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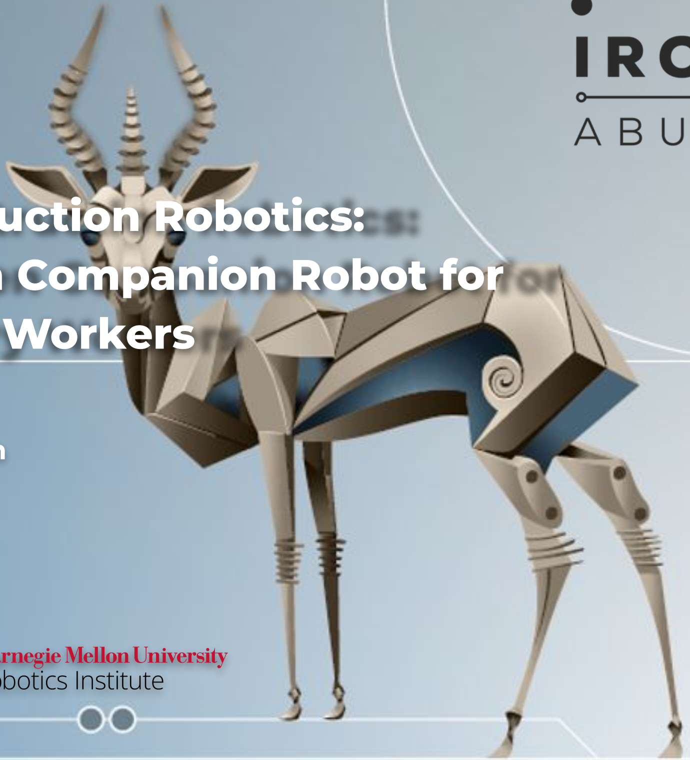
Towards Human-Centered Construction Robotics: A Reinforcement Learning-Driven Companion Robot for Contextually Assisting Carpentry Workers



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Background and Problem Statement

- **Background**
  - **In-situ task-specific automation in construction**
    - E.g., in-situ 3D printing, floor leveling, spray painting, bricklaying.
  - **Assistive robots in various domains**
    - E.g., healthcare, public tour guiding, hospitality, domestic settings.
  - **Robot navigation and mobility on construction site**
    - E.g., quadruped robots for monitoring and documenting construction site progress.
  - **Reinforcement learning for social robot navigation**
    - Utilizes deep reinforcement learning (DRL) to enable robots to adapt to the dynamic movements of neighboring agents. E.g., CADRL, GA3C-CADRL, SARL.

- **Common challenges in construction robotics research and application**
  - Focused primarily on **material-centric, design-centric, and robot-centric** approaches.
  - **Lack of adaptability** to handle nuances of labor-intensive construction work and provide in-situ solutions.
  - Challenges in maintaining the **endurance and workability** of robotic systems outside controlled lab environments.

- **Ours to address**
  - **A human-centric approach:** Positioning intelligent robots in assistive and supportive roles, integrating them into existing workflows.
  - **Tangible support:** Focusing on peripheral tasks, enabling workers to concentrate on skilled, nuanced, bespoke aspects of their work.
  - **Worker safety and strain reduction:** Reducing physical strain, mitigating workplace injuries, and enhancing workflow fluency.

Context and Hypothesis

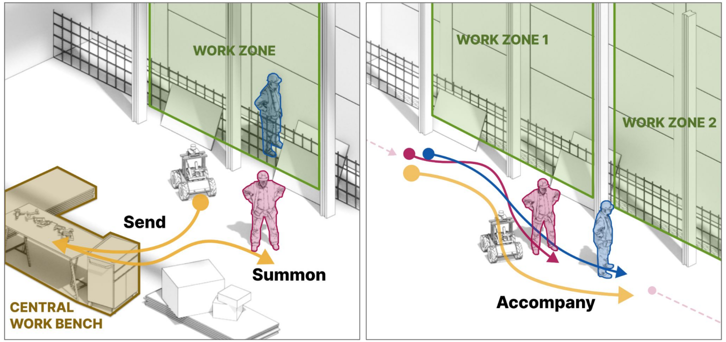
Robot Support Scenarios and Functions

- **Carpentry formwork**
  - Chosen as a representative construction workflow amenable to robotic support following a **15-week in-depth site study**.
  - A workflow part of the “rough carpentry stage”, involving **mold installation** before concrete pouring.
  - **Two workers collaborate** to set up aluminum panels around tied rebar cages:
    - **Worker A** (primary) installs mold panels.
    - **Worker B** (assistant) handles preparation tasks and frequently delivers tools/materials.

- **Support scenarios and opportunities**
  - **Tool and hardware delivery** between a distant workbench and the workers’ current work zones.
  - **Load-bearing** and **accompanying** workers as they move between adjacent zones.

- **Envisioned robot support functions**
  - **Send:** Dispatches the robot to the central workbench (approximately 20m away) to retrieve tools and materials.
  - **Summon:** Remotely recalls the robot once the load is ready.
  - **Accompany:** Comfortably assists workers by carrying tools and materials as they transition to new work zones.

Site observation captures of the carpentry formwork activity and construction site condition



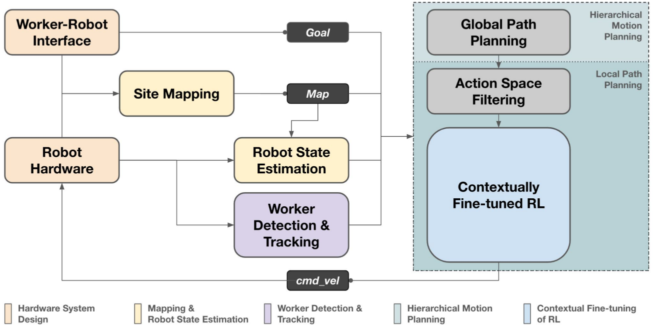
The robotic support scenarios and functions

Markov Decision Process (MDP) Formulation

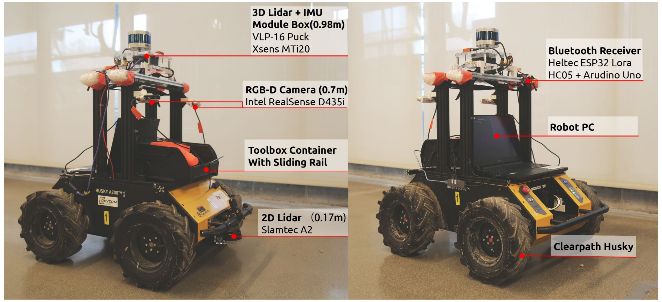
- **MDP components**
  - State $(\mathcal{S})$ → Observable states for worker and robot, including:
    - Position $\mathbf{p} = [p_x, p_y]$
    - Velocity $\mathbf{v} = [v_x, v_y]$
    - Safety radius r
    - Robot's preferred speed v_{pref} and goal position $\mathbf{p}_g = [p_{gx}, p_{gy}]$
  - Action $(\mathcal{A})$ → Robot's possible movements, with the assumption $\mathbf{v}_t = \mathbf{a}_t$
  - Transition $(\mathcal{P})$ → Environment dynamics, determining next state based on the current state and action
  - Reward $(\mathcal{R})$ → Encourages socially comfortable and safe navigation
  - Discount (γ) → Balances immediate and future rewards
  - Initial State $(\mathcal{S}_0)$ → Initial condition of the robot
- **Joint state representation** : $\mathbf{s}_t^{\text{joint}} = [\mathbf{s}_t^{\text{full}}, \mathbf{w}_t^{\text{obs}}]$
  - $\mathbf{s}_t^{\text{full}}$ → Robot's full state (position, velocity, goal, etc.)
  - $\mathbf{w}_t^{\text{obs}}$ → Observable states of all neighboring workers
- **Optimization objective**
  - Solve the MDP using Reinforcement Learning (RL) to maximize the expected return: $R_t = \mathbb{E}\left[\sum_{k=t}^{T} \gamma^{k-t} r_k\right]$
  - **Consideration of contextual information such as cluttered layout** L **and unique worker activity patterns** P

Research by Prototyping
Systematically Building a “Work Companion Robot” For Carpentry Workers

- **A modular robotic framework**
  - **Robot hardware and system design**
    - Mid-sized robot chassis (Clearpath Husky A200) as the base.
    - Sensor package includes 3D LiDAR, 2D LiDAR, IMU, RGB-D cameras, etc.
    - Custom-designed structure and container for tools and materials.
    - Interacted via Bluetooth remote control or phone app.
  - **Unstructured site mapping and robot state estimation**
    - Efficient 2D mapping of 3D geometric complexities.
    - Integration of multiple odometry sources, including LIO-SAM, AMCL, wheel encoders, etc.
  - **Worker detection and tracking**
    - Multimodal detection fusion using multiple sensors (LiDAR, camera).
    - Feature-based multi-object tracking.
  - **Hierarchical motion planning**
    - Search-based approach ensures safe navigation in cluttered environments.
    - RL-driven social navigation enables socially comfortable interaction.
  - **Contextualized fine-tuning of RL**
    - Aligning the RL model’s generic social navigation capabilities with context-specific worker behavioral patterns.



The modular robotic framework



The “work companion robot” prototype

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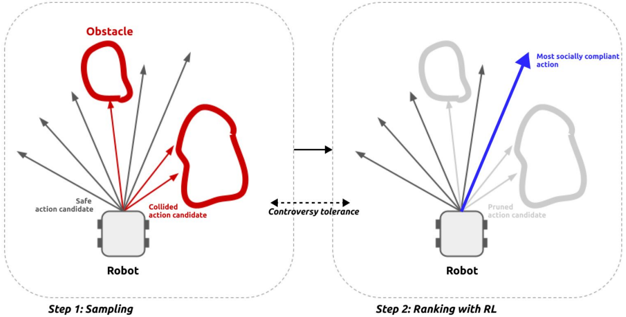
RL-Driven Social Navigation as Technical Backbone
Hierarchical Motion Planning Stack

- **Hierarchical motion planning stack**
  - 1st layer → **safe navigation** through search-based approach (e.g. DWA).
  - 2nd layer → **socially compliant navigation** through value-based RL selection (e.g. SARL).

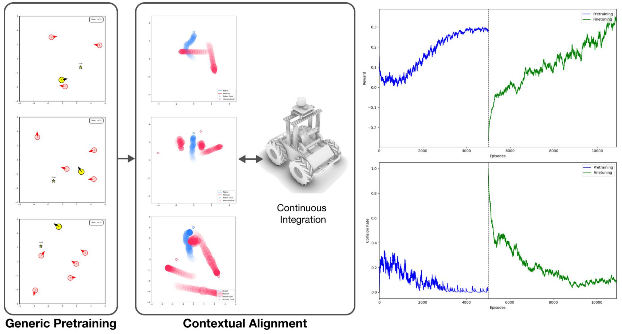
- **Contextualization and domain-specific alignment**
  - **Workers are not pedestrians.**
  - They have unique work-related behavioral patterns.
  - Finetune a pretrained RL model with **additional context-inspired agent behavioral modeling** in the simulation environment.
    - "Stop-and-go"
    - "Back-and-forth"
    - "In-place hesitation and fluctuation"

- **Continuous adaptation and deployment while preventing policy shift**
  - Leverage **Plackett-Luce model** and **KL-divergence** to penalize drastic policy shift or over-memorization to specific pattern.

$$P(\mathbf{a}_i|V) = \frac{V(\mathbf{a}_i)}{\Sigma_{j=1}^{m} V(\mathbf{a}_j)} \qquad D_{\mathrm{KL}}(\pi_{\mathrm{old}}\|\pi_{\mathrm{new}}) = \Sigma_{i=1}^{m} P_{\mathrm{old}}(\mathbf{a}_i) \log\left(\frac{P_{\mathrm{old}}(\mathbf{a}_i)}{P_{\mathrm{new}}(\mathbf{a}_i)}\right) \qquad r = r_{\mathrm{ori}} - \lambda D_{\mathrm{KL}}$$



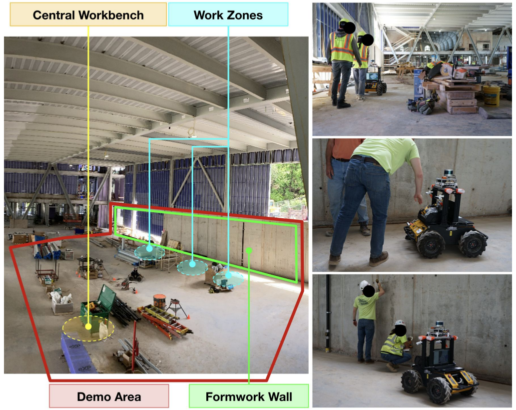
The hierarchical motion planning stack



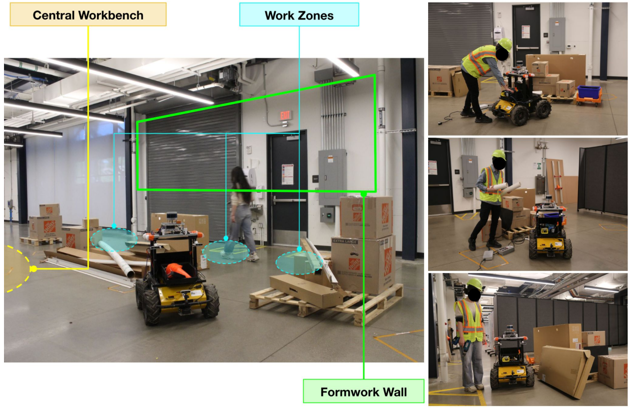
Context-specific adaptation while preventing drastic policy shift

Demonstration and Evaluation
On an Actual Construction Site / In a Lab Sandbox

- **On-site demonstration and qualitative evaluation**
    - Workers **directly** operated the robot while engaging in the carpentry formwork installation tasks and workflows.
    - **Three interaction scenarios** were tested using customized controllers.
    - A **post-demonstration group interview** was conducted with participating workers.
- **Quantitative evaluation in lab sandbox**
    - A **sandbox** was created based on site observations and challenges.
    - **Two layout scenarios with 40 test cases were tested over 160 runs.**
    - Evaluation metrics.
        - Comfort-related metrics (comfortable delivery rate, comfortable encounter rate)
        - Common navigation metrics (collision rate, freeze rate, success rate, navigation time)
- **Result summary**
    - Workers found the robot's support functions **effective and useful**.
    - RL-driven social navigation improved the robot's ability to **comfortably support** workers.
    - Context-specific fine-tuning further **reduced the robot's freeze rate**, enabling **smoother** support and navigation.



On-site demonstration with workers



Quantitative evaluation in lab sandbox

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Conclusion and Future Work

- **Towards human-centered robotics in construction work**
  - Introduced **a human-centered “work companion rover” prototype** to support carpentry workers in labor-intensive tasks.
  - Developed **a lightweight, modular, and hierarchical framework** using RL-based social navigation for safe and comfortable robot navigation in construction environments.
  - Showcased **an efficient pipeline for contextually aligning and improving pretrained RL models** with site-specific features.
  - Proposed **a feasible, alternative approach to integrate autonomous robots in labor-intensive industries**, enhancing safety and workflow while valuing human skills and expertise.

- **Future Work**
  - Expand **manipulation capabilities** and broader deployment.
  - Utilize **the modular framework as an expandable navigation base**, adaptable to other support scenarios and applications.
  - Envision a future where human expertise and AI-driven robotics collaborate seamlessly to improve labor-intensive industries.

Thank you!

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