Preliminary Evaluation of Human State-Aware Adaptive Robot Motion Control for a Quadruped Robot in Construction Workspaces

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***Abstract*— Construction robots operating near workers must adapt their motion to human states and spatial conditions. This study presents a human state-aware adaptive motion control framework for a quadruped robot that integrates trust and distraction assessment with reinforcement learning–based motion control. Collaborative workers' trust was classified from physiological responses, while co-existing workers' robot-induced distraction was classified from body pose, orientation, and movement. A decision gate activated either a Trust-Aware or Distraction-Aware Proximal Policy Optimization agent according to the worker closest to the robot. The framework was evaluated by comparing adaptive and non-adaptive operating conditions using robot velocity and human–robot separation metrics. Adaptive control reduced mean linear velocity by 8.2% and reduced angular velocity by 40.0%. Mean separation distance increased by 16.8%, with more observations occurring beyond 3 m. These findings indicate that the framework promoted slower, smoother, and more human-aware robot motion in shared construction environments.**

I. Introduction

Human-robot collaboration (HRC) refers to situations in which humans and robots work together or operate within a shared workspace to accomplish related tasks [1]. In construction, robots can support repetitive, physically demanding, and hazardous activities; however, the dynamic and unstructured nature of construction environments requires robots to account for nearby workers while navigating and performing tasks. Previous construction HRC studies have examined the use of workers' physiological and cognitive responses to support human-centered robot operation [2], measured workers' trust during interaction with construction robots [3], and demonstrated that robot movement, proximity, workspace characteristics, and interaction conditions can influence trust and psychophysiological responses [1], [4]. Robot interaction can also affect worker productivity, further emphasizing the need to consider human responses when designing robotic systems for construction [5].

Human-aware robot navigation is the process of planning and controlling robot motion while considering the presence, movement, safety, and comfort of nearby people [6]. Related socially aware navigation research has increasingly applied learning-based methods to allow robots to move efficiently without violating human spatial expectations [7], [8]. Deep reinforcement learning has also been used for navigation and collision avoidance in cluttered and dynamic environments [9], [10]. Proximal Policy Optimization (PPO), a policy-gradient reinforcement-learning algorithm designed to produce stable policy updates, provides a suitable approach for learning adaptive motion-control strategies [11]. Nevertheless, many existing human-aware navigation approaches primarily focus on collision avoidance, path efficiency, and socially acceptable spacing, with limited consideration of workers' internal states during robot motion. This study addresses that gap by integrating trust for collaborative workers and robot-induced distraction for co-existing workers, together with proximity, into adaptive motion control. Unlike conventional approaches that respond mainly to spatial or environmental information, the proposed framework modifies robot behavior according to both the worker's role and estimated human state.

Accordingly, this study develops and evaluates a human-centered adaptive control framework for a quadruped robot operating near construction workers. The framework uses human-state and proximity information to dynamically regulate robot motion through trust-aware and distraction-aware control policies. The objectives are to: 1) compare robot linear and angular velocity characteristics under adaptive and non-adaptive control; and 2) evaluate how adaptive control influences human–robot separation and the distribution of close, moderate, and far proximity observations. The study provides a preliminary motion-level assessment of whether adaptive control can support more cautious and human-aware robot operation in shared construction environments.

II. Adaptive Control Framework

Building on the need for human-aware robot operation identified in the previous section, this section presents the proposed adaptive control framework and its decision-making process. The framework integrates human-state assessment and proximity information to select appropriate control strategies and generate adaptive robot-motion commands.

A. Worker-State Classification Framework

The proposed framework considers two types of workers who may be present near a construction robot: collaborative workers and co-existing workers. A collaborative worker directly interacts with the robot to complete a shared task, whereas a co-existing worker performs an independent task while occupying the same workspace. Because these workers experience different forms of interaction, the framework evaluates trust-on-robot for collaborative workers and robot-induced-distraction for co-existing workers.

The trust-assessment component uses a previously validated machine-learning model [4] to classify a collaborative worker's trust in the robot as low, moderate, or

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high based on physiological features, including mean heart rate, RMSSD, and mean RR interval. In contrast, the distraction-assessment component uses a vision-based classification framework developed and evaluated through prior experimental work to classify robot-induced distraction among co-existing workers as low, moderate, or high based on head orientation, torso orientation, and body movement. These trust and distraction classifications provide the human-state information used by the corresponding adaptive controller.

The framework assumes that the worker closest to the robot has the immediate influence on its motion behavior. Based on the identified worker role, only the corresponding human-state assessment is activated at a given time. The resulting trust or distraction level, together with human–robot proximity, is then used to determine whether the robot should maintain its current behavior or adopt more cautious motion.

B. *Human-Aware Decision Framework*

The decision framework first identified the worker visible within the robot's operating area and estimated the worker–robot distance. Worker roles were distinguished using helmet-color information: the collaborative worker wore a white helmet, whereas workers wearing other helmet colors were classified as co-existing workers. When multiple workers were detected, the closest worker was selected as the primary individual influencing the control decision. The worker role determined which human-state assessment component was activated. For collaborative workers, a trust-prediction model estimated low, moderate, or high trust using physiological responses. For co-existing workers, a vision-based distraction framework classified the worker's distraction level as low, moderate, or high using head orientation, torso orientation, and body-movement indicators. Only one assessment component was active at a given time, and its output was supplied to the corresponding trust-aware or distraction-aware control policy.

C. *Adaptive Motion Control*

Adaptive motion control was implemented using two reinforcement-learning agents trained with Proximal Policy Optimization (PPO). The Trust-Aware PPO agent was activated when the nearest worker was collaborative, while the Distraction-Aware PPO agent was activated for a co-existing worker. For both agents, the state space included the classified human state (trust or distraction level), current robot motion, and human–robot separation distance. The continuous control outputs adjusted the robot's linear velocity, angular velocity, and separation distance. At each decision step, the worker-selection gate identified the closest worker and activated only the corresponding PPO agent. The reward functions encouraged motion consistent with the detected human state while maintaining adequate separation, smooth movement, and task efficiency. Penalties were assigned for close-range operation, excessive speed near workers, abrupt directional changes, and increased collision risk. Consequently, lower trust, higher distraction, or reduced separation promoted slower and more cautious motion, whereas higher trust, lower distraction, and sufficient separation allowed more efficient movement. Under the non-adaptive condition, the same baseline motion-control structure was used, but the robot followed predefined motion commands without using human-state or proximity information.

III. EXPERIMENT

The proposed framework was evaluated through a controlled experiment designed to compare robot motion under adaptive and non-adaptive operating conditions. The following subsections describe the experimental setup, procedure, evaluation measures, and telemetry-data analysis.

A. *Experimental Setup*

The experiment was conducted in a controlled construction-like environment using a Unitree Go2 quadruped robot. Eight participants were assigned to one of two roles: four participants served as collaborative workers, while four served as co-existing workers. Collaborative workers performed an information-retrieval task while interacting with the robot, whereas co-existing workers completed a tool-sorting task while the robot operated within the shared workspace. Participants remained in the same assigned role throughout the experiment. The robot's onboard RGB camera was used by collaborative worker for information retrieval task, while an Insta360 X4 camera captured postural and behavioral information for distraction assessment (Fig. 1). A Polar H10 chest strap provided physiological data for trust estimation of collaborative workers. A Raspberry Pi 4 supported real-time perception, human-state assessment, and communication with the ROS2-based robot-control system.

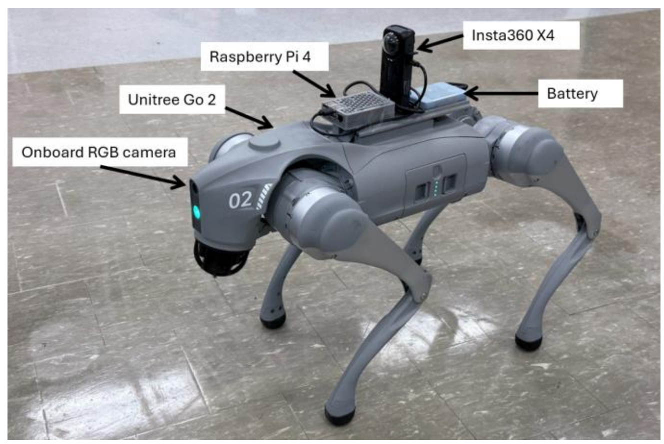

Figure 1. Unitree Go2 robot and instrument setup for experiment.

B. *Experimental Procedure*

Each participant completed two experimental sessions: one under adaptive control and one under non-adaptive control. The session order was counterbalanced across participants to reduce potential learning, fatigue, and order effects. During the adaptive session, the robot dynamically modified its motion according to the detected worker role, estimated human state, and worker–robot proximity. During the non-adaptive session, the robot followed predefined motion commands without using trust or distraction information. Before each session, participants received instructions regarding their assigned task and were familiarized with the experimental environment and robot operation. Each session continued for approximately eight minutes, until the assigned task was completed.

C. *Data Analysis*

ROS2 recorded the robot's linear and angular velocity data as log files for each interaction, while human–robot distance measurements derived from the camera feed were stored on the Raspberry Pi. The data were organized by participant and control condition. Robot motion was evaluated using linear velocity, angular velocity, and human–robot separation. Descriptive statistics were first calculated separately for each participant per session and then summarized across participants for each control condition. Velocity observations were classified as low (< 0.5 m/s), moderate (0.5–1.5 m/s), and high speed (> 1.5 m/s), while separation was classified as close (<1 m), moderate (1–3 m), and far (>3 m). These thresholds were selected as study-specific analytical ranges based on the robot's operating behavior and the spatial characteristics of the experimental environment. The percentages of observations within each category were then compared between the adaptive and non-adaptive control conditions.

IV. RESULTS

The adaptive and non-adaptive control conditions were compared based on robot velocity characteristics and human–robot separation distance. The reported results combine collaborative and co-existing worker interactions and therefore represent the overall motion-level performance of the adaptive framework across both worker roles.

A. Robot Velocity Characteristics

Table I summarizes the robot velocity characteristics under the adaptive and non-adaptive control conditions. The adaptive controller reduced the mean linear velocity from 0.547 to 0.502 m/s, corresponding to an 8.2% decrease, while the 95th-percentile velocity decreased from 1.066 to 0.914 m/s. A more substantial reduction was observed in angular velocity, which decreased from 0.512 to 0.307 rad/s, representing an approximately 40.0% reduction. The median and maximum velocities remained unchanged at 0.500 and 3.000 m/s, respectively, indicating that the primary influence of the adaptive controller was on the robot's typical and upper-range motion rather than its maximum allowable speed.

TABLE I. ROBOT VELOCITY CHARACTERISTICS.

	Adaptive		Non-Adaptive	
	Mean	SD	Mean	SD
Mean Velocity (m/s)	0.502	0.086	0.547	0.016
Median Velocity (m/s)	0.500	0.000	0.500	0.000
Maximum Velocity (m/s)	3.000	0.000	3.000	0.000
95th Percentile (m/s)	0.914	0.339	1.066	0.270
Angular Velocity (rad/s)	0.307	0.109	0.512	0.438
Low Speed (%)	18.150	14.936	9.845	2.763
Moderate Speed (%)	76.812	13.975	84.695	2.657
High Speed (%)	5.038	0.978	5.461	0.156

As illustrated in Fig. X, the adaptive condition produced a greater proportion of low-speed movements and fewer moderate-speed movements than the non-adaptive condition. Low-speed samples increased from 9.85% under non-adaptive control to 18.15% under adaptive control, whereas moderate-speed samples decreased from 84.70% to 76.81%. The proportion of high-speed samples remained relatively similar, decreasing slightly from 5.46% to 5.04%. These results indicate that the adaptive controller shifted robot operation toward comparatively slower motion, while high-speed movements remained relatively unchanged.

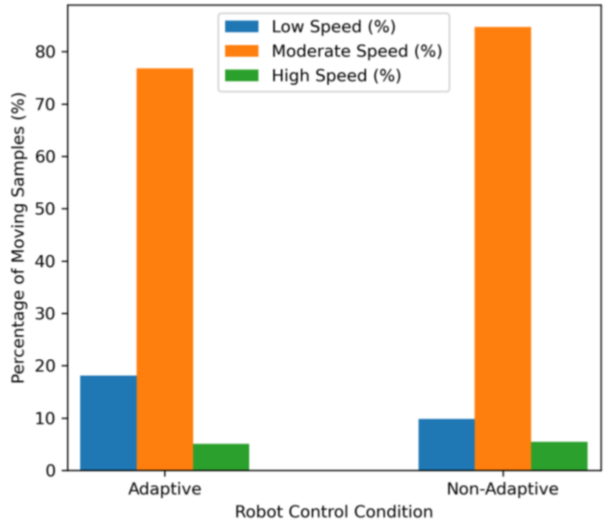

Figure 2. Robot speed-zone distribution.

B. Human–Robot Separation

Table II summarizes the human–robot separation distances under the adaptive and non-adaptive control conditions. The mean separation distance increased from 3.218 m under non-adaptive control to 3.760 m under adaptive control, representing an approximately 16.8% increase. Similarly, the median distance increased from 2.542 to 3.255 m, while the 75th- and 95th-percentile distances increased from 3.878 to 4.738 m and from 7.436 to 8.469 m, respectively. The minimum separation also increased slightly from 0.459 to 0.512 m, indicating that the adaptive controller generally maintained greater separation between the robot and workers.

TABLE II. DESCRIPTIVE STATISTICS OF ROBOT–HUMAN PROXIMITY.

Condition	Adaptive	Non-Adaptive
Mean Distance (m)	3.75952	3.21808
SD of Distance (m)	2.3443	2.08472
Median Distance (m)	3.255	2.542
Minimum Distance (m)	0.512	0.459
Maximum Distance (m)	14.387	14.477
25th Percentile (m)	1.944	1.928
75th Percentile (m)	4.738	3.878
95th Percentile (m)	8.4685	7.4355

As illustrated in Fig. X, the adaptive condition produced a higher proportion of observations in the far proximity zone and fewer observations in the moderate zone. Approximately 53% of adaptive-control samples occurred at distances greater than 3 m, compared with approximately 36% under non-adaptive control. In contrast, the proportion of samples within the moderate zone of 1–3 m decreased from approximately 63% to 44%. Close-proximity observations below 1 m remained limited under both conditions, suggesting that the primary effect of the adaptive controller was to shift robot operation from moderate toward farther separation distances.

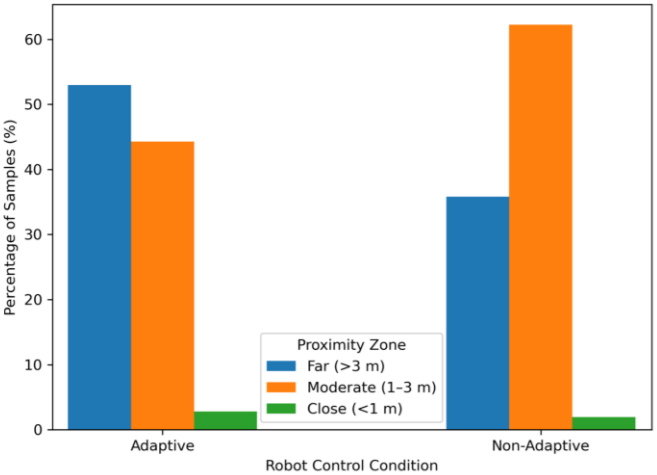

Figure 3. Robot–human proximity zone distribution.

V. Discussion

The results indicate that the adaptive control framework modified the robot's movement in a more cautious and human-aware manner rather than simply reducing its speed uniformly. The lower mean and 95th-percentile linear velocities, together with the approximately 40% reduction in angular velocity, suggest that the controller limited rapid movements and abrupt directional changes when responding to nearby workers. This interpretation is also supported by the increased proportion of low-speed samples and the reduced proportion of moderate-speed samples, while the percentage of high-speed movements remained nearly unchanged. Thus, the adaptive controller appears to have selectively adjusted the robot's typical operating behavior while preserving its ability to move faster when required. Similarly, the increases in mean, median, and upper-percentile separation distances, along with the shift from the moderate to the far proximity zone, indicate that the controller generally maintained a larger working distance from humans. These combined changes may reduce the intrusiveness and unpredictability of robot motion and support safer and more comfortable human–robot coexistence. However, because close-proximity observations were still present and no inferential statistical analysis was conducted, these findings should be interpreted as preliminary evidence of improved motion regulation rather than definitive proof of enhanced safety. The observed motion changes align with the intended human-state-aware control logic, where lower trust or higher distraction promotes slower motion and greater separation. However, because the analysis aggregates human-state levels, the results reflect overall framework behavior rather than state-specific responses.

Despite these findings, this study has several limitations that should be considered when interpreting the results. The study was conducted with a small participant sample in a controlled experimental environment using a single robotic platform. The reported results are primarily descriptive and may not represent the variability encountered on active construction sites. The current comparison does not isolate the effects of human-state awareness from proximity-based adaptation because both are used only in the adaptive condition. Close-proximity and high-speed movements were not completely eliminated under adaptive control. Further validation with larger samples, inferential statistical analyses, multiple robot platforms, and diverse construction tasks is therefore required.

VI. Conclusion

This study presented a preliminary evaluation of an adaptive robot control framework by comparing robot velocity characteristics and human–robot separation under adaptive and non-adaptive operating conditions. The adaptive controller produced lower mean and upper-percentile linear velocities, substantially reduced angular velocity, increased low-speed operation, and maintained greater separation from workers. These findings suggest that the framework can regulate robot motion in a more cautious and human-aware manner while preserving operational capability. Such adaptive behavior may be valuable in construction environments where mobile robots must operate near workers under changing spatial and behavioral conditions.

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