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# SAFE ROBOT TO HUMAN TOOL HANDOVER TO SUPPORT EFFECTIVE COLLABORATION

**Jeon Ho Kang, Paolo Limcaoco, Neel Dhanaraj, and Satyandra K. Gupta** *
Center for Advanced Manufacturing, University of Southern California, Los Angeles, California 90007
Email: jeonhoka@usc.edu, paololim@bu.edu, [dhanaraj,guptask]@usc.edu

## ABSTRACT
Robot-to-human mechanical tool handover is a common task in a human-robot collaborative assembly where humans are performing complex, high-value tasks and robots are performing supporting tasks. This paper discusses an approach to ensure the safe handover of mechanical tools to humans. We introduce a framework to enable smart robotic assistants to safely and efficiently perform robot-to-human tool handovers. Our system utilizes a specialized gripper design capable of firmly grasping objects with irregular geometries. We utilize a tool end detection method so that the robot grasps the tool end and ensures that the human can safely grab the handle during handover. Additionally, the system is able to detect if the tool moves during the grasping process and either restart the pickup or account for the new orientation during hand-off planning. Lastly, the hand-off planning ensures the robot releases the tool at the appropriate time when the human has safely grabbed the handle. Our experimental results indicate that our system can safely and effectively hand off many different types of tools. We have tested the system's ability to handle contingencies that may occur during the handover process successfully.

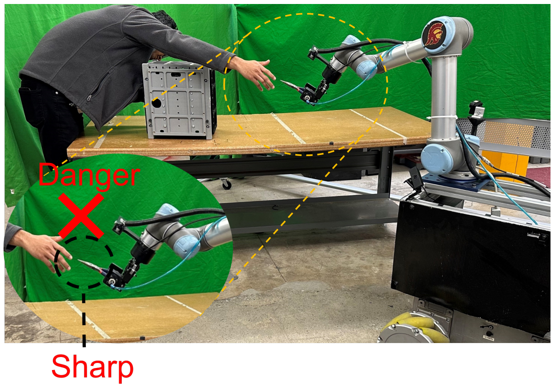
## 1 INTRODUCTION
Recent developments in collaborative robots have opened up new possibilities for humans and robots to work together in manufacturing applications such as assembly, service, and maintenance operations. By leveraging their respective strengths, humans can focus on tasks that require advanced dexterity and critical thinking, such as assembling fragile sensors on satellites, while robots like mobile manipulators can function as intelligent assistants that perform supportive tasks such as retrieving and handing over tools as needed [1]. However, robots must not compromise safety while helping humans. Humans may become immersed in their tasks and they may lose awareness of their surroundings. Therefore, when robots assist humans, for example, by handing an operator a sharp tool, they must consider the human's safety. To accomplish this, smart robotic assistants must be capable of 1) deciding how to pick up and handover the tool properly and 2) ensuring safety during the handover process.

Generally, we would want to handover tools to the human operator by holding onto the unsafe end of the tool, allowing the recipient to grab the handle safely. Using collaborative robots allows us the opportunity to grab the unsafe end of the tool. To begin with, when picking up the tool, the robot must identify where the human operator is likely to grasp the tool (the handle end) and determine the best approach for holding the unsafe part of the tool (the tool end). Lastly, when handing over the tool, the robot will need to consider the orientation of the handle end for planning the tool hand-off so that the human can ergonomically grab the tool.

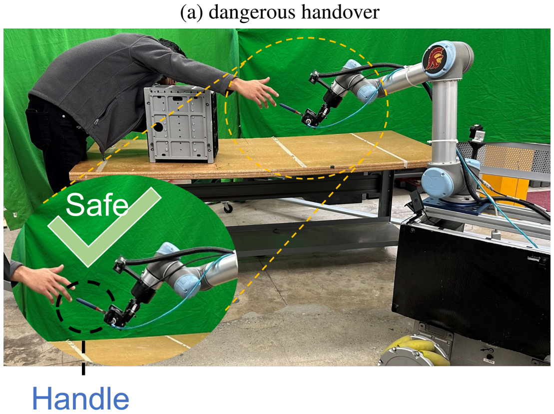
In this paper, we focus on ensuring safety during all stages of the handover process. For example, when the robot picks up the tool, the heavy and irregularly shaped tool end can cause the tool to slip from the robot's grip. We must design a gripper that can conform and firmly grasp the tool end to address this issue. Even then, the tool may still slip or rotate within the secure grasp.

*Address all correspondence to this author.




(a) dangerous handover




(b) safe handover

**FIGURE 1**: A human operator is assembling a miniature satellite and has requested a tool from the robotic assistant. The figure shows a) a dangerous tool handover and b) a safe tool handover by the smart robotic assistant.

In such cases, the robot must detect the severity to which the tool has moved and decide whether to restart the process or continue the tool handover. During hand-off execution, effective communication between humans and robots is crucial to ensure safe tool release and prevent errors. The human must be able to indicate to the robot when to release the tool safely or halt the handover if the wrong tool is detected.

Various aspects of this problem have been studied in different contexts. General object handover planning has been explored extensively concerning human-robot interaction, and enabling the robot to recognize the handle and tool end is a version of tool affordance modeling for the robot [2]. Additionally, research has been conducted on gripper design and grasp planning for both general and human-centric applications [3–7]. This paper builds upon these ideas and presents an end-to-end system for robot-to-human tool handover that ensures safety at each stage of the handover process. We describe our hybrid gripper design, which is designed to firmly grasp tool ends in Section 4. We discuss our approach to determine the tool end and select the robot grasp location on the tool end in Section 5. Finally, in Section 6, we present our method for hand-off planning and execution. We individually evaluate the robustness of each module in our system and validate our system design decisions. Moreover, we execute the entire system and show that our proposed approach is robust, with minimal failures. Lastly, we introduce simulated failures into the system and show how our approach handles these contingencies. Our work demonstrates a new, robust, safe-tool handover framework that can be used with smart robotic assistants to enable safe human-robot collaboration.

## 2 RELATED WORK

**Grasp Planning.** Grasp planning is a challenging problem in robotics, as it heavily relies on the geometry and physics of the object. Researchers have extensively studied object manipulation to develop safe and efficient grasping methods. Several methods have been proposed to tackle this problem in recent years. For instance, sampling-based methods, neural network models, and 6-DOF pose estimation have been utilized to generate stable grasps [8–16]. Additionally, some researchers have presented deep reinforcement learning methods to generalize grasping techniques to unseen objects [17]. Other studies have proposed algorithms to measure grasp quality [18] or reduce the computational costs associated with grasp sampling [19]. However, many of these approaches do not consider the context in which grasping occurs. Recently, context-aware grasp planning has emerged as an important area of research [20]. In particular, human-aware grasping has gained considerable attention to ensure safety in human-robot interaction. For instance, [7] proposed a method called Co-grasp that predicts the human hand based on the point cloud data of the object and maximizes the grasp-approach vector of the human and the robot.

**Robot-to-Human Handover.** Robot-to-human handover is a complex task that requires careful consideration of safety and efficiency. While grasp planning is an essential aspect of handover, it is not the only factor determining safety in many contexts [21]. As a result, many studies have proposed various solutions to address the challenges associated with robot-to-human handover.

Approaches to enable robots to work collaboratively with humans include designing custom controllers, communication systems, and human-aware motion planners [3, 5, 22–24]. Real-time vision capabilities in robotic systems have also been shown to be important for fluid robot-to-human handover [4] [6]. In some cases, tool affordance models have been developed to facilitate the handover of mechanical tools [7] [25]. In manufacturing, studies have explored the impact of trust in humans on the efficiency and safety of manufacturing tasks and the role of robotic assistants in those settings [1, 26–28]. Additionally, behavioral traits of humans and robots have been considered to optimize human-robot collaboration. [29–32].

In this paper, we focus on the entire system involved in robot-to-human handover, particularly emphasizing the manufacturing context. We aim to develop a comprehensive approach that addresses the various steps in ensuring safe tool handover and handles the contingencies that may arise during each step.

## 3 SYSTEM OVERVIEW

**System Requirement.** Our objective is to create a secure and reliable system in which a mobile manipulator is able to hand over tools to a human collaborator. To evaluate the system's performance, we conducted experiments with various hand tools typically found in mechanical workspaces. We examine tools with varying physical dimensions, including length ranging from 8.2cm to 30.4cm, width ranging from 2.1cm to 11.4cm, and height ranging from 2.6cm to 8.1cm. The weight of these tools ranges from 0.6kg to 3.2kg and encompasses common items such as pliers, files, tape measures, and scissors. To retrieve a requested tool, a robotic manipulator scans potential storage locations such as cabinets, tool chassis, or tables. The robot then generates a safe and effective grasp plan with contingency plans for any unsafe events. Finally, the robot hands over the tool to the human and releases the tool after receiving feedback from the human.

**System Hardware**. We use a mobile manipulator platform for our hardware system. Our mobile manipulator consists of a UR5 robotic manipulator mounted on a custom mobile base equipped with mecanum wheels. To locate and identify the object to be picked up, an Intel Realsense D-435 camera is mounted on the hand of the robotic manipulator, which provides RGB-D data of the workspace. Additionally, another RGB camera is attached to the base of the mobile manipulator to detect failures during the grasping process. Also attached to the mobile base is the Oak-D camera for human hand gesture recognition. The system includes a specialized hybrid end-effector design, which we explain in detail in Section 4. Fig. 2 shows the complete setup of our mobile manipulator.

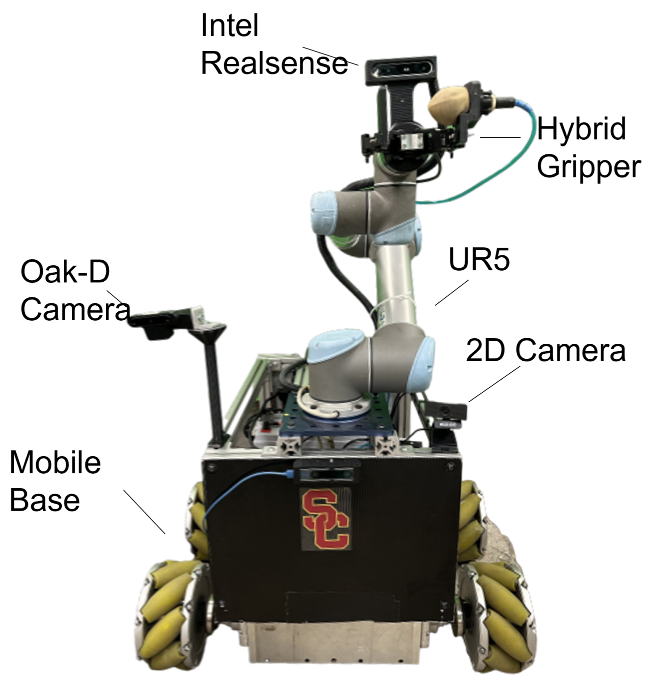



**FIGURE 2**: The mobile manipulator hardware.

**System Software**. In order to ensure a smooth and safe handover of tools from the robot to the human collaborator in the mechanical workspace, we have carefully considered potential contingencies that may arise. One of the key factors we addressed is the detection and localization of the tool end. The tool end detection is crucial for the safe tool handover, as shown in Fig. 1. Our method for tool end detection is discussed in detail in section 5. Another critical consideration in the system is the motion planning framework, which is essential to avoid collisions with the environment and generate a secure grasp on the object. To achieve this, we utilize the ROS MoveIt! framework to combine multiple sub-components into a robust integral system.

To plan the grasp, we use Grasp Pose Detection (GPD) [33]. The pose detector samples different grasps along the tool end to generate an adequate grasp for our application. A more detailed discussion of grasp planning is provided in section 5. To ensure that the grasp is successful, an RGB camera mounted on the manipulator arm detects a poor grasp by observing the in-hand pose of the tool and reads the angle to determine whether the grasp has been successful. Finally, hand-gesture recognition allows the robot to know when to hand off the object. The later section provides more details on the contingency planning for the hand-off. By addressing potential contingencies at every step of the process, we have designed a reliable, safe, and efficient system in the manufacturing workspace.

**System Operation.** When a human collaborator requests a tool, the mobile manipulator navigates to the surface where the tool is located, scanning and searching the workspace for the requested tool. Then, it detects the tool location in the workspace using an object detection module [34], and detects the tool end for grasp sampling and location selection for the optimal grasp. The robot generates an optimal motion plan to reach the object without colliding with the environment and picks up the tool from the table. To ensure a safe hand-off to a human agent, the RGB camera on the robotic manipulator detects the in-hand angle to determine the quality of the grasp. We use different algorithms to plan the safest hand-off based on the in-hand angle. When the robot generates a motion plan to hand off the tool to a human, the Oak-D camera on the mobile base of the manipulator takes human hand gestures to safely release the tool from the gripper. If the tool has been handed-off with the dangerous side pointing towards the human or if any perilous event occurs, human intervention prevents any mishap by showing a stop gesture. The robot stops, puts down the tool, and replans the grasp. The system architecture of the handover system, which handles multiple contingencies, such as when to reorient the tool or abort and retry for another grasp, is presented in Fig. 3.

## 4 GRIPPER DESIGN

**Gripper Requirements.** While designing the gripper for our robotic system, we had to consider multiple factors to ensure efficient and reliable handling of tools:

1. Ability to grasp flat tools on a table. This requirement is critical since many tools used in the workspace have a flat geometry and require a gripper that can handle them without displacement.
2. Ability to handle varying irregular geometries, which can be challenging for some grippers due to the limited contact surface of their fingertips. A robust and adaptable gripper was necessary to handle tools of different shapes and sizes effectively.
3. High payload capacity, as some tools in the workspace have a maximum weight of 3.2kg.
4. Ability to handle uncertainties in maintaining a good grasp quality while transporting the object. A reliable grasp requires the gripper to hold the object firmly without displacement or rotation during handover. Such grasps can be challenging when dealing with tools with a high moment of inertia due to their long geometry.
5. Adaptable to the varying geometries and materials of the tools, ensuring a reliable and stable grip during the handover process. We had to consider the material of the objects, as typical tool ends are metallic and have different friction coefficients than handles.

We evaluated various gripper types, such as two-finger, multi-finger, malleable, and suction grippers, to meet the requirements. Due to their low payload capacity, we eliminated suction grippers as viable options. We ultimately chose two-finger parallel grippers due to their low cost and ease of actuation compared to multi-finger grippers. However, two-finger grippers with rigid fingertips tend to perform poorly when grasping tools with irregular geometry. Therefore, the rigid fingertip was replaced with a malleable fingertip. Ultimately, we used rigid fingers with a soft granular jamming finger-tip to improve the gripper's adaptability. The soft pads on the fingertips mold to the tool's shape, providing additional support against in-hand torque and generating more excellent stability when grasping irregular geometries. Initially, we considered using two soft fingertips on both ends of the gripper. However, we found that using a rigid fingertip on one end did not significantly affect grasp quality. Thus, we selected only one soft fingertip for the final design to minimize the cost of an additional vacuum pump and supporting components.

**Design Concept Selection.** To address the limitations of traditional gripper designs, we introduce a novel specialized gripper concept that combines the strength and adaptability of two-finger parallel-oriented grippers with the granular jamming technology of malleable grippers [35]. Our design is tailored explicitly for the pick and place of the tool end by being able to completely conform to irregular geometries, thus ensuring a good grasp on each object. The granular jammer, connected to a vacuum pump capable of supplying positive and negative pressure, conforms to the object's shape and solidifies the state of particles inside the flexible, elastic membrane structure to firmly grasp the object without displacement or rotation during handover. When finished with a task, positive pressure quickly resets the gripper for the next operation, increasing speed and reliability. For sharp edge pick operations, the hybrid form of our gripper utilizes both mechanical forces from the parallel gripper and friction forces from the granular jammer to ensure a secure grip. Our design offers adaptability, reliability, and speed compared to traditional gripper designs and is promising for robotic pick and place of tools. See Fig. 5 for a visual representation of our gripper design.

**Evaluation.** We experimented with testing the performance of our gripper in meeting the requirements we listed earlier and to ensure it can safely transport various mechanical tools. We carefully selected tools with different geometries that would pose significant challenges for conventional grippers, like suction or two-fingered grippers. The tools used in the experiment are shown in Fig. 4. To demonstrate the robustness of our gripper, we chose seven commonly found tools in a workspace and repeatedly tested the gripper's success rate in grasping them. We conducted 20 experiments with arbitrary orientations for each tool to determine the gripper's ability to grasp the tools in various configurations. We evaluated the grasp quality in three classes: robust grasp (success), semi-robust grasp (mixed, i.e., the grasp that resulted in in-hand rotation of the object), and failed grasp (failure, i.e., the grasp that could not hold the object). The experiment results, showing the percentage of each class of grasp quality, are presented in Tab. 1.

**Experiment Results.** The experimental results demonstrated that the novel gripper is capable of picking up a variety of objects without rotation, with only one instance of failed grasp observed on the saw. This is due to its flat geometry hindering the robot from selecting grasps that produce a large area of contact with the fingertips in certain orientations. However, in other cases, the gripper successfully picked up the saw with high stability, and one rotation of the wrench was intentionally

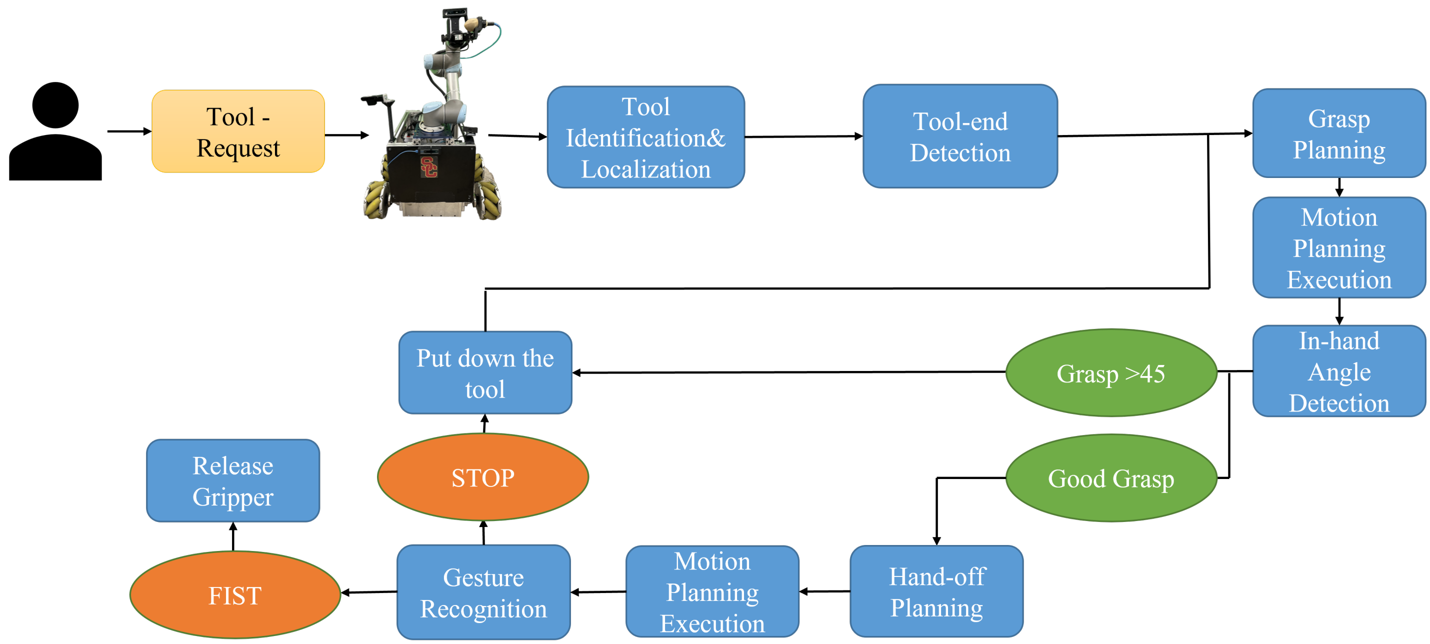



**FIGURE 3**: Overview of the system architecture

**FIGURE 4**: Tools used for testing hybrid granular jammer gripper.

selected to test the gripper's ability to handle difficult grasp configurations. Even in this case, the gripper still provided support from the granular jamming fingertip and prevented the wrench from rotating beyond a 45-degree threshold. It is worth noting that the 45-degree threshold was chosen to test adaptability during hand-off, but users can choose different values. The gripper exhibited high repeatability in producing a firm grasp on different mechanical tools with complex geometries. Even when the granular jamming fingertip is conformed into different geometries, the gripper produces another firm grasp due to the positive pressure applied before the next grasp. Fig. 6 provides examples of gripper grasping tools with irregular geometries.

**TABLE 1**: Result from grasp success rate test. Mixed grasp refers to in-hand tool rotation less than 45 degrees; failed grasp includes all the grasps resulting in the tool's dropping of the rotation larger than 45 degrees.

| Mechanical Tools | Success | Mixed | Failure |
|---|---|---|---|
| Hammer | 20 | 0 | 0 |
| Screw Driver | 20 | 0 | 0 |
| Box Cutter | 20 | 0 | 0 |
| Wrench | 19 | 1 | 0 |
| Pliers | 20 | 0 | 0 |
| Saw | 19 | 0 | 1 |
| Tape measure | 20 | 0 | 0 |

## 5 TOOL END DETERMINATION AND GRASP LOCATION SELECTION

In this section, we propose a method of determining the tool end of the mechanical tools and the selection method for grasp location. The system must grasp the tool so that the handle part of the mechanical tool is exposed and the tool end is pointed

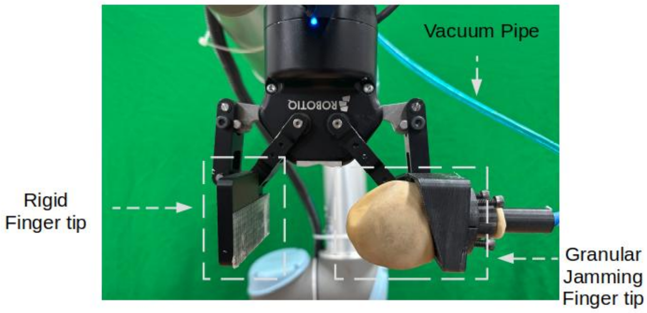



**FIGURE 5**: Gripper design for grasping irregular objects.

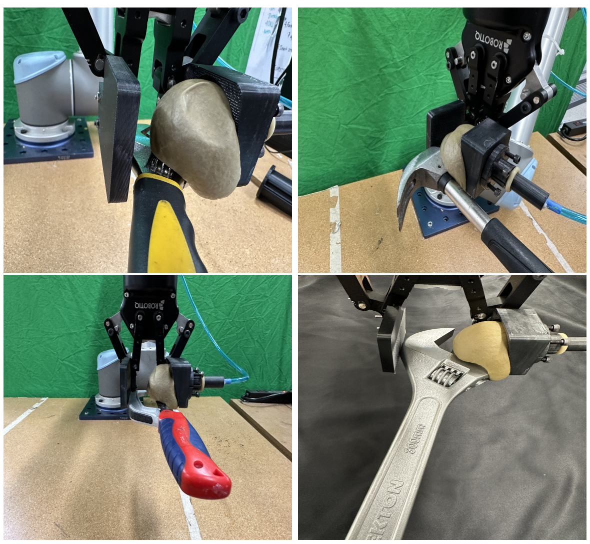


**FIGURE 6**: Example of granular soft finger-tip molding into the shape of irregular geometries of mechanical tools.

toward the robot. The goal is also to ensure that the robot grasps the tool with maximum stability so that tool does not slip or fall while transporting it to the human agent. To achieve all these requirements, we propose a method of determining the tool end of the object using computer vision.

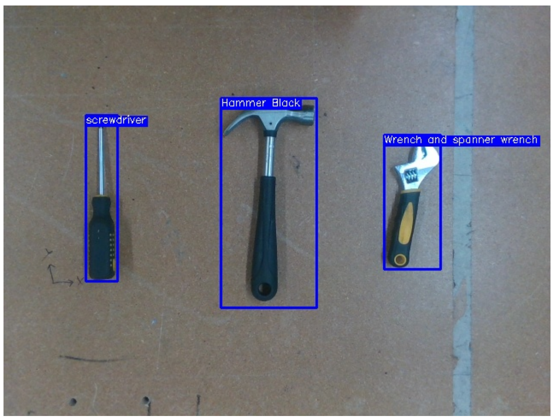
There were two methods considered for determining the tool end. The first method relied on intuition about the general geometry of mechanical tools. Typically, the tool end has sharp corners to interact with the environment and generate force and torque, while the handles are designed to be round and easy to grasp for maximum stability. Based on this intuition, we plotted points on a pixel with a sudden change in value to predict the tool end. However, corner detection has uncertainties due to pixel discontinuities and faulty recognition of corners towards the handle. Additionally, some tools have writings or spikes that provide friction to prevent slipping, making corner detection unsuitable for those kinds of tools.

To address the challenge of detecting the grasp location on mechanical tools with different tool end geometries, we propose a method that involves training a neural network to generate a mask for the optimal grasp location. However, given the wide variety of tool end geometries, it is difficult for a deep neural network to detect the grasp location for all types of tools universally. To overcome this challenge, we first gather a dataset that includes multiple tools and generate a hierarchical taxonomy of tools that groups similar tool end geometries. Fig. 8 provides an example of a taxonomy. Once the robot has determined the tool end, we sample the grasp along the tool end and determine the grasp location.

Our approach consists of the following steps:

1. *Searching for the Graspable Object*: When the human agent asks for a tool, the robot drives to the location where the tool is located. Then, the robot searches for the asked tool and determines the location of the tool. The procedure is shown in Fig. 7
2. *Feature Extraction for Tool End Detection* Once the robot recognizes the tool, the robot identifies the class it belongs to. For example, hammers and mallets would belong to the same class of impact tools with similar tool end geometries. Based on the taxonomy of tools, the model for that object class will detect the region of interest and return a mask that provides the graspable tool end region. The hierarchical taxonomy of tools enables a more straightforward determination of the most suitable grasp for that class of tools.
3. *Acquiring data about the workspace:* The in-hand camera can provide both RGB and depth information about the tool for processing the 2D image and depth image. With the acquired 2D image, we run the safe grasp region detection model to segment the support surface as well as the handle part from the object of interest.
4. *Point Cloud Data Processing*: After generating the mask, we project it on the depth information in order to filter the point cloud data. The filtered point cloud data represents only the tool end side of the graspable object, which is the region we are interested in generating a grasp. By employing this method, the robot can exclude the handle portion of the tool from grasp planning, thus ensuring that the handle is oriented towards the human during hand-off. By filtering out irrelevant data, the robot can focus on determining the optimal grasp location for the tool end.
5. *Grasp Location Selection*: Once we have the point cloud of the tool end, we use Grasp Pose Detection (GPD) to sample possible grasps. Typically, the planner generates grasp candidates around the tool, as it is designed to handle cluttered

(a) Base localization of the robot.




(b) Wrist camera's view of the workspace

**FIGURE 7**: Mobile Manipulator localizes the base and searches for the tool in the workspace. Trained model provides the label and the xy-coordinates of the tools.

grasps. Therefore, the robot needs to select a grasp that will not collide with the supporting surface of the object. Also, we had to consider offsets and some rotation to the sampled grasps because our gripper has a different tool center point from traditional 2-finger grippers. We aim to generate a robot grasp as close to the tool end as possible while achieving a moderately good grasp score. Fig. 9 depicts the entire pipeline.

## 6 HAND-OFF PLANNING

When retrieving a tool, uncertainties and challenges can arise during the pick-and-place operation and hand-off. Even with specialized grippers designed for picking up tools with irregular geometries and high moments of inertia, there may be unforeseen contingencies that must be addressed. Therefore, it is critical for a smart robotic assistant to be able to handle such contingencies and safely transport the tool to the human operator. Once a grasp location has been selected, the robotic manipulator must plan and execute a safe motion to reach the desired hand-off position. In addition, if the tool rotates within the robot's grasp, the robot must be able to quickly and accurately determine whether to continue with the motion or abort the plan and attempt a different grasp. To plan for a successful hand-off, we introduce the following steps:

1. *Pick Motion Plan Execution*: To execute the motion plan for the pick operation, the robotic arm needs to go through three poses: the pre-grasp, grasp, and post-grasp poses. Initially, the robot moves from its initial pose to the pre-grasp pose. These steps are critical because it allows the robot to position the end-effector near the tool without any collision with its geometry. Next, the robot approaches the tool at the proper location and closes the gripper to grasp the object. Since we are picking the object from a flat table in this example, the robot approaches it from the top. After approaching the object, the robot pauses for two to three seconds. This pause allows the vacuum on the soft fingertip to let the granular jamming finger conform to the shape of the tool correctly, ensuring a firm grasp on the object. Once the robot has a firm grasp on the object, it retreats in the opposite direction of the approach vector. The motion planning steps for the pick operation are illustrated in Fig. 10.
2. *In-hand Angle Detection*: To ensure the safety of human-robot interaction during tool hand-off, the robot must detect any potential tool rotation. To enable accurate detection of the tool angle during hand-off execution, the system utilizes an RGB camera mounted on the robot's base link to facilitate the detection process. If the angle exceeds a threshold of 45 degrees, the robot aborts the grasp. If the rotation is less than 45 degrees, the robot reorient the tool's handle towards the human.
   To accurately determine the angle of the tool while in the robot's hand, an angle detection algorithm is used on an RGB image. Initially, we considered a method of selecting a region of interest and drawing a bounding box around the tool using contour detection. However, this method has limitations due to the need for the robot to manually show the camera the tool's orientation and the potential for noise and background interference in the RGB image.
   To overcome these limitations, we train a deep neural network based on Mask RCNN using an image dataset [36] of the robot holding mechanical tools [37]. This approach provides a more robust mask on the region of interest, making angle detection more accurate. The size of the dataset is not critical to the accuracy of the model output, as only the orientation of the tool needs to be calculated. The entire process is illustrated in Fig. 11.
3. *Human Hand Gesture Recognition*: Preemptive releasing can lead to an unsafe handover, so the robot must confirm that the human has a firm grasp on the tool before open-

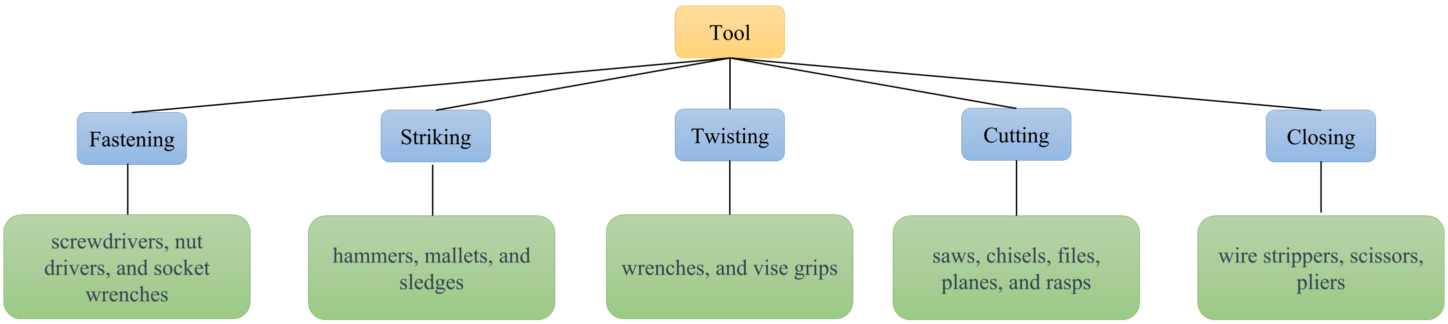



**FIGURE 8**: Example of taxonomy based on the geometry.

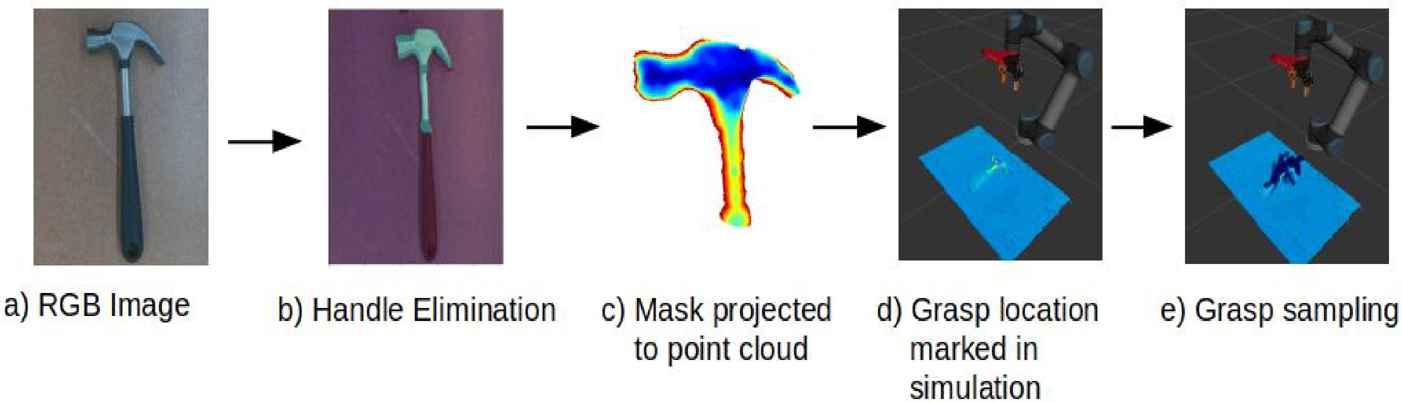



**FIGURE 9**: Diagram showing the sequence of steps taken to ensure safe grasp planning on the tool end of the hammer.

ing the gripper. To achieve this, we implemented a gesture recognition framework using an Oak-D camera to give the robot feedback on the human hands. Naturally, when a human grasps the tool, the hand is prone to make a fist. An example of the framework's execution is shown in Fig. 12. Then, the system recognizes the fist gesture to confirm that the human has grasped an object. The system reads the gesture for three seconds before releasing the gripper for a safe hand-off to prevent faulty detection. Furthermore, suppose the human collaborator believes that the robot performed a dangerous hand-off due to faulty tool end detection. In that case, the human agent can show open palms to signal a stop. The robot is equipped to detect this intervention and will place the tool back on the table, relearn the affordance of the tool, and replan the hand-off, thereby ensuring a safer handover.

## 7 RESULTS

The previous sections presented testing to confirm the robustness of each component of our proposed system. In this section, we describe our testing process of the full tool handover system. To validate a safe tool handover system, we conducted a comprehensive series of experiments on multiple objects. We prepared five sets of tools and ran 30 iterations on diverse tools to evaluate the percentage of safe handovers achieved. For a handover to be considered successful, it must have been completed without any collisions during the planning and execution phase, and the tool must have remained securely gripped by the robotic gripper without slipping. Additionally, the handle-end of the object must have been oriented correctly towards the human for the safety criteria to have been met. Finally, the robot should know when to let go of the tool, coordinating for optimal safe tool handover.

All 30 iterations of the handover met the safety criteria without any violations. The success of our system was partly attributed to the use of a specialized gripper designed for irregular objects, which prevented any in-hand rotation of the tool and eliminated the need for angle detection contingency handling. This ensured that the tool remained stable and secure during the handover process. Examples of grasps that occurred during the experiment are shown in Fig. 13, and the safe handover pipeline working on various tools is demonstrated in Fig. 14

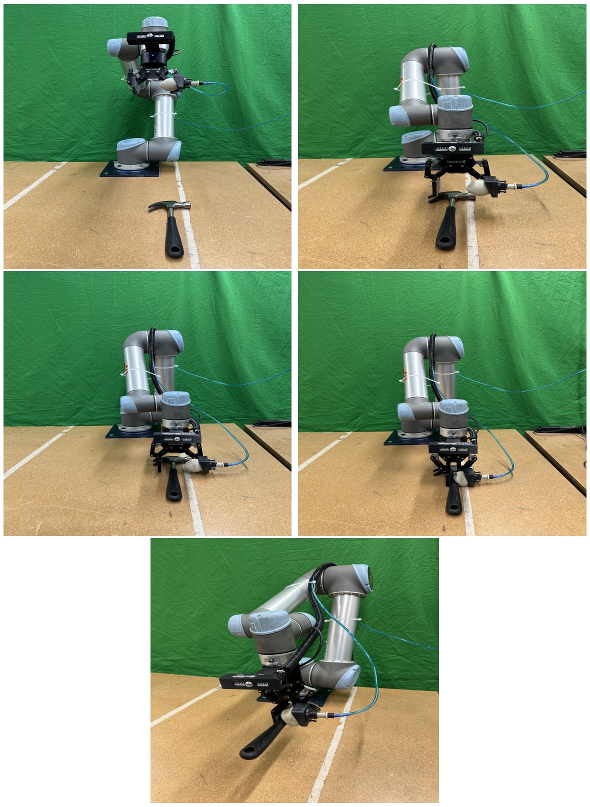


**FIGURE 10**: Sequential pick process which starts from the initial pose to the retreat position with tool in hand.

Our previous testing did not experience any failures, and we were unable to validate the contingency handling aspect of our approach. To address this, we introduce failures to validate the system's performance for different contingencies. We performed multiple real-robot case studies to test how effectively the system can handle contingencies and prevent unsafe situations. Overall, these tests allowed us to identify any weaknesses and refine our feedback system to ensure its reliability in preventing dangerous situations and providing effective assistance to users.

*Case 1.* The robot successfully grasps the object, yet results in in-hand rotation under the 45-degree threshold set by the system. Hence, the robot recognizes that it is a viable grasp for transport and hand-off but reorients the tool towards the human agent to ensure that the handle side is maximized towards the human for the safe hand-off. The remaining procedure is the same as before. Fig. 15. shows the demonstration of this case.

*Case 2.* The robot grasps the tool unsuccessfully, and the in-hand rotation is bigger than 45 degrees. In this case, the camera successfully captures the rotation angle and gives feedback to the planner that the robot should place the object back on


**FIGURE 11**: Mask generated from trained Mask RCNN.

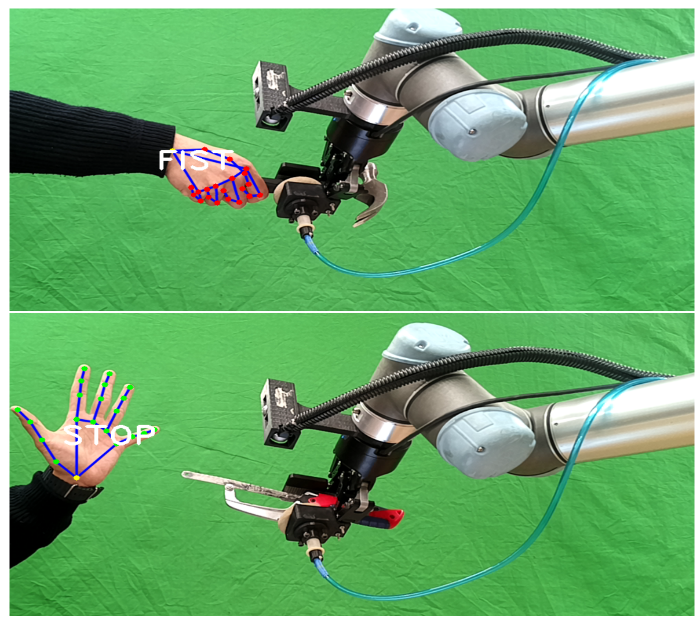



**FIGURE 12**: The system recognizes human gestures by detecting the fist for three seconds to confirm a firm grip on the tool, as shown in the top figure. The bottom figure shows the human intervention of the robot to stop the handover under dangerous circumstances.

the table and replan it for another grasp. Fig. 16. shows the demonstration of this case.

*Case 3.* Another contingency introduced to the system is the false detection of the tool end. We assumed the robot had grasped the tool by the handle or incurred collision while executing the motion plan. Then, the human shows the palm as an intervention, and the robot places the tool on the table. And the robot tries to detect the tool end and replans a safe grasp. Fig. 17. shows the

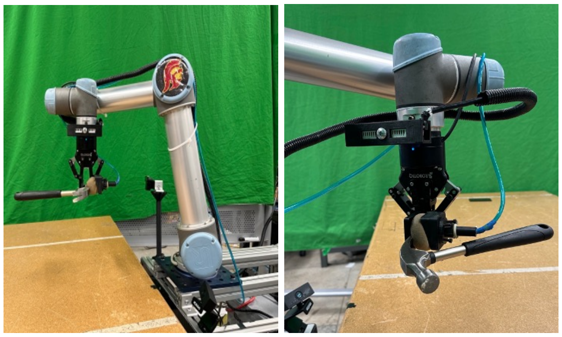


**FIGURE 13**: Examples of various hammer grasps generated from experiments.

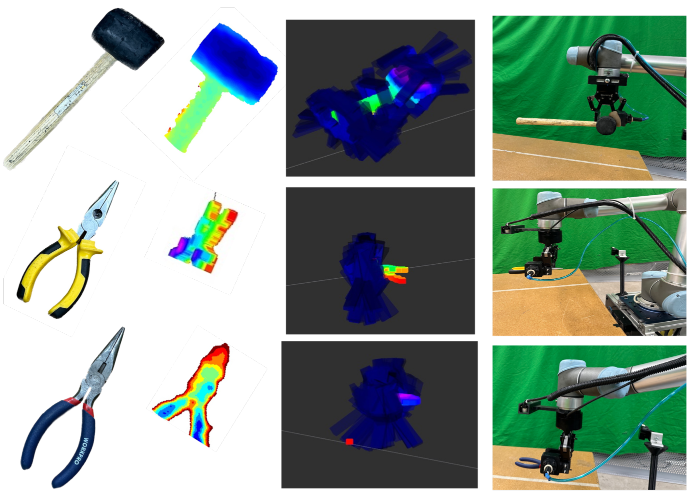


**FIGURE 14**: Handover pipeline working on various mechanical tools. It is worth noting that the mallet has a thick geometry and generates occlusion on the bottom part of the point cloud. Despite the occluded point cloud, the robot can still plan a secure grasp, ensuring a safe handover of the tool.

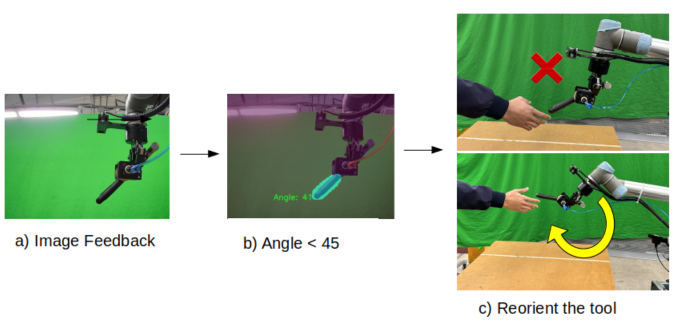



**FIGURE 15**: Demonstration of case 1. The robot reorients the tool if the in-hand angle is under 45 degrees.

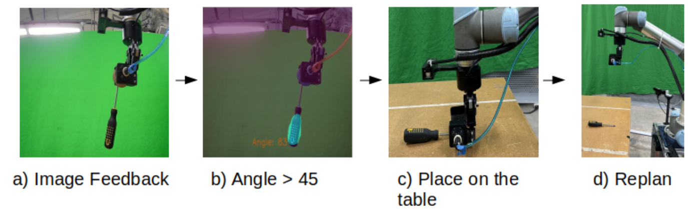



**FIGURE 16**: Demonstration of case 2. The robot puts down the tool and replans if the in-hand angle is over 45 degrees.

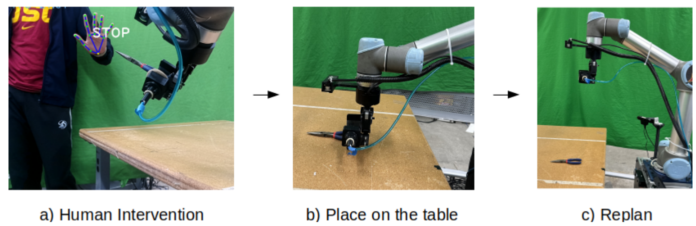



**FIGURE 17**: Demonstration of case 3. The robot puts down the tool and replans when the human collaborator intervenes.

demonstration of this case.

## 8 CONCLUSIONS

Our proposed system aims to enhance the safety of tool handover in manufacturing settings. We have designed the system to include essential components, including tool end detection, stable grasping, grasp stability feedback, and safe release of the tool. We have shown that a specialized hybrid gripper can safely and effectively pick up various tools by the tool end. The robot employs deep learning to detect the tool end and plan the grasp, thereby orienting the handle of the tool towards the human. Furthermore, our system incorporates vision feedback from cameras to ensure safe tool handover. We have demonstrated the system's ability to hand over a wide range of tools safely. Each component of the system effectively assists the robot in ensuring a secure handover process. We have also tested the system's capability to handle contingencies that could arise during the handover. Our results suggest the proposed system is a promising solution for safe human-robot collaboration in mechanical tool handover applications. However, we acknowledge that our system requires multiple models to detect tool ends of different tools. To address this issue, our future work will explore a universal tool end detector, ensuring safe handover for a wider variety of tools.

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