

Active Robot Vision with Perception-Aware Navigation for Worker Monitoring

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Research Background

■ Computer Vision Applications for Safety Monitoring

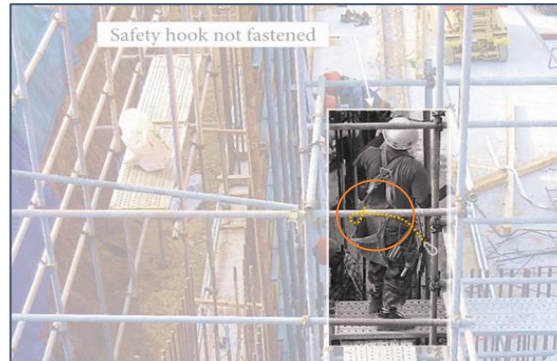
- Vision sensors are used for **verifying personal protective equipment (PPE) compliance through object detection models** on construction sites.
- Fixed-viewpoint monitoring systems struggle **with occlusion** and **limited Field of View (FoV)**, which hinder accurate detection and classification(Paneru et al., 2021).



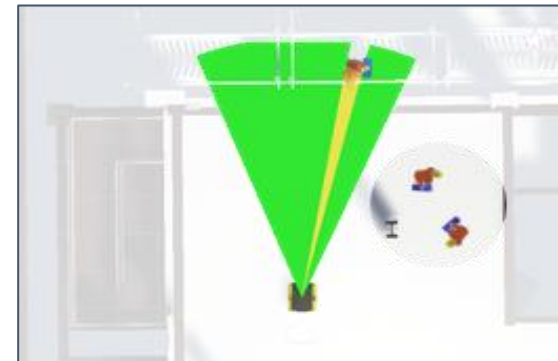
[Occlusion by Obstacle]



[Self-Occlusion]

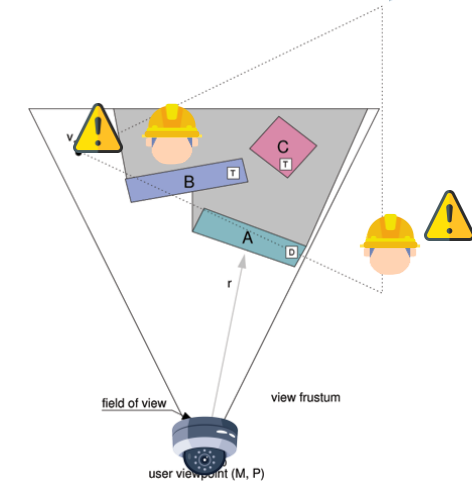


[Self-Occlusion]



[View Occlusion]

✓ Types of Occlusion Problems

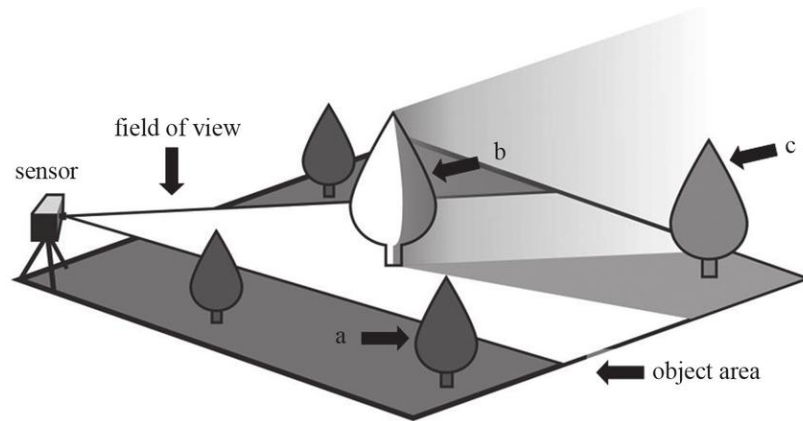


✓ Occlusion problem

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.



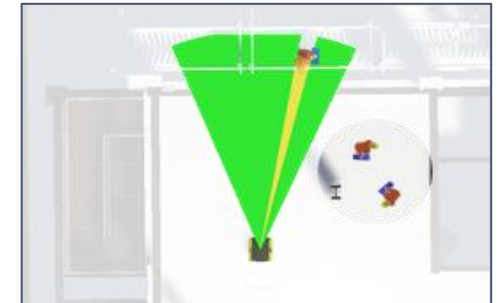
✓ Occlusion



[Occlusion by Obstacle]



[Self-Occlusion]



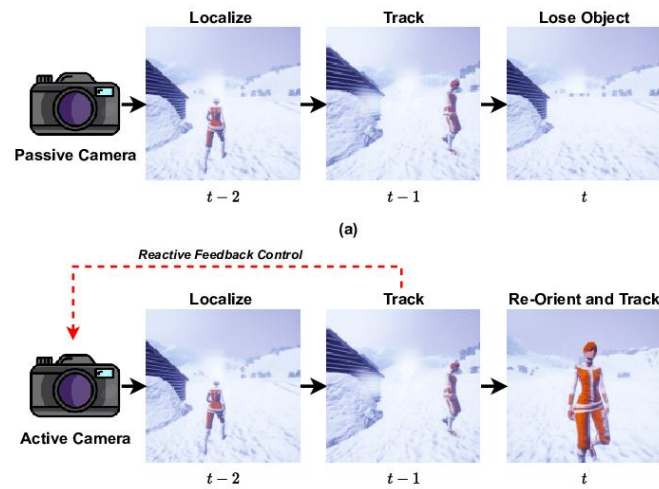
[View Occlusion]

✓ Types of Occlusion Problems

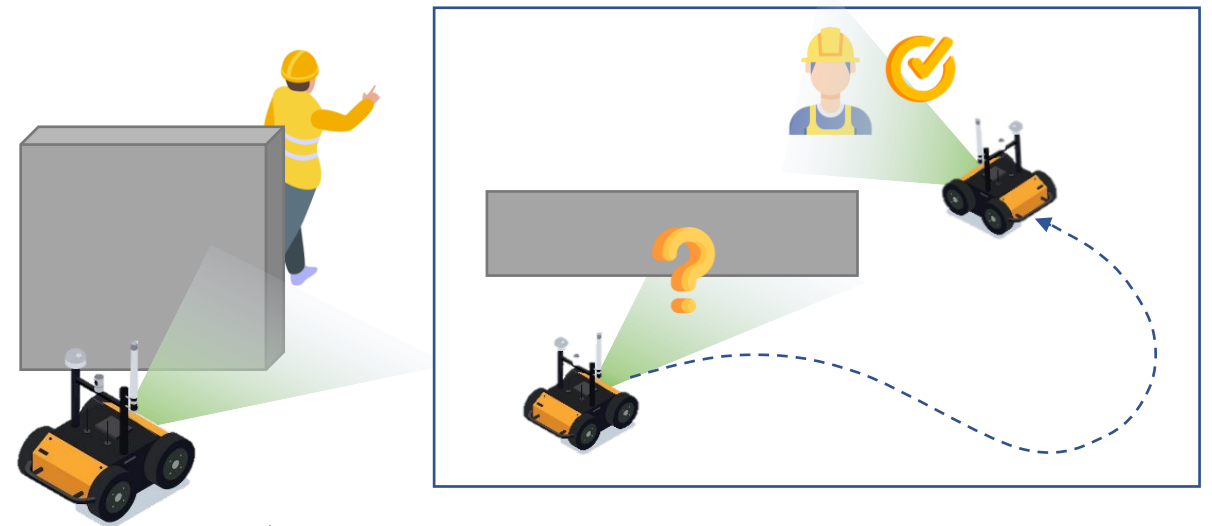
Research Background

■ 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

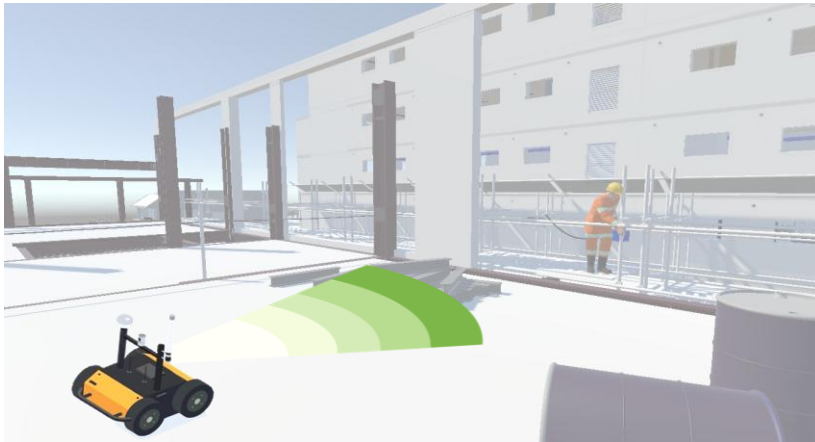


✓ Active Vision Robot Navigation

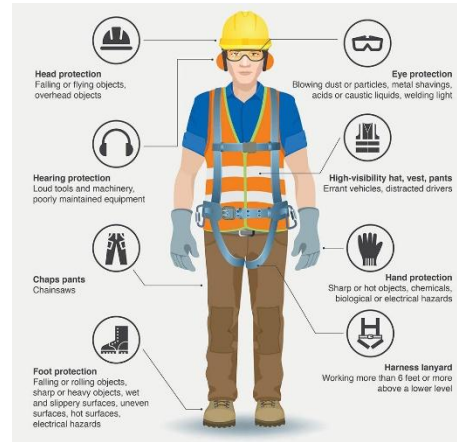
Research Framework

■ 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.

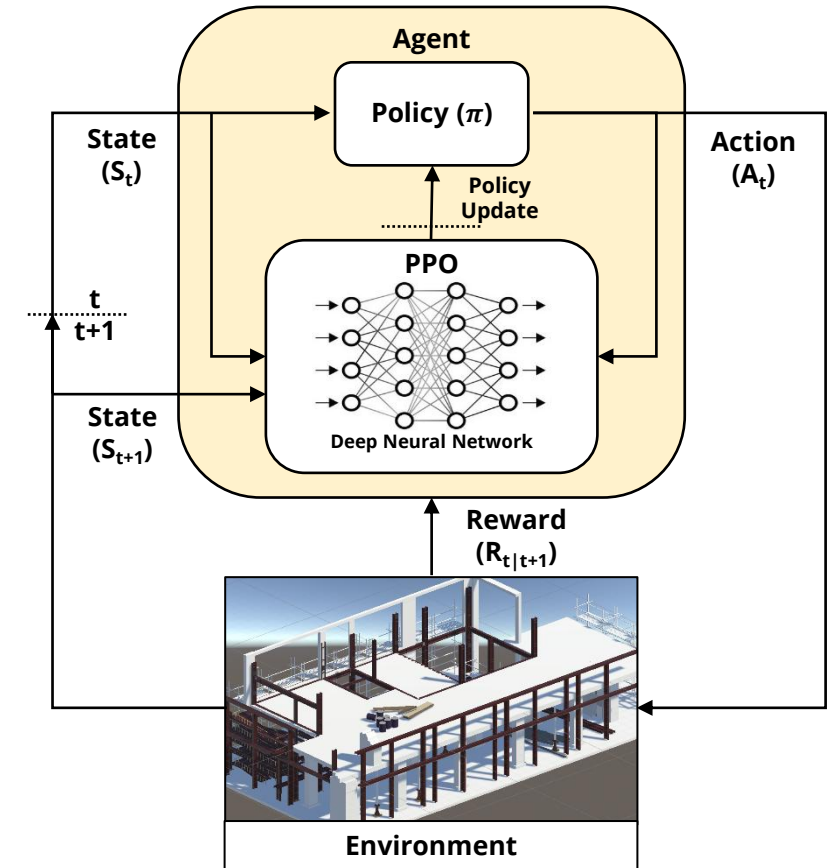


✓ Detection Field



✓ PPE

✓ Reinforcement learning framework



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

References

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Thank you!

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