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Mutual physical state-aware object handover in full-contact collaborative human-robot construction work

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ABSTRACT

Full-contact physical interactions inherent in typical construction workflow, such as material handovers, have yet to be adequately resolved or adopted in Human–Robot Collaboration (HRC) due to safety concerns. Replicating protective behavior norms for robots can help achieve safe robot material handovers to human workers. To build such a human-adaptive model, firstly, we present a comprehensive receiver grip state indicator that encompasses both gripping strength and gestures with whole-hand tactile sensors. Secondly, a Learning from Demonstration (LfD) model built to replicate the human grip state-reactive behavior norms for robots is described. The proposed method outperforms other robot-to-human object handover methods using only one-shot demonstrations of natural handovers. Additionally, the LfD-based programming interface is accessible to construction workers without programming expertise and can continuously collect data for a future large-scale LfD model covering a wide range of handover materials, users, and gestures to further enhance worker safety during close-proximity material handovers.

1. Introduction

The ability to efficiently procure, store, transport, and stage materials and components on construction sites is a key determinant of project success [1]. Construction material handling and staging connect warehouses and laydown areas with installation locations on job sites, and efficiency in these steps often determines overall job site productivity [2]. However, due to the unstructured nature of construction sites, material handling and staging incur a significant cost to the health and well-being of construction workers. Multiple studies have shown that material staging workers are more susceptible to Musculoskeletal Disorders (MSD) than those in other trades, which is correlated to the accumulation of physically demanding work over long durations, especially that involving handling and transporting heavy materials and components [3–7]. Since 2001, around $50 billion has been spent annually to compensate for the productivity and wage losses resulting from the occurrence of MSD in construction workers [8–10]. This state of affairs often compels construction workers to retire early [2,10] and discourages individuals in younger generations or of different abilities from considering careers in field construction [11].

The deployment of robots in field construction work has often been proposed to relieve human workers from physically challenging tasks and to provide an ergonomically favorable construction site environment [12,13]. Specifically for construction sites, Human–Robot Collaboration (HRC) has recently been widely accepted in the literature as a feasible method of adopting a co-robotic workforce to boost the productivity of field construction work while reducing the occurrence of errors and rework [14–17]. However, most of these construction HRC studies propose or assume the physical separation and sequential cooperation of human workers and robots, primarily to ensure human safety [18]. The types of work and job site conditions that require or can benefit from rich physical interactions between human workers and robots are not abundantly considered. This lack of physical interactions in HRC risks impeding sustainable innovations in the workforce structure and slows down the introduction of productive and human-centric construction robotic applications on account of the following reasons.

On the one hand, many tasks involving dexterous manipulation of construction tools often require creativity and improvisation. Such abilities are currently associated only with experienced human workers, making the full robotization of several field construction tasks

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particularly challenging. On the other hand, many workers have a strong passion for construction and a deep sense of pride in craftsmanship and the physical manipulation of construction tools [11,19,20]. The possibility of such workers serving as remote supervisors potentially improves their safety but is also likely to take away crucial elements of job satisfaction which they achieve from performing field construction work.

Thus, a practical human-centric HRC [21] must ensure the ability of construction workers to directly participate in the performance of field construction tasks. In such an HRC scheme, the carrying, handling, and transporting of heavy construction materials and components can be outsourced to co-robots, with technical studies and safety standards well developed to avoid direct collisions with human workers by the robots and the robot-held objects. [22–28] In conjunction, human workers can be near the robots and use their knowledge, experience, and improvisation skills necessary to install the materials and components successfully with physical separations from the robots [29,30]. With the worker's safety ensured in both steps, the feasibility of this physical Human–Robot Collaboration (pHRC), therefore, heavily depends on the safety and fluency in the robot-to-human material transfer dynamic.

In this regard, this paper proposes to replicate the mutual physical state aware and adaptive collaboration mechanisms inherent in human-to-human partnership within the context of human–robot teams. The research develops an overarching two-step framework that enables rich physical interactions between human workers and co-robots to create a symbiotic HRC construction site environment. The proposed approach starts with safety baselines on contact energy limitations to minimize human injury and pain in case of unintended contact and collisions [26–28]. In addition, the method also features adaptive and human-aware robot motion planning that is based on the robot's real-time understanding of the human workers' physical state, such as the strength of their grip on clasped materials. Such human-aware systems have been proven effective for functions such as robot path planning in other pHRC applications [31–33].

The contribution and novelty of the research described in this paper lie in the following facts:

1) This paper proposes a new method that uses 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 as the machine learning model input.
2) This paper is also among the select few in the literature that recognizes the importance of Imitation Learning to the robot-to-human object handover problem. In our research, we also propose to use a 25-s one-shot natural object handover as the demonstration to minimize the human worker's workload. Our method is much more efficient and accurate compared to other prior work that, for instance, requests humans to repeat purposeful touch to the robot 50 times to only teach the robot two elementary actions in the handover problem.
3) By combining the above novel methods and carefully testing several machine learning models, we achieved one of the highest observed human grip state accuracies. This method was also shown to be very effective for inferring a human's grip state under unseen scenarios, as mentioned in the Results section of the paper.

This paper is organized to first provide a literature review on adaptive robotic behaviors based on human's physical state in pHRC, especially the observations used to profile the human giver's behavior during object handovers. Second, the pHRC construction material handling framework focusing on co-robot to human worker object handover is illustrated in the *Technical Approach* section. The supplementary indirect collision mitigation safety standard is also introduced in this section. Finally, a case study with objects of various shapes, weights, and mass distribution patterns is used to test the validity of the construction object handover model under different conditions.

2. Literature review

This section summarizes relevant previous studies and safety standards to identify the gap between existing work and practical on-site pHRC applications, particularly those relevant to construction sites.

To propose safety measures, the first step is to understand the sources of safety risks [33]. The whole material staging phase can be divided into two parts: the material pre-handover (material pickup and transport) and the robot-to-human material handover. Firstly, in the material pickup phase, the robot needs to recognize the intended material accurately and pick it up accordingly. Many pieces of research have ensured accurate object recognition and adaptive object pickup [22,31,34–38]. In the material transport phase, the robot first needs to operate under a given speed and force threshold defined in the ISO 15066:2016 standard [26]. In addition, the robot also needs to be aware of the human's physical location to adaptively plan and modify its path to avoid physical contact with proximate humans [23,39–50].

In a robot-to-human object handover, two conditions can inflict injury upon the human: 1) direct collisions between the end-effector and the human, and 2) indirect collisions between insecure or falling objects and the human receiver [26–28,36]. Extensive prior research has studied and formalized human-aware and direct collision-free robot control schemes by understanding the human's hand locations and availability to receive objects [24,25,51–55]. The risks from indirect collisions are, however, not extensively studied or organized. Therefore, this section primarily reviews the state-of-art studies that addressed indirect collision mitigation during robot-to-human object handover processes.

2.1. Human grip state awareness in robot-to-human object handover

The most intuitive measure to reduce the risk of indirect collision is to increase the object transition success likelihood [56]. The corresponding technical methods have progressed through three phases, as outlined below.

Phase 1: *Understanding the giver's or receiver's physical state changes that trigger the human giver's release actions in human-to-human object handovers* [38,57–59].

In this phase, the goals of studies are to track the physical states of human givers and receivers during the handover process and model the giver's release actions based on certain physical state changes. As for the giver's physical state, parameters such as the intentional waiting time after the receiver's first grasp [58–60], the grip force counterbalancing object force [58], and the grip force change ratio [59], have been studied. Furthermore, the receiver's grip force values [58,59], the grip force change ratio [60], wrist accelerations [38], and upper arm muscle activities [61] have also been assumed to trigger the giver's release decision. However, these studies have the following three limitations.

First, the test objects have light weights and single grip locations. However, construction materials and components are typically heavy and arbitrarily shaped with multiple grip locations [57]. As a result, the applicability of the above conclusions to construction materials and objects needs to be tested. For example, the variation of static grip force along the object has been observed, which seems to be correlated with the distance between the human's holding hand and body mass center. As shown in Fig. 1, a 2.4 kg. wood board will impose an average of 1.1 kPa pressure on the holding hand when grasped in the middle. The contact pressure of the object will increase to 0.52 psi when it is held at the farther end.

Second, the quantitative measurements from different studies are not in alignment. For example, in [60], the giver intentionally waits for an average of 0.036 s after the receiver's first contact with the object (weight = 0.09 kg). However, in [62], the experimental observations of intentional wait were 0.323 s (weight = 0.15 kg). The object weight appears to be correlated with the intentional waiting time change. However, without a quantitative study of the causal effects, it is unclear how the value will change for any new objects with different weights.

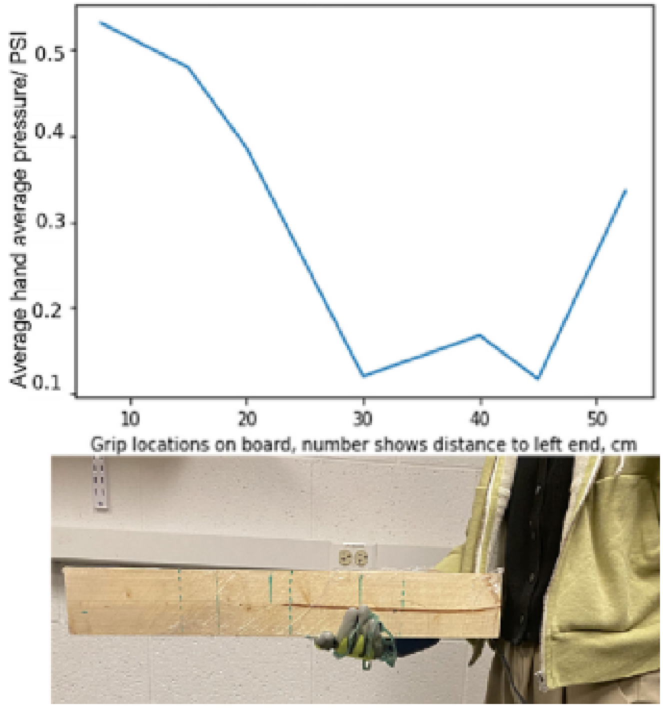


Fig. 1. The average grip pressure when holding a wood board.
*number marked in the lower graph shows the grip location where the hand pressure was sampled.

Third, the force change ratio is also easily affected by wrist flexions and extensions [63], which can happen during the handover process and introduce noise in real-time wrist force tracking.

Moreover, the human receiver may have different expectations towards the behavior of the robot giver and the human giver. As a result, the robot controller that is built considering the above human giver behavior profiles might not be trusted by human collaborators [64]. For example, when the robot used conclusions from [57] and immediately released objects after the receiver's initial grasp, the human receiver evaluated it with a lower level of confidence and acceptability [64]. These limitations motivated the Phase 2 studies.

Phase 2: Preprogramming a human-giver-inspired robot controller and optionally using human evaluation to determine or improve parameters in a handover controller [56,61,64–68].

In this phase, handover controllers are developed by directly letting humans evaluate preprogrammed robot controllers to select trustworthy controllers. For example, [64] let human receivers compare their preferences for three sets of the robots' intentional waiting time. Most human receivers favored the intentional waiting time of 0.25 s, but this study also observed a high variation in personal preferences regarding waiting time. However, this posterior evaluation method can only test a limited number of robot controller parameter settings. Therefore, this method is not efficient for capturing the personally most comfortable setting for each receiver [64].

Moreover, in [64], the authors taught the robot to release grasped objects when it detected or predicted the human receiver's pull event as the trigger based on probabilistic inference. However, this study did not provide the range for the perceptible force exerted by the user, and its generalizability for different objects was not evaluated either. These missing conclusions limit the application of the study to other receiver and object scenarios.

In addition, other similar preprogrammed controllers have also shown to be effective in teaching the robot safe handover behaviors [51,64,66,67]. However, the common disadvantages are: Firstly, the analysis and programming are strenuous. Secondly, the controllers show weak generalizability to unseen handover settings. Furthermore, although differences in personal preferences are observed, the above methods only illustrate how to adapt to the majority of users. The user experience of some users will thus be affected when they are not in alignment with the majority. Therefore, a readily programmable and personalized method would be needed.

Phase 3: *Humans directly demonstrating some physical states and their corresponding action intents, and a machine learning model being automatically tuned to imitate this demonstration without extra programming* [69].

Learning from Demonstration (LfD) fits the above readily programmable requirement and directly illustrates personal preferences to co-robots. LfD is a method that translates the human's actions directly with a robot controller by tuning controller parameters to minimize the inconsistency of human behaviors [70]. For example, to teach the robot to differentiate the subtle intent, such as "mild touch" and "proper grasp", a supervised classification model was used to map the grip forces to the human's action intent [69]. However, the demonstration of efficiency in this study is still a concern. Fifty instances in ten trials were needed for every small table object to achieve a 93.9% accuracy in recognizing the human's intent. However, on a construction site, although with the increased popularity of LfD [71], the demonstration of heavy construction materials will increase the physical workload of human workers and defeat the purpose of the study. Therefore, this study aims to leverage the intuitiveness of the LfD scheme but improve the learning efficiency and handover success rate.

2.2. Falling objects mitigation in current safety standards

Another problem with existing robot-to-human handover studies is the inherent desire to achieve handovers with a 100% success rate. However, the cost to improve the success rate from an already high level to 100% can be significant [72]. Therefore, safety standards usually allow technology adoption when the risk is acceptable [26,73]. The acceptability of physical collision risks is determined based on the human's subjective pain [26]. For example, ISO 15066:2016 provides contact speed and energy limitations to limit human pain from a potential collision to a mild level [26].

However, such risk quantification and mitigation are only provided for the direct collision between humans and the robot end-effector. The indirect collision, from objects held by the robot, is only included by adding to the mass of the robot's body. Such calculations neglect the secondary harm of the objects falling or being insecurely held by the robot gripper, although they are also identified as hazardous in multiple safety standards in construction and robotics [49,50,73].

In quantifying the collision risk, the United States (US) Occupational Safety and Health Administration (OHSA) standards have two similarities with ISO standards. Firstly, unintended object drops have always been considered hazardous [73]. Based on the height difference of the falling location, the hazardous level varies as well. Falling objects across multiple stories are the most dangerous due to the highest contact energy. Those from the same story and overhead are treated as comparatively less dangerous. This leads to the second similarity in evaluating the level of danger based on the collision energy. However, OHSA does not provide quantitative limitations either. Therefore, this paper also aims to extend the contact limitations in ISO standards to fulfill the OHSA requirement of reducing falling objects.

3. Technical approach

3.1. System overview

Based on the limitations in existing studies identified above, the critical components in mitigating physical risks for material handling in HRC include: 1) enhancing handover success rate with robust human grip state understanding; and 2) alleviating human perceived pain by limiting falling objects' collision energy.

To establish robust grip state understanding with the slightest programming effort, the LfD-induced physical state classification model was deployed, as suggested in [69,71]. A short natural handover process is proposed to serve as the demonstration to further reduce human demonstration efforts. The human participant thus only needs to perform a short object handover with another human giver to provide a demonstration. This approach is more intuitive and less repetitive than the previous study [69].

Moreover, this study aims to simplify the computing model to reduce the computational load and enhance robot responsiveness. Based on suggestions from [69], innovations in sensor systems are also leveraged to improve sensory information density. Tactile gloves are used to capture both the human's grip force and grip gesture simultaneously. Under the LfD method structure, the human should also show the robot an expected action corresponding to each demonstrated grip state. With the *haptic map – expected action* pairs demonstrated, a grip state haptic map classification model was built, which can be used to build the robot handover controller. In addition, as most robot-to-human handovers cannot achieve 100% success, additional safety measures were proposed to minimize the perceived pain [26] in case of objects falling on humans.

Therefore, the robot workflow for material transport was modified with the above technical approach, as illustrated in Fig. 2. After picking up materials [37–41], the robot started by calculating the maximum permissible handover height based on the confidence of handover success. Using this height and the human hand detected [35,38] as the path destination, the robot can therefore navigate to the handover location and start the material transition [42–48]. With a human's haptic map detected, the robot can infer the grip state in real-time and decide whether to release the object with the classification model built with the human's demonstration.

The detailed steps for building such a framework are described in the following sections.

3.2. *The receiver's grip state profiling*

The core of the safe robot-to-human handover is the robust human grip state understanding. Therefore, as the start of technical details for the safe handover framework, this section illustrates how this study proposes to analyze the grip state and combine natural LfD and human grip state understanding.

3.2.1. *The receiver's force profiling*

To efficiently quantify the human's preferred intentional waiting time, the backward analysis described in [57,58] was first repeated to retrieve the human giver's preferred release time. Even though this backward analysis cannot be used to guide the real-time robot action, its numerical conclusions will reveal the human receiver's personalized preferences more efficiently than those reported in [64].

Grip force has been a popular choice to record and analyze the receiver's grip force change during the handover process [56,57,59,69]. Even without the LfD model, this sensory data still contains rich information about the receiver's intent. As mentioned in Section 3.1, a potential giver's action can be inferred from the giver action profiles described in [57]. Although our data has slightly different forms compared to wrist grip force in [57], the conclusions in that study still apply to our haptic map data. The reasons are shown as follows. As can be seen in Fig. 3, the whole hand-holding force, which is the product of contact pressure and contact areas, counterbalances the grip force. For the same user, the area of the hand will be a fixed coefficient, making the contact pressure proportional to the grip force, as shown in Eqs. (1) and (2). Therefore, the giver's preferred release moment [57], in terms of its first-order derivative change, can be inferred from the contact pressure change.

As the receiver's expected release moment was also collected, its difference from the giver's release moment can be calculated. This difference shows the receiver's expected giver waiting time after the receiver's first grasp of objects and before the giver's release action. The receiver's expected waiting time has crucial importance for the following reasons. First, human givers tend to have very short waiting times [58,60,62], which was tolerable within the original human workforce. However, the HRC team usually has a clear leader-followership, with the human (receiver) being the leader [17]. Therefore, the preferred collaboration flow of the human receiver should be well understood and passed on to the robot. Observing the non-negligible waiting time helps oppose the giver-centric robot imitation learning scheme by addressing the difference between the giver's and the receiver's preferences. Therefore, the receiver should lead the demonstration for robots to enhance the user experience for human receivers.

In addition, this calculation is more efficient in addressing the receiver's personal preference for robot controller design compared to that described in [64]. In that study, the research team proposed three sets of intentional waiting times used controllers and then selected one based on collective preferences. Compared to their method, this research skips the prior selection of potential intentional time and addresses the preferences of every receiver.

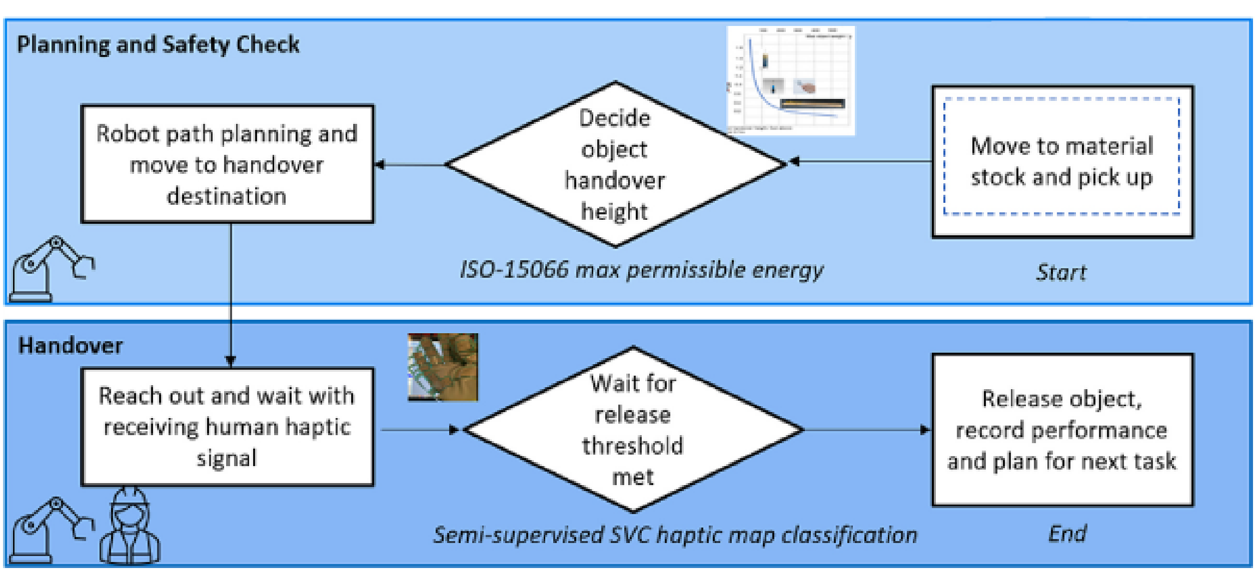
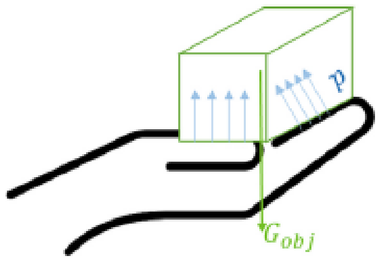


Fig. 2. Computational workflow in HRC material staging.



$$F_{grip} = G_{obj} \qquad Eq.(1)$$

$$p = \frac{F_{grip}}{A} \qquad Eq.(2)$$

p — Hand pressure when holding the object, kPa;

G_{obj} — Object gravity, N;

A — Object contact area, m^2;

Fig. 3. Static force analysis for human hand holding an object.

3.2.2. *Sensors and sampling settings*

The receiver's preference modeling method in Section 3.2.1 is a feasible but inefficient way considering the amount of data needed. A more efficient way is to include more suitable analysis models and rich sensory information. Force-based sensors are widely used in robot-to-human handover studies to understand the grip state [53,54,61,64,69]; however, only the numerical value changes were typically analyzed. In human-to-human handovers, the receiver's grip gestures also contain useful grip state information [61,65]. Therefore, in this research, firstly, as for the sensory system, tactile gloves were used to show both force and gesture changes during the handover. Haptic gloves have been commonly used in touch sense-based studies and their cost will be gradually reduced with technological advancements [74]. Secondly, as robots need fast reactions to adapt to human's constantly-changing physical state, the increased information density from the robot perception system is assumed to help simplify the corresponding computation model and provide fast robot reactions. A *Tekscan 4256E* grip sensor was selected and glued to soft tactile work gloves, as shown in Fig. 4 (right). In this way, the haptic sensors had fixed locations relative to the tactile gloves during the handover process and could capture the human receiver's grip patterns more accurately.

The pressure sensor precision was set to *one psi*, and its sampling frequency was set to *100 Hz* based on similar research experiment settings [53]. Every 0.01 s, a haptic map containing data from 52 (horizontal) × 46 (vertical) hand pressure sensors was created, as shown in Fig. 5.

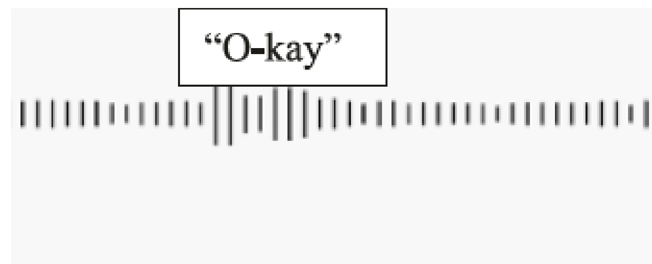


Fig. 5. The soundwave when the receiver signaled the giver to release. *Each short vertical line shows a time interval of 0.01 s.

3.2.3. *Human handover demonstration*

The demonstration process starts with the sensory system ready to record the receiver's grip state. One demonstration lasted 60 s. The giver transitions the object to the receiver at around 30 s. To shape a balanced dataset of haptic maps before and after the release, the middle 25 s (starting from 12.5 s before the receiver command object release and ending at 12.5 s after commanded release) were cropped out to establish a grip state understanding model. The recording length was selected as the shortest, providing effective knowledge transfer to the robots.

In the demonstration, the receiver's preference for release time was assumed to have a higher priority than that of the giver, considering that the receiver has a good haptic sense of whether the object is secure.

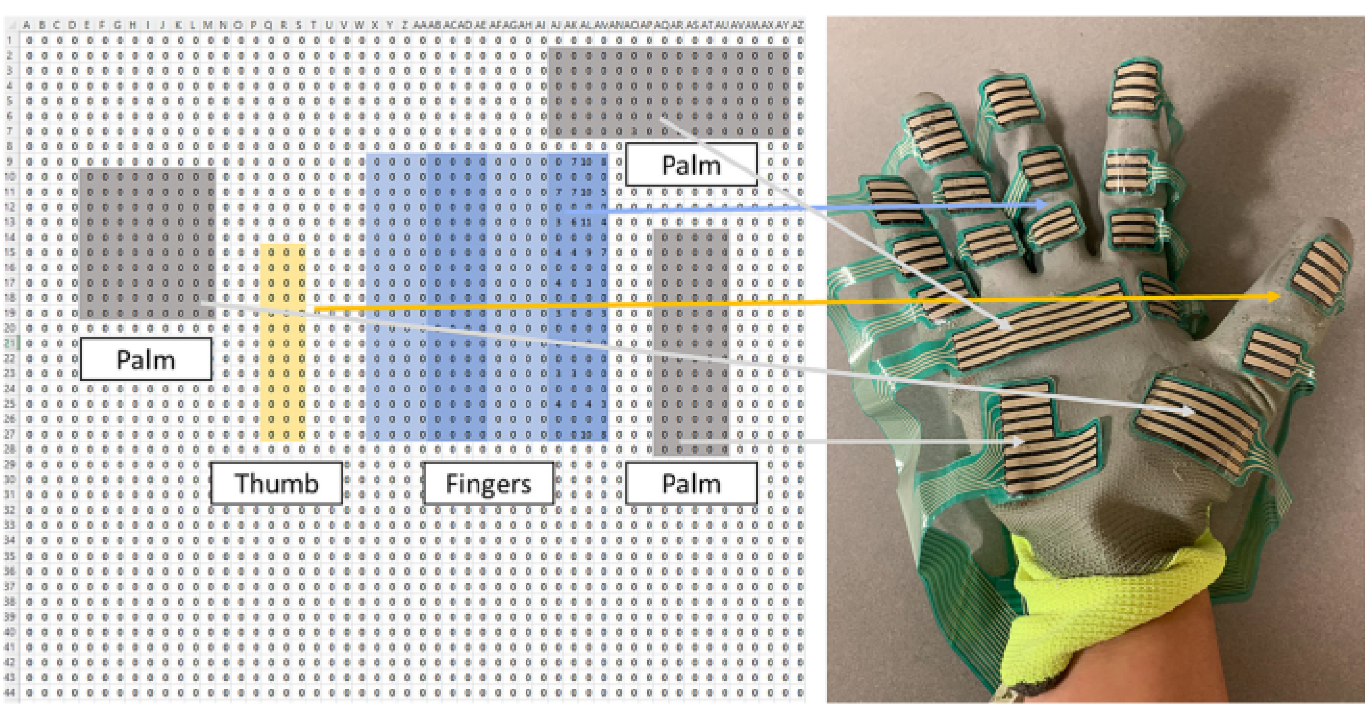


Fig. 4. The haptic map sampled by the Tekscan tactile glove.

Therefore, the receiver will lead the demonstration. The human receiver wears the haptic glove to collect the haptic hand maps during the handover. A fixed giver transitioned tested objects over to the receiver and asked the receiver to receive the objects using different grip locations and gestures. 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 s then recorded the whole handover process to understand the receiver's subjectively comfortable release moment.

The reason for using multiple-syllable words was that their soundwaves would have a distinct pattern near the release moment, as shown in Fig. 5. Therefore, the exact time of the receiver's verbal command of release can be captured with a resolution of 0.01 s. Moreover, the receiver's reaction time causes a delay between the arising of the intent of perceiving a firm grip to the outputting actions of verbal expression. With such a delay, the actual release time is assumed to be 0.25 s [75] earlier than the verbal command.

3.2.4. Grip state machine learning model

After the receiver's demonstration, an action label of "hold" was assigned 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 suggest a firm receiver grip.

The first step in building this classification model is to choose the proper preprocessing method and Machine Learning (ML) models. Several common classification algorithms were experimented with, including Random Forest, Support Vector Machine (SVM), Neural Network, and Ensemble Methods [76]. With the combination of normalization preprocessing and SVM showing the highest accuracy, only the results of this combination will be discussed further.

Moreover, semi-supervised ML was adopted to address the action labeling errors due to human reaction time. Semi-supervised ML was first proposed in [77] to reduce the cost and effort needed to annotate the noisy data. This algorithm starts with choosing a guess ratio and randomly marks this ratio of data as unknown labeled ones. Afterward, an ML model is applied to the unlabeled part of the data and tested for optimal parameters by comparing their performances in predicting the known label parts of the data. Thus, the optimal value of the guess ratio also reflects the trustworthiness of the data annotations. When the optimal guess ratio is closer to 0, the whole model is similar to supervised learning, implying trustworthy data annotations. In contrast, when the optimal guess ratio is closer to 1, the model works like unsupervised learning, suggesting high noises in the data labels. Therefore, the guess ratio from 0 to 1 (increment of 0.1) is used with SVM to test the reliability of the release moment labeling method. The whole process is shown in Fig. 6.

In addition, to reduce human demonstration efforts, this classification model also provides knowledge beyond known grip settings. For example, 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 to show the model generalizability. This leave-one-out approach will be used to test all the grip location and gesture variations in Section 4.

To summarize, as shown in Fig. 7, the audio system was adopted to mark the human receiver's statement of a firm grip on the object. A semi-supervised structure was first used to test the reliability of the verbal signal-based release moment recording process. Then, with optimal parameters selected from this semi-supervised structure, the grip state classification ML model was built and tested on various grip settings to test its robustness. Moreover, the generalizability of the classification model was also tested with unseen grip settings.

3.2.5. Receiver grip state-based robot control

The grip state classification model based on the receiver's demonstration is the core of a material staging robot controller. With the classification model built offline, the robot control system can thus be built. As shown in Fig. 8, the classification model parameter was stored in the robot control system and used to control 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. Therefore, a data transmission system was needed. ROS# serves as the data transmission conduit and connects the C# Tekscan API with the ROS system. As demonstrated in Fig. 8, the data read by Tekscan API was converted to a long string with the fastest transmission speed.

The data transmission speed was also evaluated. With the average transmission speed for one frame of a haptic map averaging 0.0693 s, the system reacts faster than the typical human visual reaction time of 0.15 s [78]. Therefore, the wireless data transmission system is concluded to have a latency that does not affect the fluency of the robot-to-human handover system.

3.3. Indirect collision mitigation

Section 3.2 explored how to maximize the robot's handover success rate as an effort to reduce the chance of early release and dropping objects on unprepared human receivers. Another important consideration in the safe robot handover is the posterior risk mitigation that minimizes the consequences of early release [66,68]. In ISO

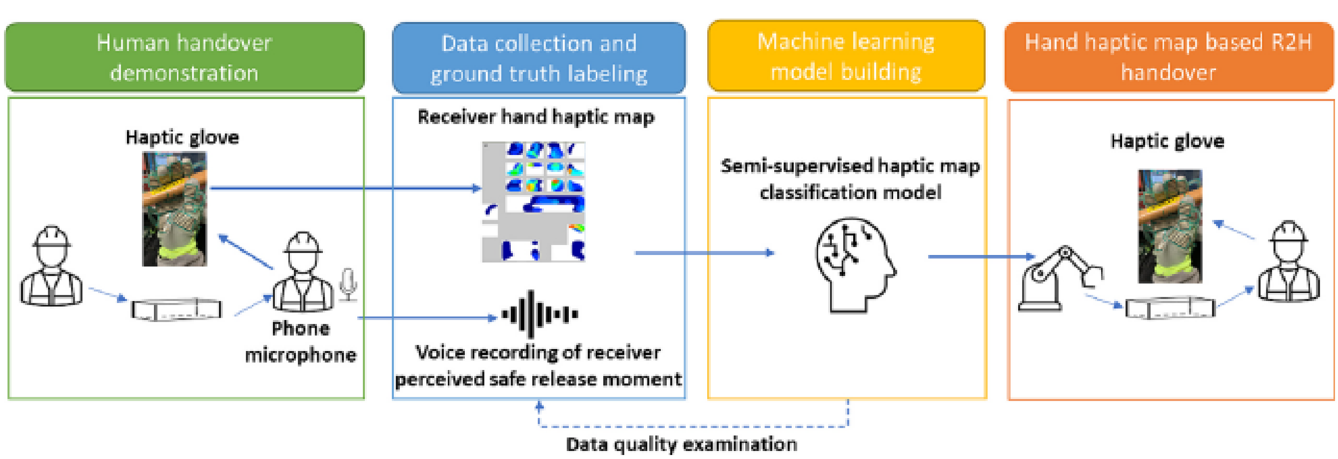


Fig. 6. Human grip state understanding analysis.

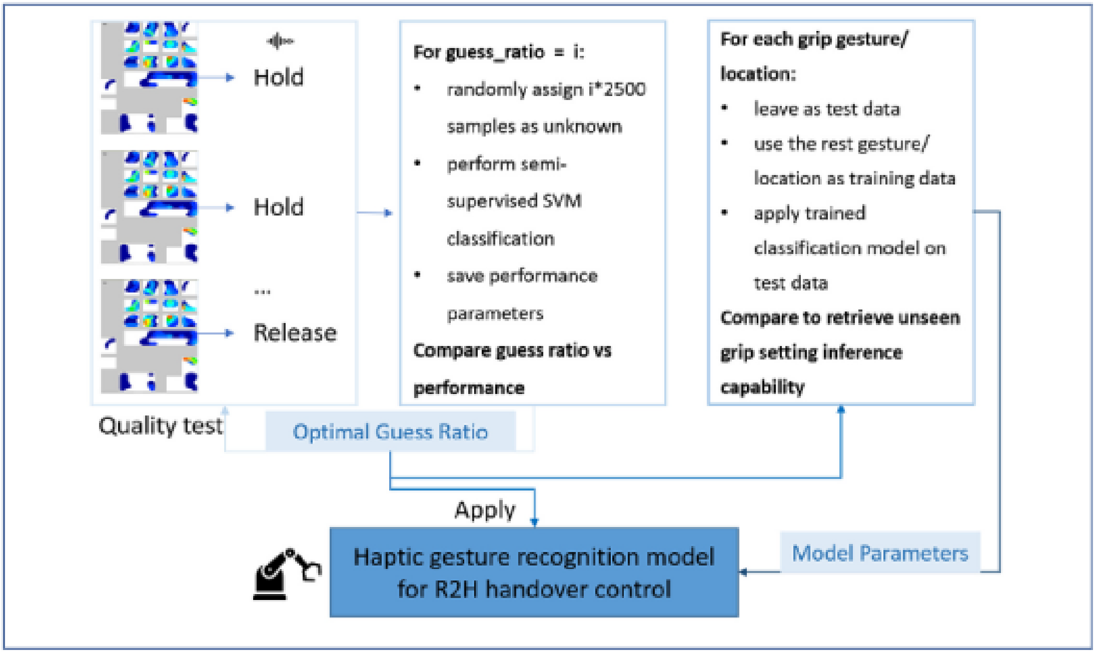


Fig. 7. Graphical abstract of model validation.

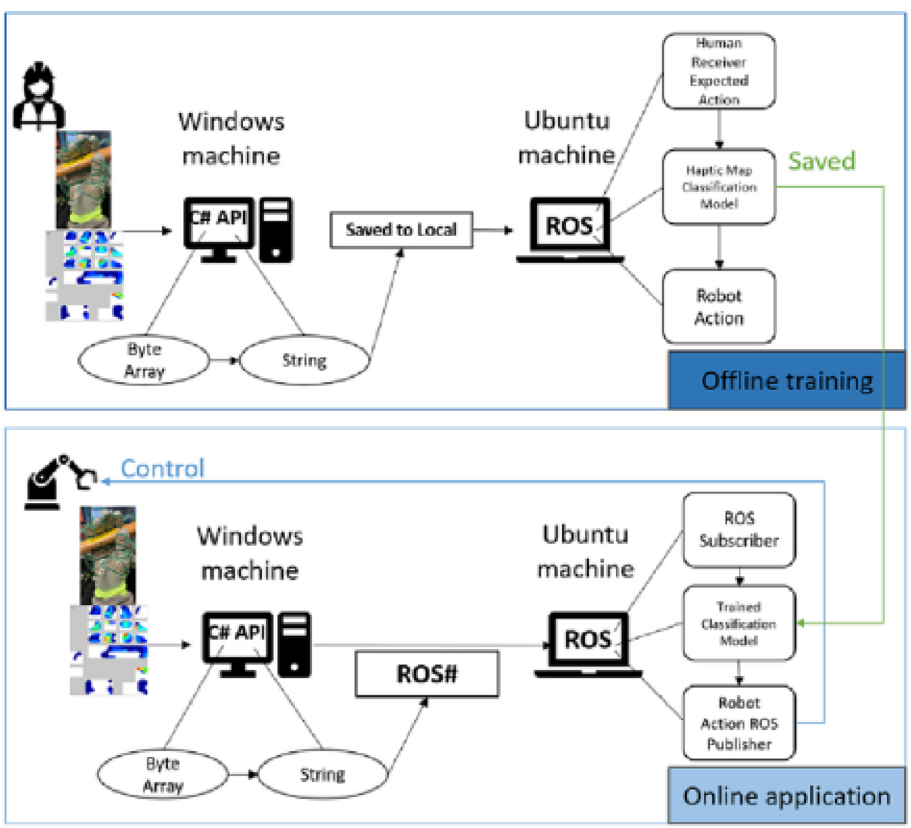


Fig. 8. Dual data logging system and data flow.

15066:2016, for mitigating human collisions, contact energy limitations are used to reduce subjective pain [24,49,50]. The ISO 15066:2016's fundamental assumption of this subjective pain limitation is that the pain is positively related to the collision energy and the collision energy is assumed to be very close and even equivalent to the end-effector kinetic energy [26] based on the Law of Conservation of Energy [79]. The ISO-prescribed limitations are therefore imposed on its two main components – mass and speed.

Similarly, this method is also applicable to falling objects with the same energy conversion scheme. When the object falls from the robot's hand, its potential energy is converted to the collision's contact energy and kinetic energy. With the instant linear velocity of contact being considered as 0 m/s [80], the collision energy will be similar to the original potential energy of the objects. In this way, as both object mass and height determine the potential energy, the maximum permissible handover height was proposed for different objects with different masses to mitigate falling objects collision. This height limitation can also be used as the path destination for robotic material transport.

Quantitative limitations are also proposed to guide the calculation of maximum permissible handover height. For any object, its potential energy is calculated as follows:

$$E_{potential} = mgh = E_{collision} + \frac{mv^2}{2} \tag{3}$$

where

h - the height where the object was held/ robot gripper location, m;

m - object weight, kg;

g - Gravitational Constant, 9.8 m/s^2;

v - object contact speed, m/s;

Therefore, suppose the linear velocity is close to 0 at the moment of collision [65] when collision energy reaches maximum permissible energy $E_{permissible}$, the potential energy also reached its upper bound. With a fixed mass for each object, the height should thus be limited.

$$E_{collision} = E_{potential} = mgh \tag{4}$$

$$h = \frac{mE_{permissible}}{g} \tag{5}$$

where

$E_{permissible}$ – maximum permissible energy for a certain contact area, as defined in ISO 15066:2016 [26];

Different human body areas have different maximum permissible energy limitations based on their vulnerabilities shown in subjective pain studies [26,32]. Therefore, the lowest limits should be chosen for each handover scenario with multiple potential contact areas to protect the most vulnerable areas. For example, for overhead handover with a potential collision with a human head as in [66], the maximum permissible head contact energy of *0.23 kJ* should be used. The maximum handover height above a human's head can thus be calculated for different objects with different masses, as shown in Fig. 9.

The possibility of object drop will be fixed with the handover success rate tested and controlled to be a fixed value. As shown in Fig. 9, under such circumstances, the robot should transfer heavier objects at a lower handover location. The proposed approach is generally applicable to various robot-to-human secondary safety risks mitigation scenarios, such as different potential primary collision areas, different robot control algorithms, and different transferred objects. However, it must be noted that the authors used the same permissible energy values as the ISO 15066:2016 collision energy limits, which only consider a flat (1.4 cm × 1.4 cm) contact surface and no Personal Protective Equipment (PPE) equipment conditions [26]. In this way, the numerical values shown in Fig. 9 can only reflect the height limitation under these scenarios. Future studies can experiment with different contact energy limitations for other contact surfaces and contacts with PPE conditions.

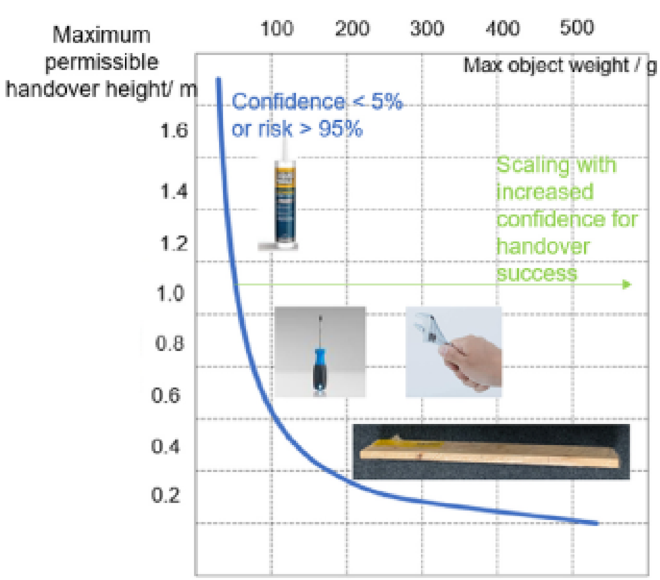


Fig. 9. Overhead handover maximum permissible handover height.

Secondly, Fig. 9 was produced under the assumption that the indirect collision risk will be 100%. Yet, the safety risk will be largely reduced with more robust algorithms and a lower possibility of collisions [26,31,81–84]. The line in Fig. 9 will also move towards the right, leading to higher permissible handover height and a more ergonomic receiving location for the human workers. With PPE-equipped situations, larger contact surfaces, and higher-performance robot control algorithms, the permissible handover height could be at higher recommended levels, despite the lack of PPE-equipped permissible collision energy studies.

Based on the above discussion, the authors propose the following recommendations for better worker protection and more ergonomic handover poses:

Firstly, the robot's handover success rate and performance should always be tested before use and monitored during use. As suggested in [81], the safety risk will be equal to the product of both possibilities of collision and the consequence of the collision. With a lower unintended object drop possibility, the safety risk from such a collision will also be lower. The blue curve in Fig. 9 will correspondingly move towards the right, increasing the permissible handover height limitations.

Secondly, human workers should always wear PPE when performing such work. OHSA requires that PPE, including hard hats and protective footwear, be worn by construction workers [73,85]. Being PPE equipped, the permissible collision energy without causing noticeable pain will also be increased. Correspondingly, the permissible handover height for the same-weight object will also increase.

Thirdly, for extreme situations, such as the objects being too heavy to be held at a safe low height, the handover can be performed with a hard and solid surface separating the potential collision source and the human receiver [26].

4. Experimental setup

4.1. Grip state estimation model validity test

Various grip settings on different construction materials were tested to validate the applicability and generalizability of the proposed method. Eight different construction materials with variations in dimension, shape, weight, and mass distribution were selected, including one iron bolt, one lightweight plastic roof board, one cuboid wood board, two hammers (uneven mass distribution), and three lightweight tubes of glue, as shown in Fig. 10. The dimensions and weight of used objects are shown in Table 1. All contact surfaces were wrapped with plastic wrap to unify contact conditions.

The detailed grip setting variations are shown as follows. First, as shown in Fig. 10 (right), considering that grip force changes along with different grip locations on the objects, five different grip locations were chosen on each wood board/roof board, and four on hammer handles. For short glue tubes, only one grip location on each was used. Secondly, grip gesture variations were considered because different grip gesture preferences cause pressure map variation for the same object. 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 [86], as shown in Fig. 11.

Additionally, as object orientation and relative location to the hand affect the grip gesture [86–70], the two most extreme object orientations (horizontal and vertical) and two grip methods (overhand, underhand)

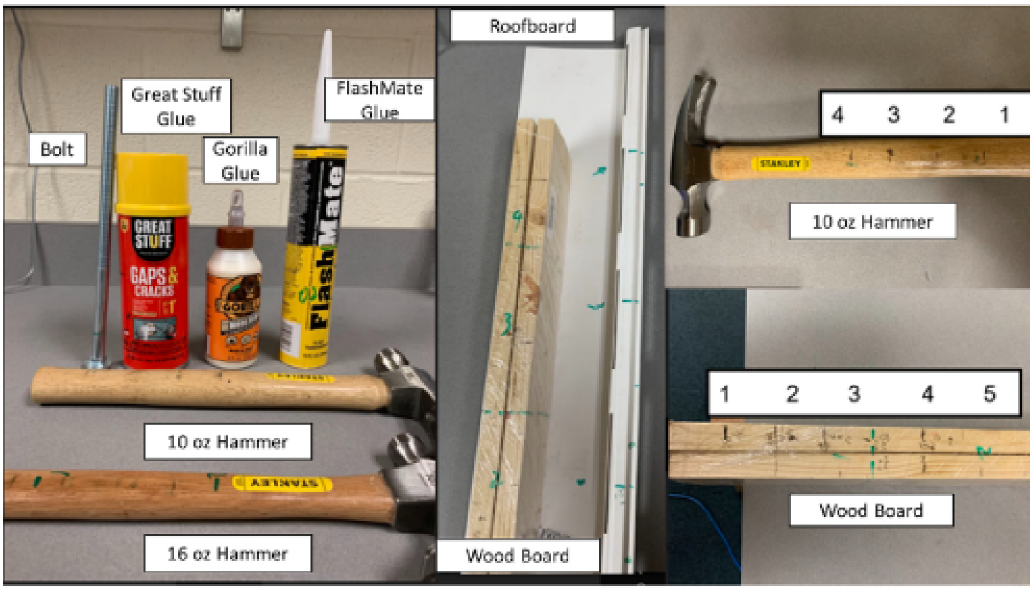


Fig. 10. Common construction materials/ tools for model validation.

Table 1
Dimensions and weights of tested objects.

Object	Weight (g)	Length (cm)	Grip area diameter (cm)
Bolt	216	26.1	1.0
Roofboard	301	75.5	2.4
Wood Board	846	59.6	9.8
10 oz. Hammer	423	29.4	2.8
16 oz. Hammer	678	33.2	3.5
Great Stuff Glue	472	19.8	6.6
Gorilla Glue	293	17.2	5.2
FlashMate Glue	272	31.4	4.2

were added to the combination to show robustness, as shown in Table 2. Therefore, six different grip gesture settings were used, with some examples shown in Fig. 11. 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 [86–90].

4.2. Grip state-aware robot controller feasibility test

Other than the model's validity, its compatibility with a robot control system should also be tested before being applied to the robot. An interactive experiment was also designed to verify the feasibility of the grip state awareness-based robot controller illustrated in Fig. 8. In this experiment, as shown in Fig. 12, a human subject interacts with a virtual robot by lifting a wood board from the edge of the table. The human's grip state naturally transitions from subtle contact to a firm grasp of the objects, and the virtual robot was supposed to react to this change. The robot's initial action was designed to be holding the object (a purple box). When detecting the human's grip state changes through the haptic glove, the robot will release the object (the purple box will detach from the robot's end-effector). A python script loaded the trained grip state classification model and used this model to control the robot's motion [91]. The pseudo-code of such a python script is shown in Table 3.

The experiment was repeated 50 times with one fixed grip location to fulfill the goal of this experiment, which was to test the system's technical feasibility and responsiveness. The robot's reaction time was also recorded and calculated, which is the gap between the robot's receiving a haptic signal through ROS# and the end of executing the object release action.

5. Experimental results

The experimental results from Section 4 were analyzed to provide answers to the following three questions proposed in Sections 2 and 3:

1) What is the preferred intentional waiting time for selected human users?
2) How robust is the proposed method in teaching robot grip state understanding with various grip settings and objects?
3) How generalized is the LfD method to unseen grip settings?

5.1. Receivers' preferred intentional waiting time

The simple analysis of grip force with the method illustrated in Section 3.2.1 answers the first question. The receiver's release command averages 2.555 s after the initial contact with objects. The temporal differences observed in seventy handover experiments with three users are shown in Fig. 13. Three users have an average delay of 1.343 s, 0.8620 s, and 5.460 s, respectively. Therefore, the robot should intentionally wait for some time after detecting human receivers' contact with objects to make the humans feel comfortable during the handover process.

Nonetheless, this finding only addressed the psychological preference of human receivers. The earlier release before the receiver's verbal command can be safe in some situations. For example, in human-to-human handovers, the givers release objects immediately after the receiver's contact [57,59], yet the object transitions are generally safe. This observation implies that receivers can react to a release action immediately after they grasp objects. Therefore, as shown in Fig. 14, though not recommended, releasing any time after the receiver's grasp of objects is generally found to be safe.

5.2. Receiver grip state classification

The following sub-sections provided answers to the second and third questions correspondingly.

5.2.1. Known grip settings

The classification model provides an insightful understanding of grip states after a human's short demonstration. The average grip state prediction accuracy is 98.52%, exhibiting robust learning ability across all

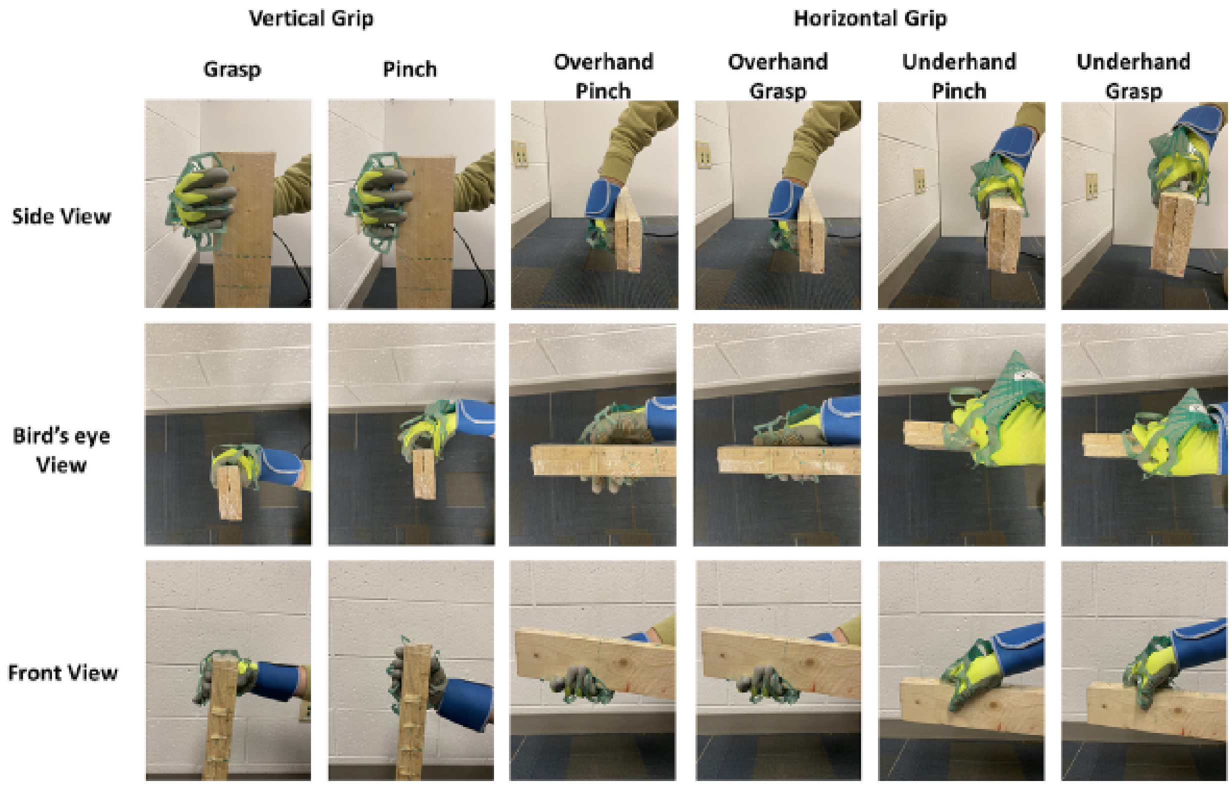


Fig. 11. Grip gesture variations in this study's experiments.

Table 2
Grip gesture settings.

Object orientation	Relative location to hand	Gesture
Horizontal handover	Overhand	Pinch [66] Grasp [66]
	Underhand	Pinch Grasp
Vertical handover	/	Pinch Grasp

demonstrated locations and gestures. As for robot control, this high accuracy suggested the broad applicability of the proposed LfD approach. With only 25-s demonstrations, the robot can transfer objects with an intentional wait customized to the receiver's preference for any receiving grip location or gesture. As the human needed to perform only one demonstration for each setting, the demonstration efficiency was largely improved compared to that described in [69].

Moreover, as mentioned in Section 3.2.4, semi-supervised ML was adopted to examine the proposed human demonstration collection system. Guess label ratio variations were used to reflect assumed trustworthiness, and the corresponding model was tested on the same data to

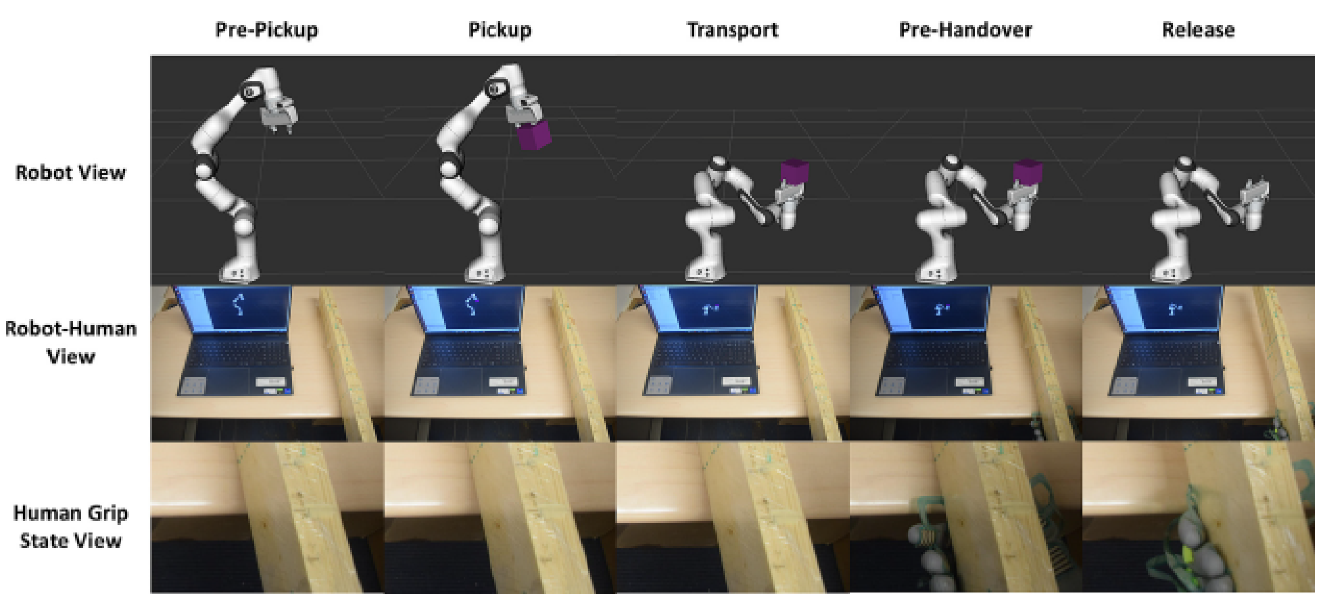


Fig. 12. Interactive experiments with a virtual robot for the grip state understanding.

Table 3
Pseudo-code for robot control algorithm.

```
Pseudo-code for the robot control algorithm
Input: haptic map of the receiver's hand
  Output: robot's action of holding/releasing the object being transitioned

  load the trained haptic map classification model
  plan a cartesian path for the robot to a designated object pickup location
execute the planned path
pick up the object
plan a cartesian path for the robot to a designated receiver's hand location
execute the planned path
for every 0.25 s do
  subscribe to the tactile signals transmitted from ROS#
  preprocess haptic map reading and use as inputs to the classification model
  run the trained haptic map classification model
  if the haptic map is classified as a firm grip
  robot release
  else
  robot hold
```

compare their performance. As shown in Fig. 15, the classification accuracy decreases when the guess label ratio increases. Furthermore, the false positive classification rate, which shows the robot's early release behaviors, also increases with the guessed label ratios.

As shown in Fig. 15, when the guess label ratio was 0, the classification model has the highest accuracy and lowest false positive rate. This observation suggested that 0 should be chosen as the optimal parameter of the guess ratio. Since the guess ratio of 0 reflects the full trust towards the data collection process, the reliability of the recording process for the receiver's physical state and expectation towards the giver's action is therefore verified.

5.2.2. *Unseen grip settings*

As for the unseen grip settings, the average grip state prediction is 88.79% for unseen grip locations and 74.22% for unseen gestures, as shown in Table 4. This result means that the proposed model has good generalizability to unseen grip gestures, especially when the demonstration was only 25 s. However, although the model has lower classification accuracy for unknown grip gestures, it does not adversely affect safety. This claim is made considering that humans usually have one habitual gesture for receiving objects. Therefore, considering that Section 5.2.1 demonstrated the proposed model's robust learning ability for all demonstrated gestures, the handover for a fixed user will generally be safe.

As for implications of this accuracy for handover safety, firstly, the predicted release time and the receiver's release command were compared. As shown in Table 5, the classification model can accurately predict the receiver's grip state for most unseen grip settings. As a result, this model will drive the robot to develop aggressive release strategies after the receiver's contact with objects. However, the grip state recognition is less robust for unseen grip gestures, with classification accuracy decreasing for all three users. This implies that the robot will be driven to perform early releases potentially. Nonetheless, humans tend to receive with one habitual gesture [85]. This implies that the variations in grip gestures are rare for one fixed receiver, and the grip location variation is more common. Considering the proposed method has proven generalizable for unseen grip locations, the proposed method will generally provide safe handover behaviors for a fixed human user.

To benchmark the performance of the proposed model, other similar robot-to-human handover studies were used for comparison. As shown in Table 6, the proposed haptic map classification model outperforms the results observed in prior studies for both known and unseen grip settings.

5.3. *Robot controller feasibility test*

In the 50 repetitions of the random grip location interactive experiment, the robot succeeded in predicting the human's grip state change in 94% of the cases. Among the failed cases, the robot released too early one time (2% chance) and did not release the object twice (4% chance). This observation verified the effectiveness of the proposed one-shot demonstration method, especially for adapting to unseen grip settings. Moreover, the robot's average reaction time is 0.000986 s, much shorter than the human reaction time. This means that the human will not recognize the robot's reaction time, and the subjective evaluation of the robot's responsiveness would not be affected by the grip state understanding. Additionally, with tested responsiveness and adaptability, the proposed framework of "sensor upgrading and computation simplification" was verified effective for handling close-proximity pHRC problems.

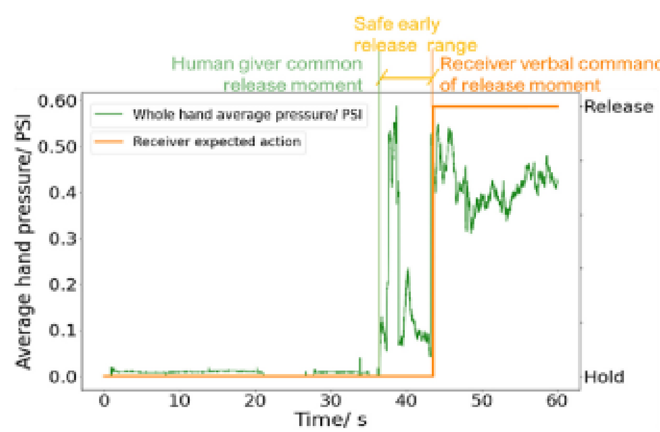


Fig. 14. The safe early release range: after the human receiver has gripped objects and before the verbal signal of release.

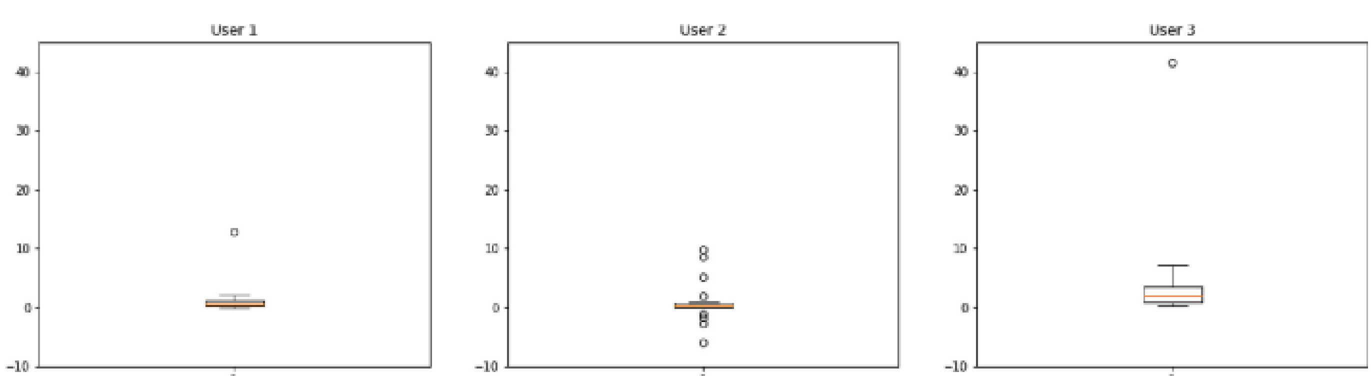


Fig. 13. Boxplot of preferred intentional waiting time for three users.

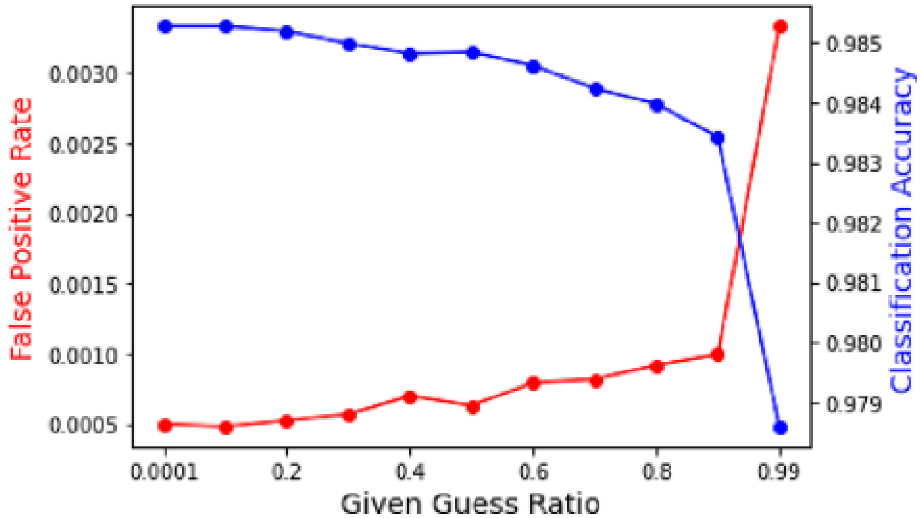


Fig. 15. Hand haptic map classification performance comparison for different guess ratios.

Table 4
Grip state understanding accuracy for *unseen* grip settings.

Unseen settings	User 1	User 2	User 3	Average
Location	98.7%	86.7%	81.0%	88.79%
Gesture	82.4%	63.4%	73.9%	74.22%

Table 5
Release time comparison with ground truth for *unseen* grip locations.

Predicted release moment vs.	User 1	User 2	User 3	Average
Receiver's commanded release (sec)	+0.9175	−2.135	−1.672	−2.832
Receiver's contact with objects (sec)	+3.059	−0.2475	+0.3933	+3.205

*"-"in predicted release time means earlier than the receiver's commanded release, "+" means later than the receiver's commanded release.

Table 6
Grip state classification model performance benchmark.

Previous study	Performance	
	Unseen data	Known data
Grigore et al. (2013)	75.63% [56]	
Koene et al. (2014)	94% [66]	
Palinko et al. (2016)	/	81.5% [67]
Wang et al. (2018)	/	86.67% [61]
Yang et al. (2020)	64.3% [65]	
Proposed model	**81.51%**	**98.52%**

6. Discussion

This study proposed a grip state classification model to teach robots to perceive the safe and preferred time instants to release handled objects to human receivers. The model had enriched sensory information to reduce computing load, which can provide prompt responses to human's fast-changing physical intents. The model also targeted the narrow applicability and weak generalizability of previous studies and provided satisfactory performance for various grip settings.

This study also verified that the human receivers prefer that givers wait around 3 s and then release the objects. However, this observation contradicts the giver's immediate release after the receiver's contact. Therefore, this observation can guide the receiver-centric robot controller to provide safe and personalized object handovers.

Moreover, this study adopted the LfD method to establish the proposed receiver-personalized robot handover controller. Only a one-shot 25-s natural receiving process is needed as the demonstration, which largely improves the robot's learning efficiency and reduces the worker's demonstration workload.

However, there are some limitations to the proposed model. The current approach requires another new 25-s demonstration for a new object. Although this is common for recent robot-to-human handover studies, this repetition can be further simplified. For example, future studies can focus on expanding the database size with this LfD interface and building a transfer learning model that can be generalized to any new object. In addition, for safety reasons, the robot controller was only tested in the virtual environment in this initial study. The authors are currently applying the findings of this work and extending them to real industrial robots in pHRC experimental setups.

Furthermore, the authors only explored the close-proximity collaboration of material transfer in this paper. The choice was made because the close-contact human–robot interaction problem is widely agreed to be one of the most challenging and underexplored areas of work particularly in construction robotics. In comparison, the safety standards and technical studies on human-aware path planning for material transport have both been well established. With a critical gap of robot-to-human object handover effectively addressed and the technical approach shown to be feasible in this paper, future studies can work towards a full robot-assisted material supply system and continue full-contact pHRC studies to help realize a field-deployable system. On this basis, the ethical and management problems with detailed software and hardware decompositions [92] can also be explored.

7. Conclusions

This research addresses potential safety concerns during pHRC on future construction sites. Instead of physical separation, this study proposes to use human physical state awareness to reduce robot collisions with human workers. The main contribution is the combination of LfD and human grip state awareness to improve the object handover success rate with reduced human effort and enhanced generalizability.

The main conclusions of this research include the following:

1) The human receiver prefers the giver to intentionally wait for around 3 s after the receiver grasps the objects in a handover process.

2) The recognition of the human grip state in a handover can be accurate and robust with an SVM classification model. For example, the proposed model achieved 98.52% accuracy for 70 grip setting variations, with only a 25-s natural handover needed as a demonstration for

each setting.

3) The short natural handover process can provide robot control knowledge beyond the demonstrated settings. The model can still provide accurate grip state recognition when test grip settings are different from the demonstration setting. For example, the proposed model has an 88.79% accuracy for recognizing a human's grip state with varying grip locations. This improvement primarily reduces the human's workload as the robot's teacher.

In summary, this research explored an intuitive programming method demonstrating 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 personalized to each human receiver's preference to enhance the user experience. 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.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Vineet R. Kamat reports financial support was provided by U.S. National Science Foundation. Corresponding author Vineet R. Kamat is a member of the Editorial Board for this journal Automation in Construction.

Data availability

Data will be made available on request.

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