

Grip State Recognition for Enabling Safe Human-Robot Object Handover in Physically Collaborative Construction Work

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ABSTRACT

Physical interactions between humans and construction robots must inevitably occur under a capacity-based task allocation scheme for successful implementation of a human-robot collaboration (HRC) based workflow. For example, in staging and installing components, a robot can complete physically challenging material handling tasks and a human worker can then creatively manipulate the materials for installation. When materials are handed over from robots to humans, tandem manipulation of objects and physical interaction is necessary. However, this poses several challenges to human workers' safety, as the objects might fall or break, if the robot incorrectly perceives the human worker's grip state. This paper considers object handovers between robots and humans and explores how to build a safe tandem HRC framework by letting the robot imitate the mutual physical state adaptation dynamics inherent in human co-workers. To build such a human physical state-aware robot controller, this paper first proposes the use of a haptic glove-based sensing system to capture the grip strength and gesture of construction workers simultaneously. Secondly, the programming by demonstration (PbD) method is used to automatically program a robot through a one-shot demonstration of natural handover processes without requiring the demonstrators (i.e., construction workers) to have computational or programming expertise. The proposed method outperforms prior robot-to-human object handover studies in handling eight construction materials of random shape, dimensions, and weight distribution. In addition, to enable such construction HRC implementations to readily comply with global safety standards, the proposed method is implemented to adhere to ISO 15066:2016 guidelines.

BACKGROUND

Human-Robot Collaboration (HRC) leverages both human cognitive advantages and robot physical capabilities to further boost productivity (Brosque et al. 2020, Wang et al. 2021a, Liang

et al. 2022, Park et al. 2023). However, there are two questions remaining unsolved. Firstly, the robotic material preparation workflows and task allocations are unclear. A suitable workflow should adapt to both humans' and robots' characteristics (Wang et al. 2020). Secondly, HRC often assumes physical separations between humans and robots to ensure worker safety (Brosque et al. 2020). Yet some construction activities inherently require tandem cooperation between two construction workers. For example, the material transport workers sometimes directly hand over objects to another worker to reduce unergonomic standing ups and travel for installation workers. Similarly, the robot must also learn when to release the material to achieve safe and fluent transitions after transporting materials to designated receivers. Such safe operations will outperform simple physical separations in enabling skilled workers to perform necessary improvisations in proximity to the robots.

Correspondingly, we develop a two-step solution. Firstly, we propose a material preparation workflow with *capacity-based task allocation* schemes (or *adaptive automation*) to include both advantages of humans and robots (Fitts 1951). Based on the classical capacity-based task allocation scheme, the heavy and repetitive material transport tasks are outsourced to robots with high physical capabilities. Moreover, the creative manipulation and installation tasks will be kept for human workers, as shown in Figure 1.

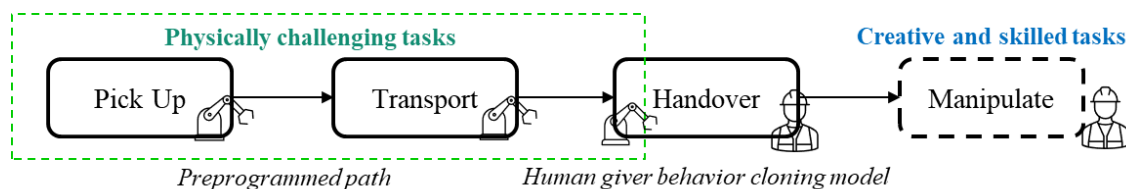


Figure 1. Full-contact construction HRC task allocation schemes

Secondly, we propose to replicate successful practices inherent in human teams to build a safe robot handover controller. An imitation robot motion planner is built to clone the mutual physical state aware and adaptive collaboration mechanisms. This controller will perceive the receiver's real-time grip states and reacts as human givers. A behavior cloning (BC) model (Fang et al. 2019) was also built to program human givers' behaviors from their demonstrations. The contributions of this paper are:

- 1) This paper discusses the material preparation and transport workflow for HRC to maximum efficiency and physical comfort. By exploring the most challenging technical part of physical state understanding, we also validate the feasibility of this workflow.
- 2) This paper studies the holding force patterns of human workers. Full-hand pressure maps collected during holding a cuboid were collected and examined with Principal Component Analysis (PCA) (Roweis 1997) applied to reveal the holding areas for both receivers and givers.
- 3) This paper proposes to use both grip strength and gesture to represent the human's grip state and pioneers the use of full-hand tactile gloves to comprehensively sample the pressure map of an entire hand. This paper is also among the select few in the literature that applied Imitation Learning to the robot-to-human object handover problem to minimize the human workers' efforts. In our research, a 25-second one-shot natural object handover process serves as the demonstration. Our method is comparably more efficient and accurate for both seen and unseen grip settings.

TECHNICAL APPROACH

Robot Material Transition Controller. We propose a closed-loop robot handover control system with a built-in behavior cloning model. As shown in Figure 2, the controller model is firstly trained offline with semi-supervised learning. On this basis, the trained control model parameters are stored in the robot control system and are achieved online control of the robot's real-time action.

Due to the low-level architecture dependencies, the *Tekscan 4256E* grip sensor can only connect to a Windows machine. However, the robot simulation and control system – Robot Operation System (ROS), runs on the Ubuntu/Linux environment. Thus, a data transmission system was needed. ROS# serves as the data transmission conduit and connects the C# Tekscan API with the ROS system.

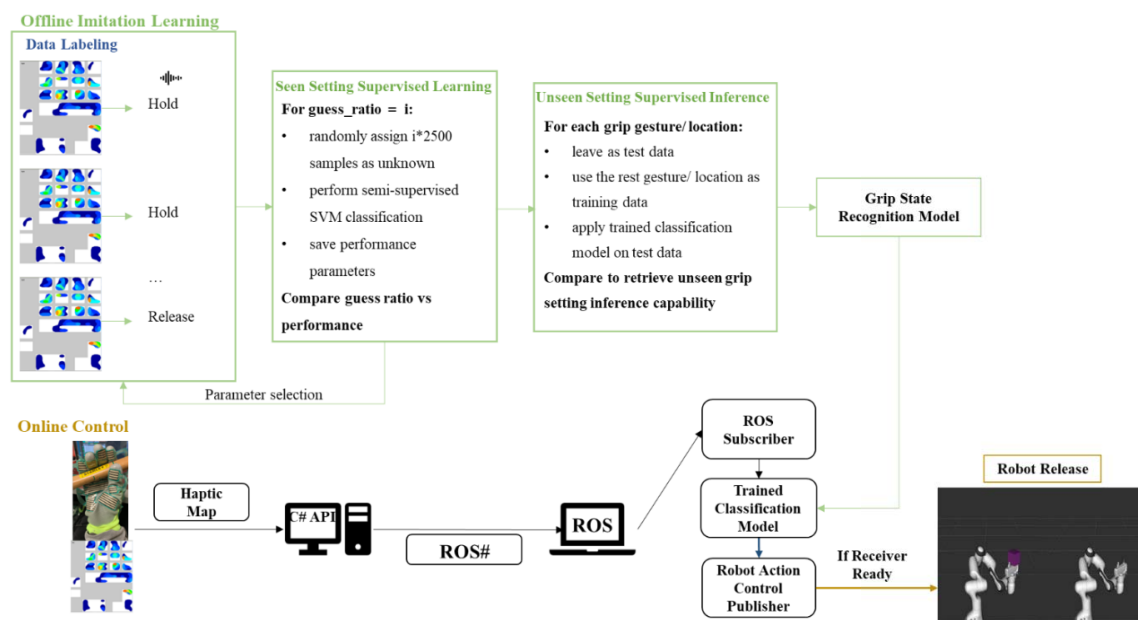


Figure 2. Graphical abstract of closed-loop robot handover controller

The data transmission speed was also evaluated. With the average transmission speed for one frame of a haptic map averaging 0.0693 sec, the system reacts faster than the typical human visual reaction time of 0.15 sec (Thorpe et al. 1996). Therefore, the wireless data transmission system is concluded to have a latency that does not affect the perceived fluency of the robot-to-human handover system.

Principal Holding Area Analysis. We applied PCA to both the giver's and receiver's haptic maps collected during the handover of three cuboid objects of different weights. This analysis could return the statistically highest weighted components that can explain more than 98% variability (hold vs. release) of the haptic maps. By understanding the spatial distribution of such elements, we can show the dominant holding areas for both hold and release phases during object transitions.

Grip State Representation and Sensors. Force-based sensors are widely used in robot-to-human handover studies to understand the grip state (Huang et al. 2015, Wang et al. 2021b, Pan et al. 2019). Yet it neglected the gesture changes which are often observed to affect the giver's

acting decisions (Wang et al. 2021b). Inspired by observations of strong correlations between receiver hand gestures and receiving activities from the above PCA analysis, we propose a new grip state indicator of both gripping force and gripping gestures. To collect both simultaneously, we used full-hand haptic sensors. The *Tekscan 4256E* grip sensor was selected and glued to soft work gloves, as shown in Figure 3 (right). Such soft tactile gloves can accurately reflect the human receiver's grip patterns during the material transition process.

The sampling frequency was set to 100 Hz based on similar research experiment settings (Huang et al. 2015). Every 0.01 sec, a haptic map containing data from 52 (horizontal) × 46 (vertical) hand pressure sensors was created, as shown in Figure 3 (left). The pressure sensor precision was set to one psi.

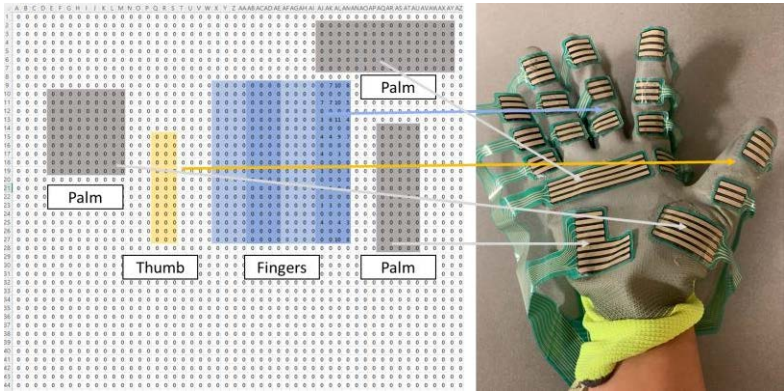


Figure 3. The haptic map and the soft tactile glove

Human Handover Behavior Cloning Model. We used the behavior cloning method proposed by Yu et al. (2023). A 25-sec natural human-to-human handover process as the demonstration. The human receivers wore haptic gloves during the handover process and gave verbal commands to show their subjective evaluation of the firmness of their grip states. For example, when the receiver subjectively feels a stable grip on the object, the receiver will verbally signal the giver by saying a short multiple-syllable word/sentence such as "okay" or "I got it". A voice recorder with a resolution of 0.01 sec then recorded the whole handover process to understand the receiver's subjectively comfortable release moment.

With the collected paired receiver haptic map-intent data, we assigned an action label of "hold" to haptic maps collected before the release moment. A "release" action was assigned to those collected after the release moment. With the labeled haptic maps, a classification model was built to teach robots to recognize the haptic maps that imply the correct time to start transitioning objects. Several common classification algorithms were experimented with, including Random Forest, Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Ensemble Methods. SVM showed the highest accuracy in this preliminary testing phase (Yu et al. 2023).

EXPERIMENT SETUP

Construction Materials. 8 common construction materials of various dimensions, shapes, weights, and mass distributions, as shown in Table 1. All contact surfaces were also wrapped with plastic wraps to unify contact conditions.

Grip Locations. Data are sampled from various grip locations on the same objects, considering that grip force changes along with different grip locations on the objects. Grasp points were sampled every 5 cm. The number of grasp points for each object is shown in Table 1.

Table 1. Dimensions and weights of tested objects

Object	Weight (g)	Grip Area Diameter (cm)	Grip Locations
Bolt	216	1.0	3
Hammer (10oz)	423	2.8	4
Hammer (16 oz)	678	3.5	4
Light Board	301	2.4	5
Heavy Board	846	9.8	5
Short Tube Glue	472	6.6	3
Long Tube Glue	293	5.2	3
Fluid Glue	272	4.2	3

Grip Gestures. The two most popular habitual grip gestures (pinch or grasp with all five fingers) were selected to cover more than 75% of preferred grip gestures for cuboid and cylinder objects (Lee et al. 2014), as shown in Figure 4. Additionally, as object orientation and relative location to the hand affect the grip gesture (Paulum et al. 2016), the two most extreme object orientations (horizontal and vertical) and two grip methods (overhand, underhand) were added to the combination to show robustness. Therefore, six different grip gesture settings were used, with some examples shown in Figure 4. Moreover, three users were invited to be demonstrators. This small user group size was found to be suitable, considering that high similarities in habitual grip gestures and orientations have been observed (Lee et al. 2014, Paulum et al. 2016).

Unseen Grip Settings. The leave-one-out test was applied to show the knowledge this model can provide beyond known grip settings to reduce future human demonstration efforts. For example, as for gripping locations, the receiver can grasp any location in a handover process, and it is exhausting to demonstrate every potential grip point to the robot. Therefore, supposing n grip points on the objects were sampled during the demonstration process, only $(n-1)$ data sets will be input to the ML model and leave one grip location as the test data. This leave-one-out approach will be used to test all the grip location and gesture variations.

EXPERIMENTAL RESULTS

Dominant Holding Hand Area. The PCA analysis shows that the thumb area is the most significant receiving activity indicator for both the receiver and giver for light to medium-weight cuboid objects. For heavy objects, the maximum PC area for the receiver is the fingers and palm for givers.

Grip State Recognition and Robot Handover Simulation. The average grip state recognition accuracy for seen gripping settings is shown in Figure 5. Firstly, when using the collected data, the recognition accuracy is 98.52%, showing the suitability of the proposed sensory input. Secondly, when assigning higher guess ratios, we notice the model accuracy will largely decrease. This observation validated the data collection and labeling process. Additionally, for unseen grip settings, we have also obtained robust performance with an average

grip state inference accuracy of 88.79%. For unseen grip gestures, the inference accuracy is an average of 74.22%. In the robot simulation experiment, the Gazebo Panda robot was controlled by this classification model to release a cube when the human lifted a cuboid wood board from the edge of the table. Random grip location was adopted, and the simulation experiment achieved a 94% success rate (release too early: once; not releasing objects: twice).

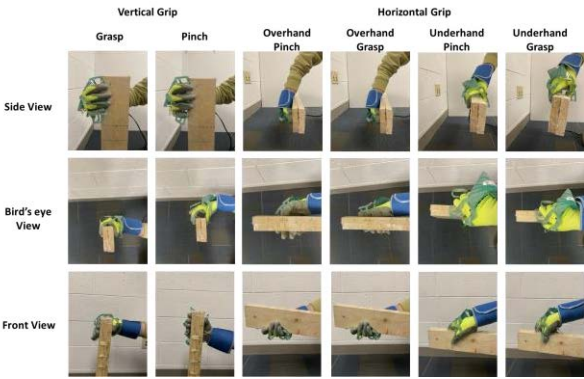


Figure 4. Grip gesture variations in this study's experiments

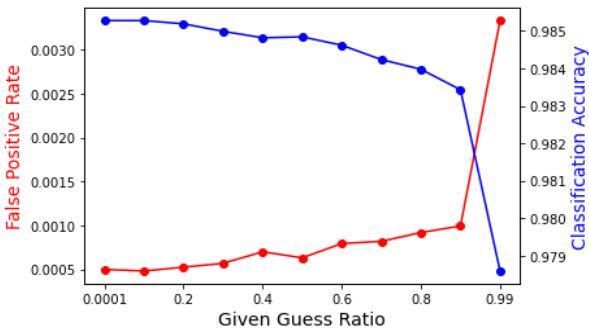


Figure 5. Hand haptic map classification performance comparison for different guess ratios

Compared to Previous studies, we also have achieved higher human grip state recognition accuracy for unseen grip settings (Grigore et al. 2013, Koene et al. 2014, Palinko et al. 2016, Wang et al. 2018). This is presumably due to the choice of a more comprehensive physical state representation of both grip gestures and forces.

CONCLUSIONS

In summary, this research explored an intuitive programming method that demonstrates robust performance in teaching the robot safe handover behavior norms. Contributions are made to both hardware and software systems to improve human grip state recognition accuracy and reduce the human workload. This controller also can be developed into a personalized model to preference to enhance each human receiver's experience based on their individual preference (Deng et al. 2022). Ongoing research by the authors is focused on further improving the generalizability to new objects. Such research will further reduce the workload and repetition required from human workers.

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