Semantic-based behavioral decision-making method for construction robots in worker-robot collaboration

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Abstract –

Worker-robot collaboration (WRC) can enhance the efficiency and performance of construction robots in complex tasks and dynamic environments. The behavioral decision-making capabilities of robots are critical for them to effectively interact and collaborate with workers. This research presents a behavioral decision-making method for automatic construction robots. First, a semantic world model is introduced to represent the on-site WRC state with graph data structures. Then, a Learning from Demonstration (LfD) method is utilized for robots to acquire behavioral policy through worker demonstrations. Finally, behavioral decision-making for construction robots is achieved using graph-matching algorithms. The proposed method was tested and validated in a virtual reality environment through panel installation tasks. The results show a 90% success rate in extracting feasible and reproducible robot behavioral policies on a single demonstration. The proposed method is promising for enhancing the intelligence of construction robots and improving the safety and efficiency of on-site WRC.

Keywords –

Worker-robot collaboration; Construction robot; Behavioral decision-making; Semantic understanding

1 Introduction

Construction robots can address urgent issues in the construction industry, including low productivity, worker shortages, and occupational health concerns. However, the ever-changing nature of construction sites presents significant challenges for the effective deployment of construction robots on-site [1]. Worker-robot collaboration (WRC) can enable robots to adapt to dynamic construction environments by introducing workers' flexibility to help robots overcome the complexity and unpredictability of construction sites [2].

Recent studies are focusing on on-site WRC with automated construction robots collaborating with workers as teammates. These collaboration tasks include common activities such as welding [3], wall painting [4], and wooden structure assembling [5]. In WRC, construction robot needs to decide what to do and when to act to ensure both safety and the smooth progress of the collaboration. However, most construction robots in existing research rely on direct commands from workers and lack the flexibility and intelligence to boost productivity [6].

To enhance the efficiency and safety of WRC, it is essential for construction robots to possess behavioral decision-making capabilities. This involves selecting appropriate actions from their built-in skills based on the situation they perceive themselves to be in, which is crucial in dynamic environments [7]. Nevertheless, several challenges remain unaddressed for construction robots: first, how to establish a structured representation of the WRC situation; and second, how to map the WRC situation to appropriate behaviours.

The objective of this research is to propose a behavioral decision-making method for construction robots in on-site WRC. A semantic world model is proposed for WRC's scene understanding. Based on the model, behavioral policies can be learned from demonstrations and embedded into construction robots' knowledge base, ultimately supporting their behavioral decision-making. The remainder of this paper is structured as follows. A literature review is first made in Section 2. Then, the proposed method is introduced in Section 3, and experiments and results are discussed in Section 4. Finally, a conclusion is drawn in Section 5.

2 Literature Review

2.1 World model of robots in WRC

A world model refers to the information the robot has about the world around it, and that needs to be shared between several activities [8]. A well-defined world model is not only crucial for the robot to understand the scene and make behavioral decisions but also enhances its explainability [9].

Syntax-based world model interprets a scene as a sequence of events driven by the behaviors of agents. For instance, Pan et al. [10] developed a scene understanding method for construction robots utilizing syntax to outline construction progress such as “Base setup” and “Framework setup.” Markov models are used to describe state transitions. Cunha et al. [11] adopted predicate symbolic representations to describe scenes and used a short-term memory layer to model state transitions.

A semantic world model analyzes a scene by leveraging the semantic relationships among entities to deduce the context. Niccolò et al. [12] modeled the assembly task with semantic descriptions, where assembly tasks are defined by the spatial relationships among components. This model was expanded into an enriched event chain model to describe state transition processes[13]. A semantic world model can also be used to guide robots in performing safe operations [14]. Markov processes and other stochastic models are used to describe state transitions within a semantic world model [15]. The semantic world model significantly outperforms the syntax-based world model in terms of reusability and scalability. However, existing semantic world models cannot characterize elements unique to the on-site WRC environment. Moreover, the transition path representations in current world models fail to account for the modeling of the concurrent operations of multiple agents, making them unsuitable for supporting construction robots' decision-making in WRC.

2.2 Behavioral policy for robots in WRC

A policy is a set of rules mapping the optimal behavior to the current state [15]. If an explicit world model is not provided, reinforcement learning (RL) is applied, allowing the robot to learn optimal policy through repeated interactions with the environment, guided by a defined reward function [16]. Nevertheless, designing a reward function for WRC is challenging, as it must account for factors related to both efficiency and safety. Additionally, RL-based decision-making is difficult to explain and may disrupt workers in WRC.

In scenarios where the decision-making process cannot easily be scripted or optimized, robots can learn the decision-making process from human demonstration [17]. The policy learned from the demonstration can be either probabilistic or deterministic. Probabilistic policy learning methods, such as Markov networks [18] and Bayesian networks, output a distribution of behaviors rather than deterministic actions. However, when demonstration data is limited, robots can only learn a deterministic behavioral policy. In these cases, the robot's policy can be represented using a finite state machine or a decision tree [19]. However, previous research rarely considers robot policies in WRC. On one hand, most world models are not designed for WRC scenarios that involve concurrent behaviors from multiple agents, making them unsuitable for supporting the robot's decision-making in on-site WRC. The other challenge is how to acquire demonstration data and learn behavioral policies from limited demonstration data for construction robots. These are the two central questions that need to be addressed in this research.

3 Method

The proposed robot’s behavioral decision-making method begins with the introduction of a semantic world model to represent the on-site WRC process. The world model abstracts unstructured WRC scenes and processes into structured data, enabling robots to establish semantic-based scene understanding and policy learning foundations. To facilitate behavioral policy learning from demonstrations, a virtual reality (VR) platform is developed to simulate the WRC environment, where workers demonstrate the robot’s behaviors through intuitive interaction. The behavioral policy is subsequently extracted from the demonstration data structured by the world model. Using the policy learned from the demonstration, construction robots can make behavioral decisions by matching their observation of the current WRC scene to the WRC state stored in the policy, thereby reasoning and determining their behaviors accordingly. The framework of the method is illustrated in Figure 1.

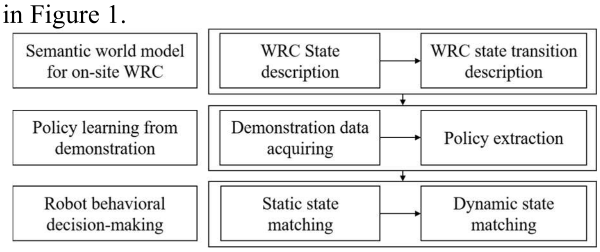


Figure 1. The framework of the proposed method.

3.1 Semantic world model for on-site WRC

3.1.1 Description of WRC state

The state of a static WRC scene is semantically described by the entities and their relationships within the environment. The entities involved in on-site WRC are identified and classified into three categories:

- **Agents**: Agents can proactively interact with other entities and drive the progress of on-site WRC, including workers and construction robots.
- **Movable objects**: Movable objects are entities that can be manipulated and relocated, including construction materials, tools, containers, etc.
- **Static Objects**: Static objects are entities that cannot be moved by agents or other objects, such as walls and floors.

Spatial relationships and kinematic relationships are defined to describe interactions between entities. A spatial relationship exists between entities that are in spatial contact, whereas a kinematic relationship denotes movement constraints between entities (e.g., a tool being held by a worker). Since multiple semantic relationships can coexist between the same entities, a multi-graph is employed to model the static scene as $G_s = (V_s, E_s)$, where the nodes V_s represent the entities and the edges E_s represent the semantic relationships. An example of the semantic state description of a WRC scene is showcased in Figure 2, where the robot is holding a tube while the worker is touching it.

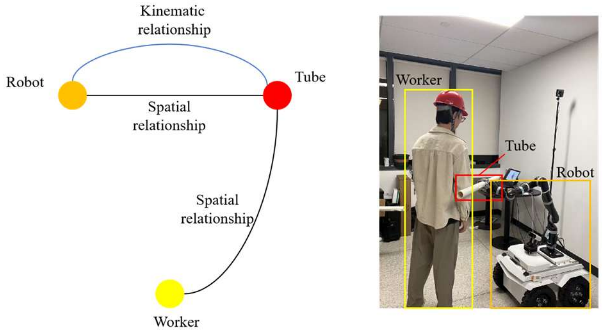


Figure 2. The semantic description of a WRC scene.

3.1.2 Description of WRC state transition

The description of WRC state transitions defines the evolution rules from one state to the next in the WRC process. The extended semantic event chain (ESEC) is introduced to describe the WRC process with concurrent agents' behaviors. ESEC models a WRC process as a quatrain (S, B, V, T), where:

- S is the set of semantic graphs representing WRC states.
- B is the set of agents' behaviors.
- V is the set of variables to be monitored during the WRC process.
- T is the set of transitions among WRC states within the WRC process.

A transition is defined by four parameters, denoted as (s, b, g, s'), where:

- s is the semantic graph before the transition.
- b is the behavior involved in the transition.
- g is the guardian condition, which determines whether the behavior can be executed.
- s' is the semantic graph after the transition.

To model a WRC process using ESEC, the WRC states in the process are serialized with an initial state and a final state identified as s_s and s_e respectively. Except for the final state, each state should have at least one associated transition to the next state. The end of a WRC process is signified by reaching the final state.

3.2 Behavioral policy learning from demonstration

A robot's policy is a mapping function that projects the state to the behavior, denoted as $s \rightarrow b$. This mapping relationship is explicitly defined in the ESEC model as a transition (s, b, g, s'). To learn the behavioral policy $s \rightarrow b$ from collaboration demonstration samples, the demonstration process is first abstracted using ESEC model to significantly reduces the state space of WRC. The behavioral policy is then extracted from the structured demonstration data.

3.2.1 Demonstration data acquiring

In the demonstration, the construction robot is controlled by a human operator, who invokes the robot's built-in behavior interfaces to collaborate with other workers. Essentially, the robot needs to replicate the behaviour policy adopted by the operator.

VR is considered a valuable tool for acquiring demonstration data due to its advantages in safety, cost-efficiency, and customization. This research creates a VR-based demonstration platform. The Unity engine is utilized to create a WRC environment with realistic physical effects. The OpenXR framework enables workers to move and interact with objects freely using controllers in the VR environment. The virtual construction robot is controlled by the Robot Operating System (ROS). Movable objects and static objects are modelled with necessary interaction functions to respond to the agents' behaviors. Semantic relationships are modeled according to their definition: a contact between two bounding boxes indicates a spatial relationship between the corresponding entities, while kinematic relationships are modeled with fixed joints between objects. The creation and deletion of the semantic relationships are controlled by specific events triggered by agents' behaviors.

During the collaboration demonstration, the following data will be recorded frame by frame: 1) entities and their relationships in the VR environment, 2) monitored variables, and 3) the virtual robot's behavior invocation events. The data will be stored along with timestamps in JSON format.

3.2.2 Policy extraction

To extract the policy from the demonstration data, the demonstration data is first processed into serialized key semantic graphs. Initially, entities and relationships in each frame are processed into semantic graphs. In two consecutive frames, if the semantic map of the latter frame undergoes any changes, it is extracted as a key semantic map. It should be noted that during the demonstration, the WRC state may undergo a rollback: for instance, a worker might pick up an object and immediately put it back down. The rollback state will then be integrated with the historical state. Finally, the key semantic graphs are serialized into a tree structure based on their temporal order, as shown in Algorithm 1.

Algorithm 1 Key semantic graphs serializing

Input: $list_G = [G_0, G_1, G_2, \dots, G_n]$
  Initiate: $node_c = G_0$
  foreach G in $list_g$ **do**
    if $G = node_c$ **then**
      continue
    else if $G = node_c.parent$ **then**
      $node_c = node_c.parent$
    else
      if $\exists child = G, G \in node_c.children$ **then**
        $node_c = child$
      else
        add G to $node_c.children$
        $node_c = G$
      end if
    end if
  end if
Output: Serialize key semantic graphs

Furthermore, the transitions are defined based on the invoke records of the robot's behaviors to create an ESEC model. For each robot behavior b, the timestamp at which the behavior begins is used to find the preceding key semantic graph s and the succeeding key semantic graph s'. If multiple robot behaviours correspond to the same preceding and succeeding key semantic graph, this indicates that these behaviours are adjacent and can be considered as one combined behaviour. Lastly, guardian conditions are manually set, typically considering the WRC safety requirements [20]. The collection of all transitions $\{t_r\}$ that include robot behaviors constitutes the robot's behavioral policy.

3.3 Robot behavioral decision-making

With the policy learned from the demonstration, the construction robot needs to recognize the WRC state to map its behavior. Due to sensor limitations and the dynamic movement of agents and movable objects, entities and their semantic relationships may not be fully recognized. To address this issue, this section develops static and dynamic state-matching algorithms to match incomplete observation results into the WRC state.

3.3.1 Static state matching

To simplify the discussion, several assumptions about the robot's observations are made as follows:

- The entities presented in the ESEC model are perceptible.
- The observation result for an entity is binary: the entity is either observed or not.
- Some semantic relationships between entities are perceptible (e.g., all spatial relationships), referred to as R_p; the remaining semantic relationships are undetectable due to the limitations of the robot's perception method, denoted as R_u.
- The observation result for a semantic relationship is binary: the relationship is either observed or not.

The above assumptions are made based on the current state of robotic perception technologies and methods, including computer vision, LiDAR, force sensors, etc. For a given WRC state s, its semantic graph is denoted as $G_s = (V_s, E_s)$, and the corresponding observation result is represented as $G_o = (V_o, E_o)$. Based on these assumptions, the observed graph is reasoned to be a subgraph of the actual WRC state semantic graph, i.e. $V_o \in V_s, E_o \in E_s$. The observed graph is then matched to all candidate WRC state graphs from the ESEC model according to Algorithm 2.

Algorithm 2 Static graph matching

Input: $G_0 = (V_o, E_o), \{S\}$
  Initiate: $\{S_m\} = \emptyset$
  foreach $s \in S$ **do**
    $G_s = (V_s, E_s)$
    match_flag = True
    foreach $v_o^i \in V_o, v_o^j \in V_o, e^{ij} = (v_o^i, v_o^j)$ **do**
      if $(e^{ij} \in E_s$ **and** $e^{ij} \in E_o)$ **or**
      $(e^{ij} \notin E_s$ **and** $e^{ij} \notin E_o)$ **or**
      $(e^{ij} \in E_s$ **and** $e^{ij} \notin E_o$ **and** $e^{ij} \in R_u)$ **then**
        continue
      else
        match_flag = False
        break
      end if
    end for
    if match_flag = True **then**
      add s to S_m
    else
      pass
    endif
  end for
Output: Candidate matched states $\{S_m\}$

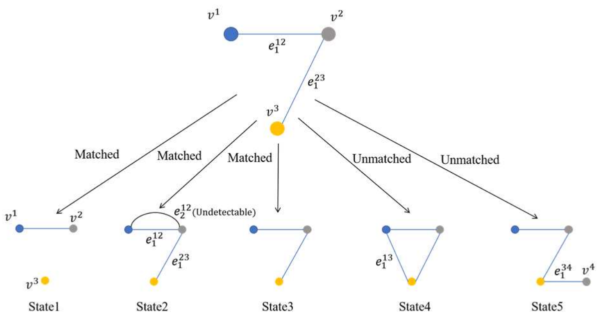


Figure 3. The static state matching process.

3.3.2 Dynamic state matching and behavior decision-making

The construction robot can reason from its historical observations to further narrow down the candidate WRC states. For two semantic graphs $G_1$and G_2, their semantic difference is defined as the symmetry difference of their edge sets, i.e. $D(G_1, G_2) = E_1 \triangle E_2$ Consider two adjusted observed semantic graphs $G_o^{i-1} = (V_o^{i-1}, E_o^{i-1})$ and $G_o^i = (V_o^i, E_o^i)$, their static state match results are S_m^{i-1} and S_m^i. The following conditions must be satisfied for matching a state pair s^{i-1}, s^i to the observation pair G_o^{i-1}, G_o^i:

- $s^{i-1} \in S_m^{i-1}, s^i \in S_m^i$;
- $D(G_o^{i-1}, G_o^i) = D\left(G(s^{i-1}), G(s^i)\right)$;
- A transition exists from s^{i-1} to s^i.

Figure 4 depicts a dynamic state match example, where the observed semantic graph G_o^i is statically matched to s_2 and s_5, and G_o^{i-1} is statically matched to s_3 and s_4. According to the dynamic match rules, G_o^i is only dynamically matched to s_5 since no transition exists from s_3 or s_4 to s_2. If the dynamic matching results filter out all static matching results, dynamic matching will not be performed in the next keyframe.

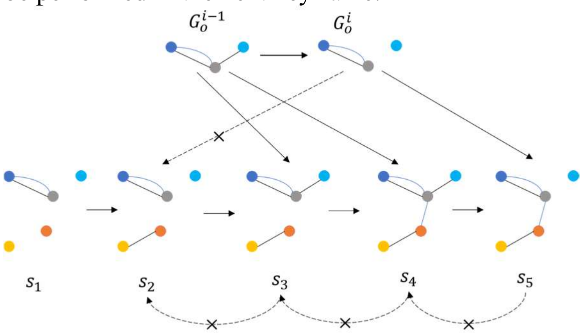


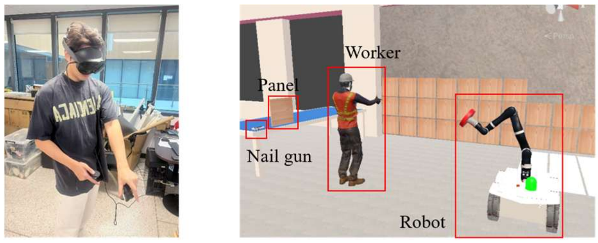
Figure 4. The dynamic state matching process.

Finally, the construction robot decides its behavior based on the matched possible WRC states and its policy. If only one WRC state is matched, or if multiple WRC states are matched but mapped to the same behavior, that behavior will be the decision-making result. Otherwise, if the candidate WRC states map to multiple behaviors, the default waiting behavior is adopted to avoid any risks.

4 Experiment and Results

An experiment was conducted to validate the feasibility of the proposed method. A typical WRC scenario was simulated in a VR environment, replicating a wall panel installation task. Wall panel installation is a common and representative task in decoration construction, which requires the worker to move the panel to the designated place on the wall and fix it using nails. Adopting a WRC method, the construction robot acts as a collaborative teammate, responsible for moving and positioning the panel to reduce manual labour and mitigate safety risks.

The experiment scene is illustrated in Figure 5. The panels and a nail gun are placed on a worktable. Workers can pick up these items and use the tools using VR controllers. The construction robot employed in the experiment is configured as a classic mobile manipulator with a suction cup serving as its end-effector. The construction robot has three built-in skills: 1) controlling the suction cup to attach or release the panel, 2) moving the robotic arm to a designated configuration, and 3) driving the chassis to a designated location. The installation place is assumed to be known by the robot.



a) VR equipment b) Experiment scene in the virtual environment

Figure 5. The experimental setup.

The experiment consists of two phases. In the first phase, a demonstration experiment is conducted, where the construction robot's behavior is controlled by an operator. In the second phase, the construction robot collaborates automatically with the worker using the behavioral policy learned from the demonstration to perform an identical task.

10 subjects were invited to participate in both the demonstration experiment and the collaboration experiment, while an additional 20 subjects were invited to participate in the collaboration experiment. None of them had prior experience in collaborating with construction robots. Before the formal experiment, the subjects were given the opportunity to practice in the VR environment to ensure they understood the collaboration objectives and could use the VR devices correctly. After the experiment, the participants were interviewed to gather their feedback on the demonstration process and their experience in collaboration with the robot.

4.1 Demonstration results

In the demonstration experiment, each subject was required to perform two demonstrations to ensure that sufficient demonstration data was collected. Collectively, the 10 subjects contributed to 20 demonstration processes. The general WRC workflow is as follows: the subject first grabs the panel and hands it over to the robot. The robot then moves the panel to the designated installation spot on the wall. Once in place, the subject uses a nail gun to secure the panel with four nails, one at each corner.

Even though the process appears intuitive, subjects still collaborated with the robot in a variety of ways, leading to significant diversity in the number of states within the ESEC models. The ESEC models of these demonstrations contained up to 28 WRC states and at least 14 WRC states. For example, some subjects chose to grasp both the panel and the nail gun simultaneously to avoid repeatedly picking up the nail gun. During the fixing stage, some subjects nailed all four nails before commanding the robot to release the panel, while others nailed two nails first and secured the remaining two after the robot released the panel and moved away. While either approach is feasible to complete the task, this flexibility poses a challenge for the construction robot to understand the variant WRC process.

In contrast to the diversity observed in collaboration, the construction robot consistently exhibits four distinct behaviors across various collaborative demonstrations. These four behaviors are defined as grasp, position, release, and reposition. Using the ESEC model, these behaviors and their corresponding prerequisite WRC states can be extracted. While the strategies derived from different demonstration data vary, a representative example is analyzed below and depicted in Figure 6.

- Grasp: Grasping creates a kinematics relationship between the robot and the panel. The pre-state of grasp requires the spatial relationship between worker and panel, robot and panel, and a kinematics relationship between worker and panel, which means that the worker is holding the panel while it is touching the robot.
- Position: Positioning includes moving the robotic arm to the installation posture and moving the chassis to the installation position. The pre-state of positioning requires a kinematic relationship between the robot and the panel, but no spatial or kinematic relationship exists between the worker and the panel.
- Release: Releasing removes the kinematic relationship between the robot and the panel. In most demonstrations, the pre-state of releasing requires four nails establishing a kinematic relationship with the panel and the work surface.
- Reposition: Repositioning includes moving the chassis to the receiving position and moving the robotic arm to the receiving posture. The repositioning behavior typically follows adjacently the releasing behavior.

The feasibility of demonstrated behavioral policies will be further validated in the collaboration experiment.

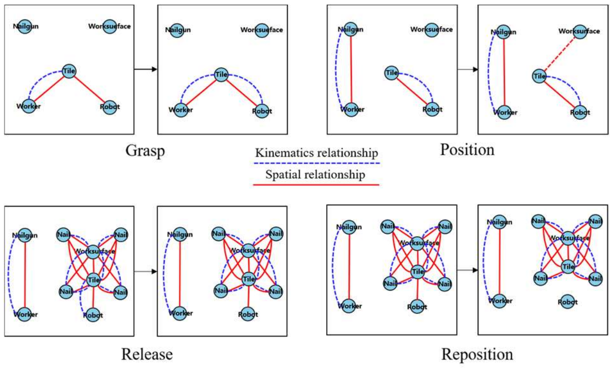


Figure 6. The behavioral policy of the construction robot learned from the demonstration.

4.2 Collaboration results

The collaboration tasks in the experiments were scaled from installing one single panel to four panels to test the robustness of the demonstrated behavioral policy. In this setup, the robot autonomously collaborates with subjects based on its observations and behavioral policies demonstrated. To simulate the construction robot's observation, a virtual camera is deployed. The camera's view follows the robot's end-effector, as illustrated in Figure 7. Entities not within the field of view along with their associated relationships will be ignored. A simulated force sensor provides information on whether a panel is attached to the robot's end-effector, indicating the kinematic relationship between the robot and the panel.

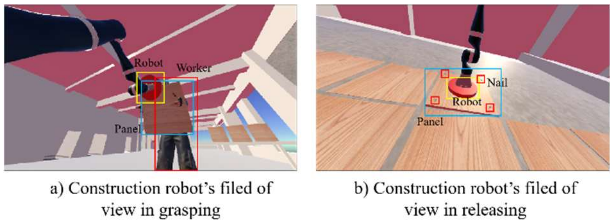


Figure 7. Construction robot's field of view in collaboration.

The 10 subjects who participated in the demonstration experiments were once again invited to participate in the collaboration experiment to validate the feasibility of the policies they demonstrated. The results of the collaboration experiment revealed that 18 out of the 20 policies were feasible, enabling the robot to successfully collaborate with the workers. However, in the remaining two unfeasible policies, the prerequisite states for some of the robot's behaviors were not correctly represented in the semantic graph. For instance, a subject demonstrated the positioning behavior while remaining close to the robot, resulting in an erroneous spatial relationship captured in the semantic graph as the prerequisite state for the behaivor. This inconsistency hindered the robot's ability to align its observations with the appropriate WRC state during the collaboration experiments.

Excluding the two unfeasible policies, among the remaining 18 collaborations with feasible policies, the tasks were successfully completed on the first attempt in 16 instances, with the two failures resulting from human error. From these feasible policies, a representative behavior policy was adopted by the robot to collaborate with the additional 20 subjects. The success rate on the first attempt was 70%, lower than the 89% observed among the 10 subjects who had participated in the demonstration experiments. Through repeated trials, all subjects ultimately completed the tasks successfully.

Since the ESEC model is explicit, the robot's behavioral decision-making process is transparent. While the construction robot's observation is often incomplete due to limitations in its field of view and the lack of detection methods for most kinematic relationships, static and dynamic matching enable the robot to match its observation to the correct WRC states. Static matching first matches observed semantics with candidate WRC states, while dynamic matching further filters the matched states. Figure 8 illustrates the behavioral decision-making process during a collaboration.

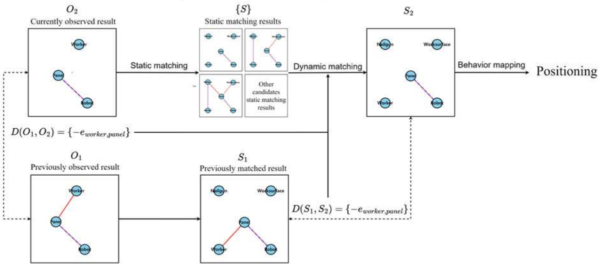


Figure 8. The behavior decision-making process in the collaboration experiment.

4.3 Discussion

The experiments utilize VR environments in both demonstration and collaboration experiments, simulating a complex and dynamic WRC task, wall panel installation. This task involves both spatial and temporal interactions between the worker and the robot, with the workflow being highly diverse and dependent on the strategies employed by the collaborating worker.

To validate the effectiveness of the proposed method, a series of measures have been implemented to ensure that the VR environments replicate real-world WRC conditions as closely as possible, including 1) utilizing the same control logic for the virtual robot as its real-world counterparts, 2) immersive VR perspectives and physical interaction logic for the participants, and 3) virtual sensors that emulate the functions and limitations of real sensors. The primary distinction from the real world lies in the simplification of the robot's perception process. In reality, the robot's detection methods (e.g. computer vision) may not always be accurate, potentially leading to mismatches between observations and correct states. In the VR environment, however, the robot's observations are always accurate. While it is reasonable to expect that the robot's observations will be accurate in most cases, establishing error recovery and correction mechanisms for behavioral decision-making may be essential for real-world construction robots.

The experiments also emphasize the flexibility of the proposed method in on-site WRC applications. In most cases, the participants need only perform a single successful demonstration to construct the robot's behavioral policy. Although the behavioral policy learned from demonstrations is task- and robot-specific, as workflows and built-in skills may vary across WRC tasks and robots, the ESEC model itself is task- and robot-agnostic. This enables the demonstration and learning process to be generalized to various construction works (such as bricklaying and welding) and construction robots (humanoid robots, etc.), allowing for the rapid establishment of corresponding behavioral policies in WRC.

The demonstration itself also provides additional benefits to on-site WRC. First, all subjects reported that the VR-based demonstration was intuitive and user-friendly. Second, subjects who engaged in the demonstration indicated that it helped them better understand the robot's behavior and intentions, thereby enhancing their sense of safety and performance in the collaboration experiments. This suggests that the proposed method holds promise for improving both safety perception and performance when applying on-site WRC.

5 Conclusion

This research proposes a behavioral decision-making method for constriction robots in on-site WRC. The proposed method comprises three main components: a semantic world model for on-site WRC, behavioral policy learning from demonstration, and a robot's behavior decision-making algorithm. The validation of the proposed framework was conducted in a virtual reality environment, exemplified by a panel installation task. The experimental results demonstrate that the framework effectively supports the robot's comprehension of complex and dynamic WRC processes, enabling accurate behavioral decision-making during autonomous collaboration with workers. Additionally, the results show that the demonstration process enhances workers' understanding of the robot's behavior and increases their sense of safety during collaboration.

The limitations of this research are summarized as follows. Firstly, the proposed method is only validated in a VR environment with simulated robots and sensors, where the impact of perception on robot decision-making may have been underestimated. Future research will focus on testing the decision-making method in real-world settings to assess the influence of environmental disturbances. Secondly, the framework currently lacks support for collaborative recovery in the event of unforeseen and erroneous WRC states. Future research can aim to integrate recovery mechanisms into the robot's policy. Finally, the experiments only involve a single worker and one robot. While the framework theoretically supports collaboration among multiple agents, the complexity of collaboration increases exponentially with the number of entities involved in the WRC process. Therefore, it is vital to validate the framework's accuracy and operational efficiency in on-site WRC scenarios involving more workers or robots.

Acknowledgement

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