 4: Robot hardware setup.

Time	ID	Class	Has Mask	X(m)	Y(m)	Status
00:20	1	person	no_mask	4.103	0.555	Not Checked
00:20	2	person	no_mask	3.815	-2.537	Not Checked
00:20	3	person'	not_applicable	8.032	2.054	Not Checked
00:20	4	person	not_decided	7.556	-2.025	Not Checked

(a) System management during tracking of four individuals

Time	ID	Class	Has Mask	X(m)	Y(m)	Status
00:30	1	person'	not_applicable	4.803	0.088	Not Checked
00:30	2	person	no_mask	3.058	-2.419	Checked
00:30	3	person	not_decided	8.023	3.052	Not Checked
00:30	4	person'	not_applicable	7.494	-1.529	Not Checked

(b) System management during robot's approach to target

Fig. 5: System visualization at two different locations.

the robot's surroundings, enabling detection within the image. Two batteries of 12V each operated with the robot. The computational platform consists of an Intel® Core™ i5-8250U CPU is used for testing. Additionally, a GPU, the NVIDIA GeForce RTX 3060Ti, is used during the training process.

5.2. Manager Module Visualization

Fig. 5a displays the manager module visualization and showcases system management details. This includes the person's track ID, class names, and face mask status. The face mask status is represented as follows: "no_mask" indicates a person without a mask, "not_applicable" is used when the person is not facing the camera, and "not_decided" is shown when there is no recognition for the face mask. Additionally, the figure includes the person's position and whether the robot has checked the individual. It also shows the timing of received updates as the robot tracks four individuals and processes their information.

Fig. 5b shows another visualization of the manager module, demonstrating system management as the robot approaches its first target, identified as "no_mask", while also displaying information about other individuals. The target person's status changes to "Checked", indicating they have been checked by the robot. In Fig. 5b, it is observed that the class of person IDs 3 and 4 has changed. At the robot's current location, the angle of the person with tracking ID 4 exceeds 90°, making their face invisible, and consequently, their class is updated to "person′". Conversely, the person with tracking ID 3 changes their direction, enabling the robot to see them, and their class is updated to "person". This clearly demonstrates that the program effectively performs real-time updates.

5.3. Experiment on Entire Area Coverage

For entire area coverage, we used two circles with a radius of 4.5m representing the sensing range, based on room dimensions of approximately 1050×700cm. Next, we defined the predetermined positions at 2.5m and 7.5m from robot's origin, directly along the robot's forward-facing axis. We evaluated this method by conducting experiments with four individuals placed at various locations.

Fig. 6a presents a graphical representation of the general experiment, displaying the robot's sensing range and predetermined positions for optimal coverage. Detected person positions are marked with red circles, and the arrows attached to these circles indicate the actual directions of the individuals. The robot's goal is represented by a cross sign. The robot's trajectory shows that it starts its movement toward the first predetermined position, detects three targets in its initial sensing area, and approaches them based on priority. After covering all targets in the first area, the robot moves to the second predetermined position, detects a target, and approaches it.

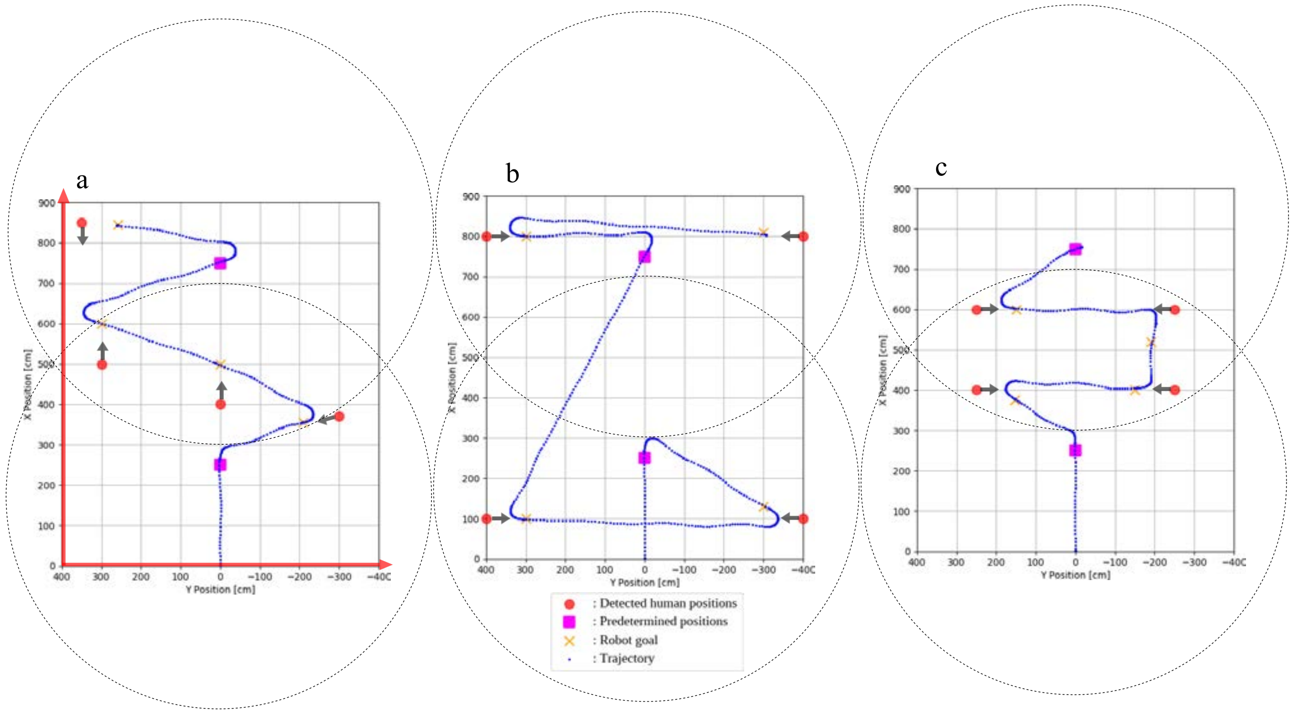

Fig. 6: Overview of the experiment: **(a)** demonstrating the robot's sensing range, predefined positions of targets, detected individuals, and its motion based on prioritized interactions; **(b)** highlighting the robot's area coverage with persons strategically positioned at varying distances; **(c)** showcasing the robot's performance in a crowded environment, emphasizing its ability to detect, prioritize, and approach multiple nearby targets effectively.

We conducted another experiment by arranging persons in a pattern of distant locations, varying their placement across the area as shown in Fig. 6b. The robot's trajectory indicates that it begins by moving toward the first predetermined position, where it detects two targets within its initial sensing range and approaches them. Once all targets in the first area are covered, the robot moves to the second predetermined position, detects another two targets, and approaches them as well. This situation challenges the robot to detect and approach targets spread over a larger area, testing the system's capability to maintain detection accuracy and effective prioritization across an extended range. As the robot navigates towards these more distant targets, it demonstrates adaptability in covering individuals placed further apart, providing insight into the system's scalability and effectiveness in environments with dispersed targets.

Next, we considered a crowded scenario where individuals were positioned in a pattern of nearby locations relative to the robot, as shown in Fig. 6c. This experiment evaluated the robot's ability to detect, prioritize, and approach multiple targets within a close range. The robot's trajectory demonstrates that it initially moves toward the first predetermined position, detecting four targets within its sensing range and approaching them. Once all targets in the first area are addressed, the robot proceeds to the second predetermined position to check for any additional targets. This experiment highlights the system's responsiveness and efficiency in environments with densely located individuals, showcasing its ability to prioritize and approach multiple targets effectively. Additionally, the robot's accurate detection and seamless navigation reflect its capability to adapt to varying scenarios.

The robot's real-time movement for general experiment is shown in Fig. 7. It first moves to the initial predetermined position Fig. 7a, detects three targets, and prioritizes approaching the one without a mask Fig. 7b. The robot then continues to approach other two targets Figs. 7c to 7d. After covering the area, it moves to the second predetermined position Fig. 7e and detects another target Fig. 7f, successfully covering the entire area and identifying all individuals.

Overall, these results demonstrate that the robot successfully covered the entire area, detecting and interacting with all target individuals in different configurations.

6. DISCUSSION

The experiments demonstrates the robot's effectiveness in covering an entire area, detecting, and approaching targets under various scenarios. An interesting scenario can be observed in the first experiment that is demonstrated in Fig 6(a), the individuals located at (400, 0) and (500, 300) were not facing the robot and were initially classified as "person′". This classification remained unchanged even when the robot reached its initial prede-

(a) Robot moving to 1st predetermined position

(b) Robot approaching its first target position

(c) Robot approaching its second target position

(d) Robot approaching its third target position

(e) Robot moving to 2nd predetermined position

(f) Robot approaching its fourth target position

Fig. 7: Experimental results for entire area coverage by robot

termined position and approached the first target. Afterward, while moving toward the second target, the robot performed calculations for case 2. However, upon reaching the nearby point, the robot received updated information from the robot behavior module, which identified the person as having "no_mask". As a result, the robot stopped at that point, which then became the new robot goal. The same process was repeated for the third target. Such scenarios demonstrates that our designed system performs continuous updates and ensures real-time monitoring of individuals. However, there are several considerations for optimizing and extending the system's capabilities.

In cases where the environment is unknown, it would be beneficial for the robot to autonomously determines its predetermined positions. However, this poses a significant challenge, so an alternative approach could involve determining these positions based on the locations of detected individuals. The number of predetermined positions can be minimized if the room or area is relatively small. In this study, predetermined positions are used to simplify the problem and ensure complete area coverage, making it easier to evaluate the robot's performance. We can see in the third evaluation experiment which is shown in Fig. 6(c), the robot senses all individuals in the area of first predetermined position. After approaching the targets in the first sensing area, the robot moves to the second predetermined position to ensure complete area coverage, as there may be individuals outside the first sensing area. Once the robot confirms that no unattended persons remain, it stops at the second predetermined position.

In this research, the evaluation experiments as illustrated in Fig. 6 assume that individuals remain stationary. This assumption enables us to focus on verifying whether the robot effectively covers the entire area and approaches all persons. Moreover, all experiments are conducted in indoor settings, ensuring that the robot is capable of covering the entire space effectively. Thus, the results indicate that our approach successfully ensures complete area coverage, with the robot detecting and approaching all persons. To validate the robot's capability to handle dynamic targets and determine the maximum number of individuals it can manage, future research should focus on tracking moving individuals and investigating denser environments where individuals are partially or fully occluded by others.

7. CONCLUSIONS

In this paper, we present a mobile robot system designed for human monitoring and complete area coverage, employing YOLO for robust object detection and DeepSort for real-time tracking. The system integrates several key modules to achieve seamless functionality. We designed a manager module that plays an important role in maintaining an updated and comprehensive list of tracked individuals, merge duplicate IDs, and estimate the locations of persons.Additionally, the robot behaviour and motion modules were developed to optimize target prioritization, manage safe navigation, and execute effective interactions with detected individuals. Priority is determined based on predefined criteria, such as mask-wearing status, if person is not facing the camera, and proximity to the robot, ensuring that the most important targets are approached first. Experimental results demonstrate that the system operates efficiently with the robot accurately detecting, tracking, and interacting with all individuals in the covered area. The use of predetermined positions ensured full area coverage, simplifying the problem and guaranteeing that no targets were overlooked. These results highlight the potential of the proposed system to address challenges in human monitoring, particularly in indoor settings.

This system offers numerous advantages, including enhanced comprehensive area coverage and robust interaction management. The developed system can be utilized in offices, malls, and airports. In future work, we aim to perform experiments with a larger number of individuals to evaluate the system's scalability and robustness in more crowded environments.

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