Active Robot Vision with Perception-Aware Navigation for Worker Monitoring

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2025. 02. 24.

Contents

Research Background

▪ Computer Vision Applications for Safety Monitoring

- Vision sensors are used for verifying personal protective equipment (PPE) compliance through object detection models on construction sites.
- As systems like autonomous robots rely on high-confidence to make informed decisions and take appropriate actions (Selvaraj et al., 2020).

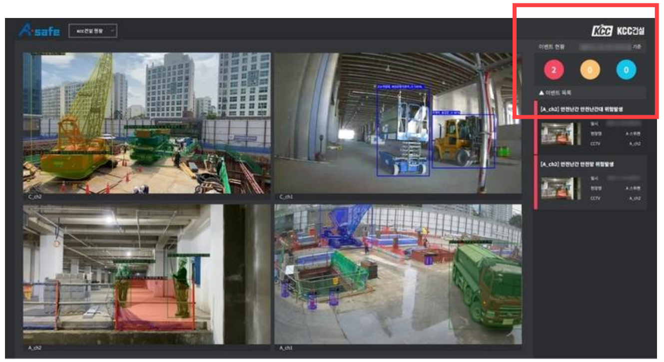
Detection Results
(Worker A)

Safety_Helmet_used 0.9

Safety_Harness_used 0.8

Person 0.9

Safety_Shoe_used 0.6



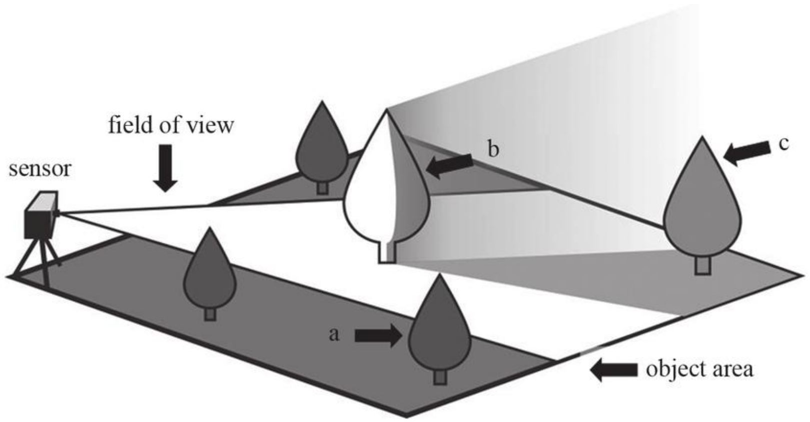
Warning System

- Worker A is properly wearing PPE

Research Background

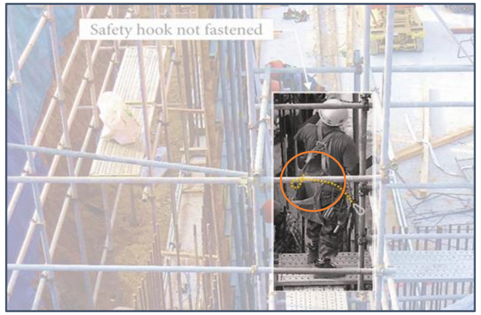
▪ Computer Vision Applications for Safety Monitoring

- Fixed-viewpoint monitoring systems struggle with occlusion and limited Field of View (FoV), which hinder accurate detection and classification(Paneru & Jeelani, 2021).
- These limitations, influenced by object angle, position, and environmental factors, reduce detection reliability and system performance.

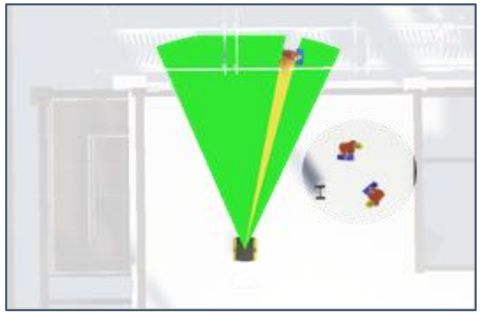


✓ Occlusion

[Occlusion by Obstacle]



[Self-Occlusion]



[View Occlusion]

✓ Types of Occlusion Problems

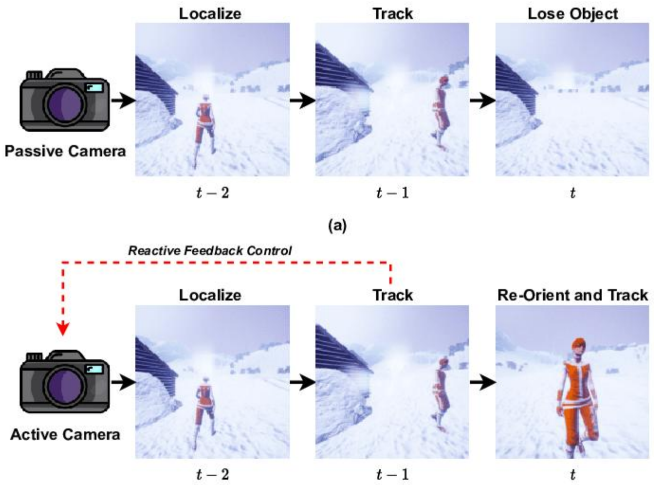
Research Background

▪ Active Vision: Related work

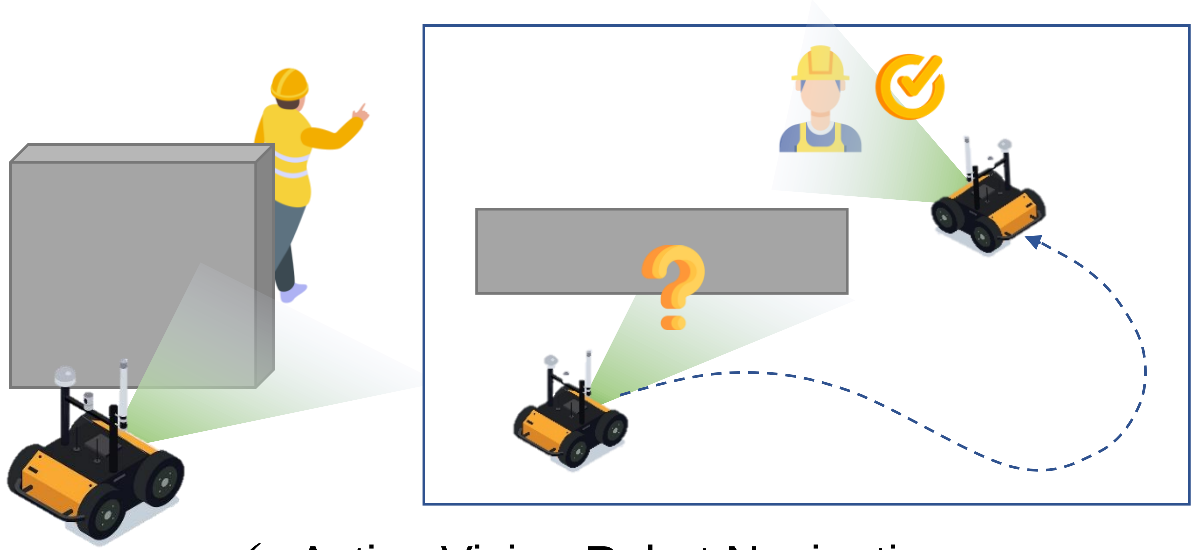
- Mobile robots offer a solution through dynamic repositioning called ‘Active Vision’ (Zhang et al., 2022).

    1) The physical movement of the camera to dynamically collect more information about the environment, allowing it to overcome the limitations of FoV without additional visual devices.

    2) It should be learned to move actively while continuously checking the surrounding environment according to the robot's own goal.



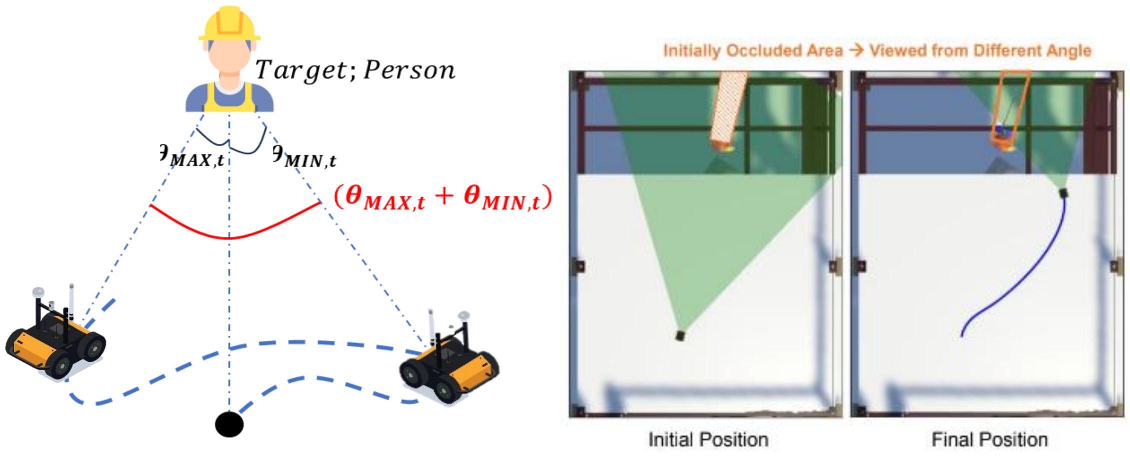
✓ Concept of Active Vision



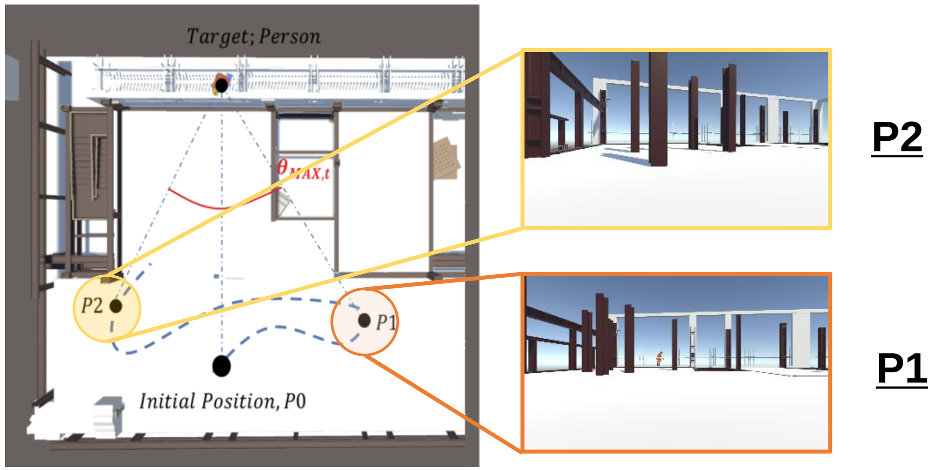
✓ Active Vision Robot Navigation

Research Background

- **Active Vision for Occlusion-Aware Robot Navigation**
  - Previous study has shown that reinforcement learning methods can enhance the proactive capabilities of autonomous monitoring systems in obstacle-rich environment. (Park et al. 2024)
  - Limitations
    1) It is difficult to detect when the distance is too far depending on the performance of the model.
    2) Additional occlusion also occurs in the moved location.



[J Park et al. 2024]



[Limitations]

Research Background

▪ Human-Robot Proxemics.

- The presence of robots introduces potential risks, including physical collisions and perceived threats, which must be mitigated to ensure both physical and psychological safety (Kim et al., 2020)
- Monitoring tasks such as safety management were classified as distant human-robot interaction distances, and were recommended to maintain a certain distance (Sun et al., 2023)

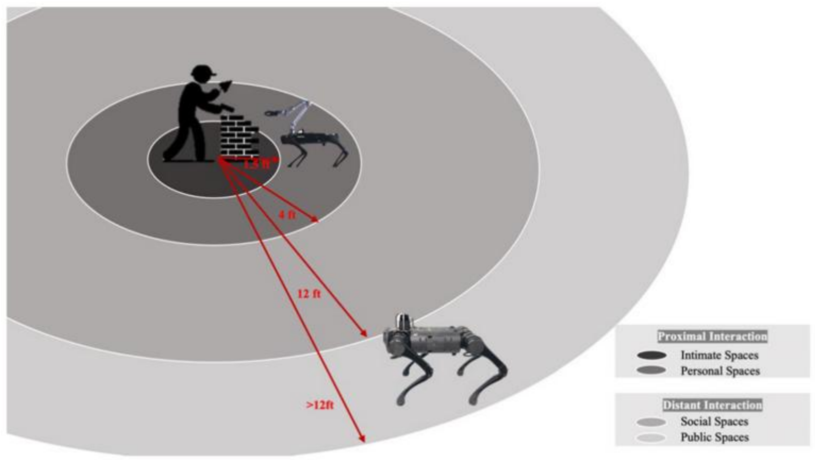


Fig. 1. Proximal and distant interaction spaces between human and robot.

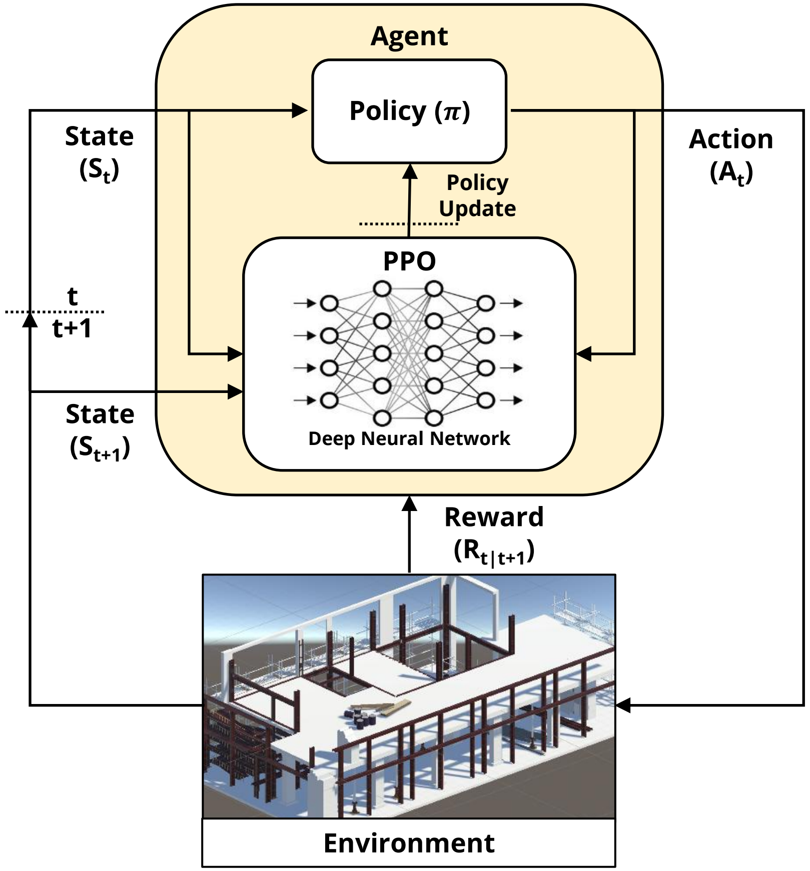
▪ Research Objectives

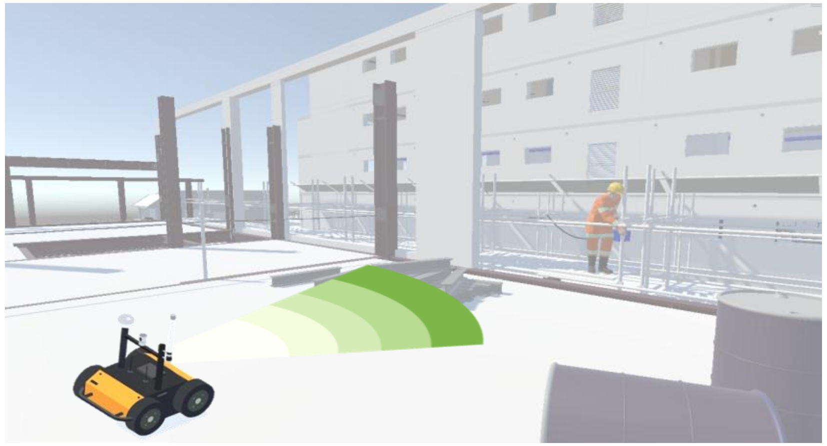
- The robot navigates to achieve the most reliable occlusion-aware monitoring results within its field of view while maintaining a reasonable distance from the worker.

▪ Research Framework

- It focuses on the detection of PPE compliance that may cause self-occlusion during safety monitoring.
- The path planning, in which the robot finds the best viewpoint to locate the target within its detection field, was learned through reinforcement learning DRL.

✓ Reinforcement learning framework





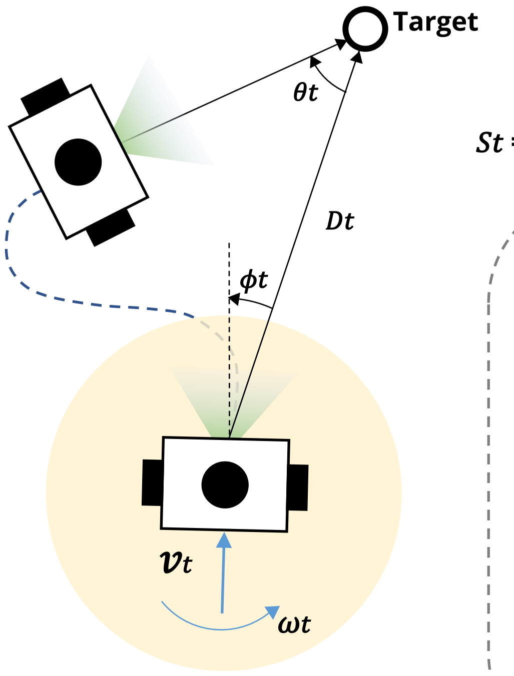
✓ Detection Field

✓ PPE

Methodology

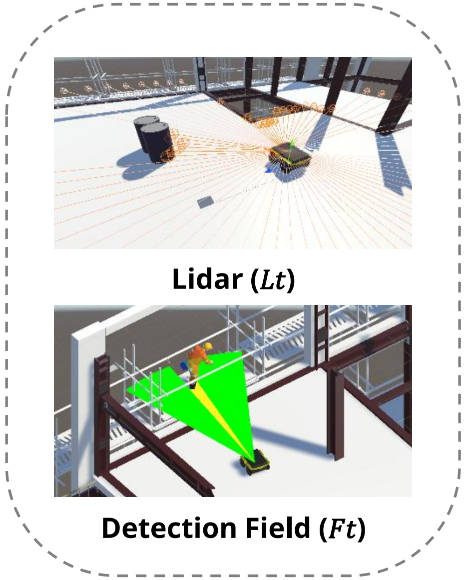
▪ Design of State – Action Space, Reward

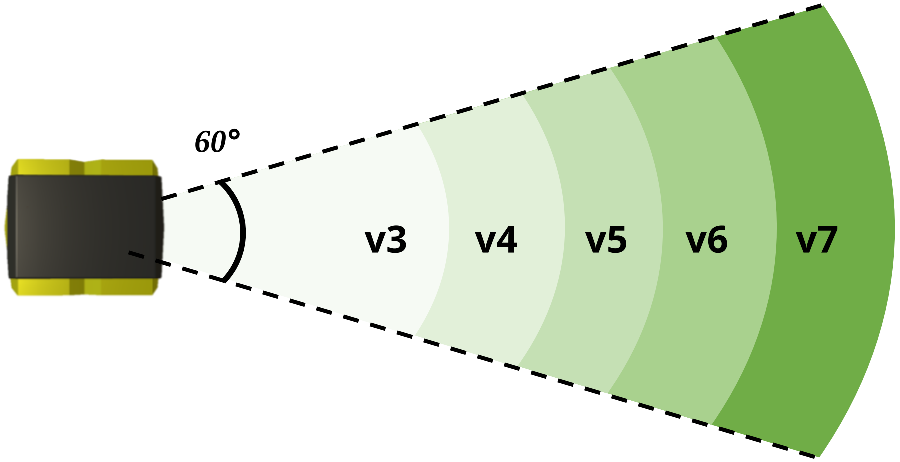
- Develop a dynamic construction site with moving worker in virtual environment.



Action
$At = (v_t, \omega t)$

State
$St = (Dt, \theta t, \phi t, Lt, Ft)$



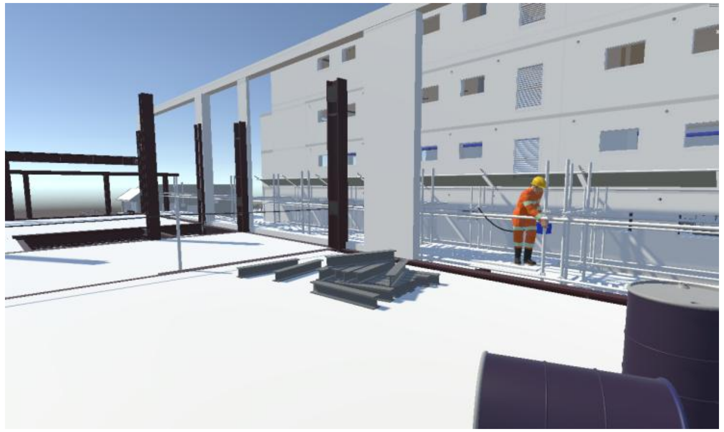


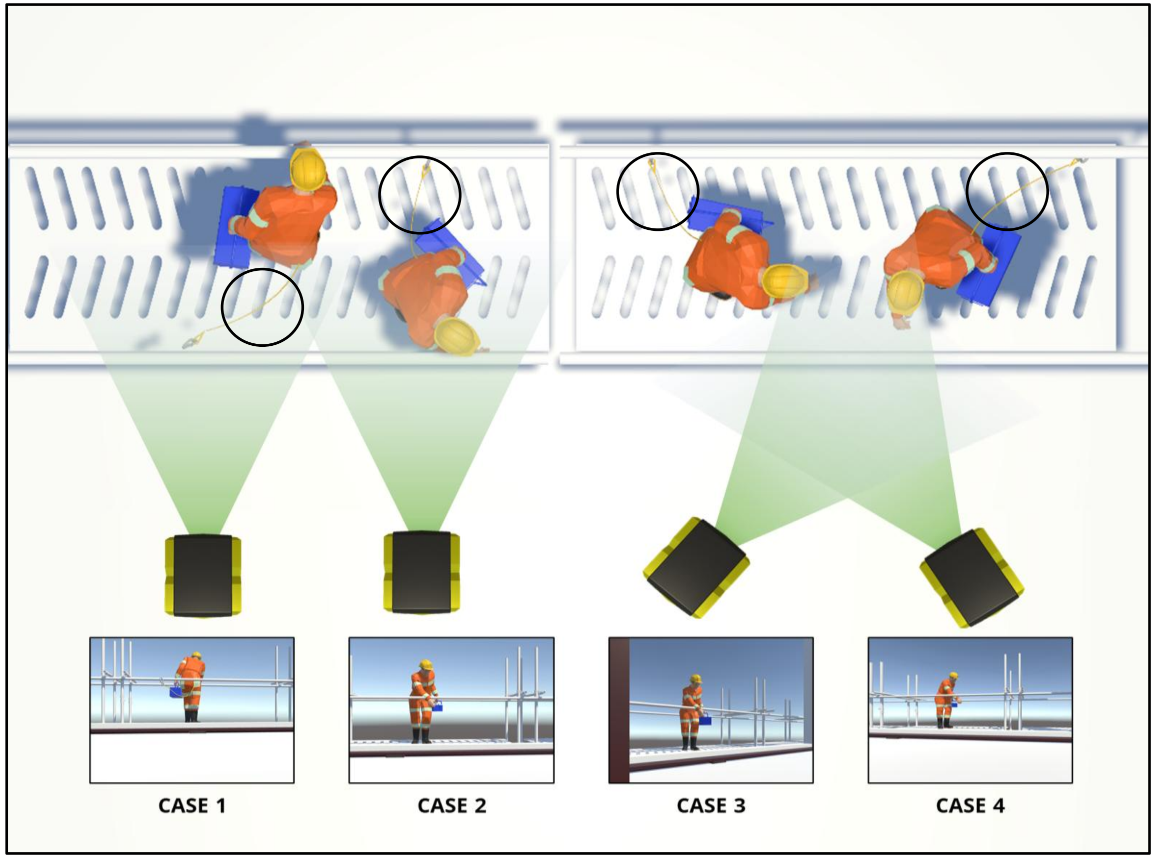
$$r_t(s_t, a_t) = \begin{cases} r_{detected} & \text{if target enters the detection field,} \\ r_{collision} & \text{if collision occurs,} \\ r_{time} \cdot \Delta t & \text{otherwise.} \end{cases}$$

Experiments

▪ Experimental Setup

- Develop a dynamic construction site with moving worker in virtual environment.





Experiments

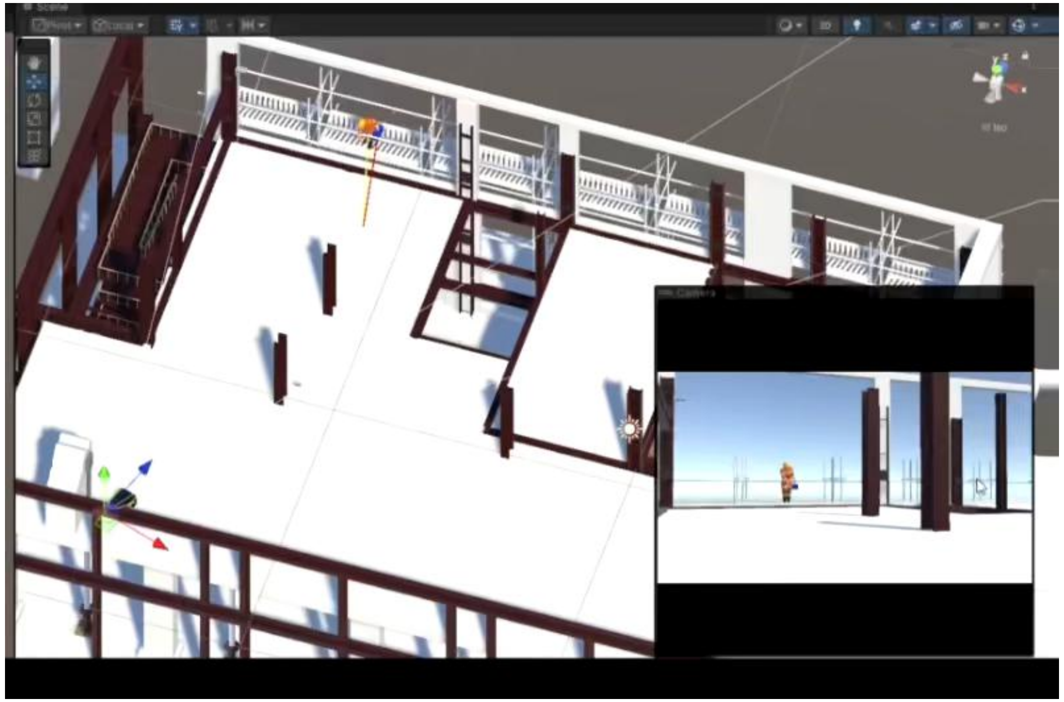
▪ Evaluation Metrics

- Success Rate (SR): the proportion of episodes in which object detection exceeds a predefined confidence threshold 0.8.

$$SR = \frac{1}{N}\sum_{i=1}^{N} S_i$$

Success Rate

- Trajectory Length (TL)
- Minimum Distance (D_{min}): the target along the path to assess the robot's proximity to workers



✓ Sample video of Experiment

Results

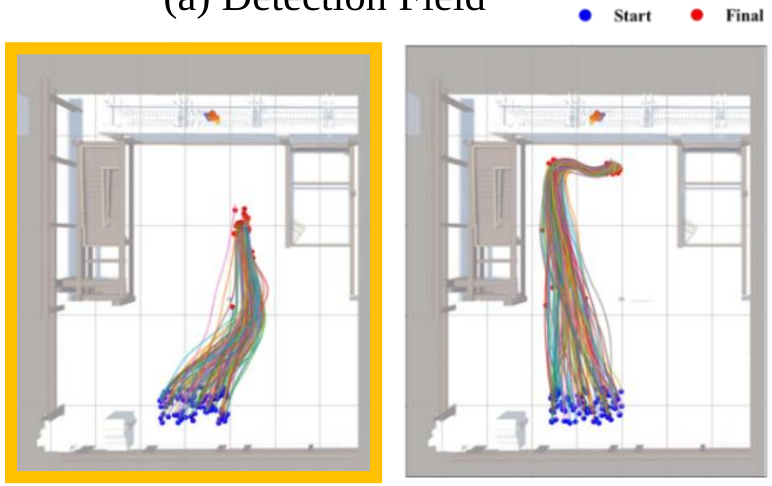
▪ Experiment Results

- The results of this study highlight the significant impact of detection field configurations on the robot's performance.

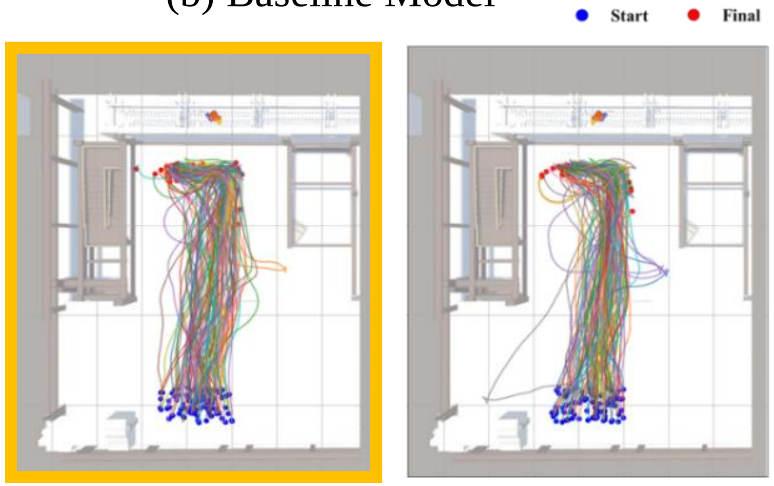
	Experimental Setups								
	w/ occlusion (n=300)			wo/occlusion (n=100)			Total Scenario		
Method	**SR**	**TL**	D_{min}	**SR**	**TL**	D_{min}	**SR**	**TL**	D_{min}
Baseline	0.42	39.53	2.25	0.92	40.13	2.10	0.55	39.68	2.22
Detection Field v3	0.80	35.68	1.52	0.98	28.91	2.65	0.85	33.99	1.80
Detection Field v4	0.77	36.00	2.98	0.95	32.01	4.22	0.82	35.00	3.29
Detection Field v5	0.78	40.00	3.5	0.96	24.45	4.99	0.83	36.11	3.68
Detection Field v6	0.59	37.12	3.62	0.91	26.86	5.20	0.67	34.56	4.02
Detection Field v7	0.56	40.90	4.95	0.89	25.46	5.38	0.65	36.94	5.06

- This highlights the trade-off between maintaining worker safety by increasing distance and ensuring high detection reliability.

(a) Detection Field



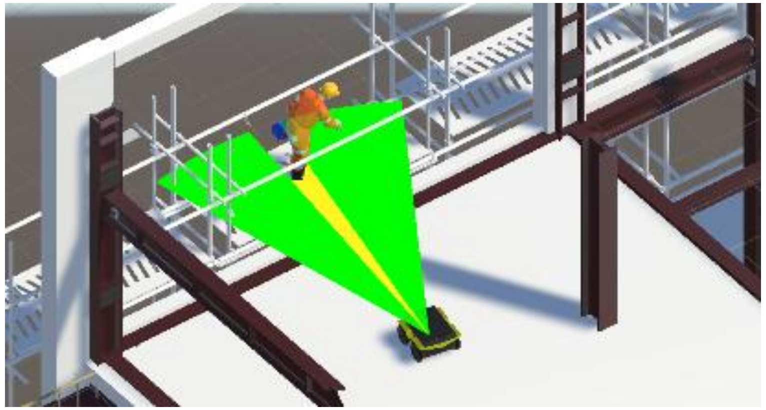
(b) Baseline Model



Conclusion

▪ Impact of Detection Field

- The robot's detection range significantly influences its navigation policy. Expanding the range allows for non-intrusive monitoring of workers, but long-distance detection reduces reliability.
- In disocclusions, detection is possible without additional movement. In occluded conditions, the robot must move closer to the target, reducing the minimum detection distance.



▪ Further Research

- Further research should focus on multi-worker monitoring and addressing interference between robots.
- Test the system in real construction environments to verify its performance under diverse conditions.

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Thank you!

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