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Adaptive Tool-Use Strategies for Anthropomorphic Service Robots

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***Abstract*— Tool-use is one of the most complex object manipulation abilities of humans and robots. In this paper, we present strategies for implementing tool-use with anthropomorphic service robots. Based on the observation that human tools are specifically designed for the human body, we augment tools with handles that adapt the tool to the specifics of our robot. We develop methods for perceiving the tools and their end-effectors in RGB-D images. We also describe our control approaches used in our tool-use examples. We demonstrate tool-use by our service robot publicly at RoboCup@Home competitions, and report on the lessons learned through implementing such complex manipulation skills for our robot.**

I. INTRODUCTION

The use of tools is a complex object manipulation skill that necessitates a variety of perception as well as control capabilities. In this work, we detail our approaches to implementing several examples of tool-use with a mobile manipulation robot.

In our working definition of robotic tool-use, the robot manipulates an environmental object, i.e. the tool, to change the state of another object. To successfully operate the tool, the robot needs to know the pose of the tool as well as the pose of the affected object. It has to utilize the tool through adequate control strategies. The affected object can be attached to the environment or the robot can hold it with its other hand.

The range of tool-use tasks that can be handled by a robot clearly depends on the specifics of the robot hardware. Its kinematic structure defines the workspace of one or several end-effectors—and also the manipulation capabilities of the end-effectors which could be, e.g., parallel grippers or highly articulated hands.

The sensor equipment of a robot has additional significant impact on tool-use capabilities. For controlling the forces and torques exerted on objects, touch or force-torque sensors can be used to provide feedback. In order to pick up the tool and to perceive how it is positioned relative to the robot, visual sensors are useful.

In this work, we use a personal service robot with an anthropomorphic upper body. Our robot Cosero is equipped with two 7 degree-of-freedom (DoF) arms. The grippers are built from Festo FinGripper fingers that can be opened and closed on objects using rotary joints. The light-weight actuators in the arms and the grippers support position control. We perceive tools using an RGB-D camera mounted on the robot head.

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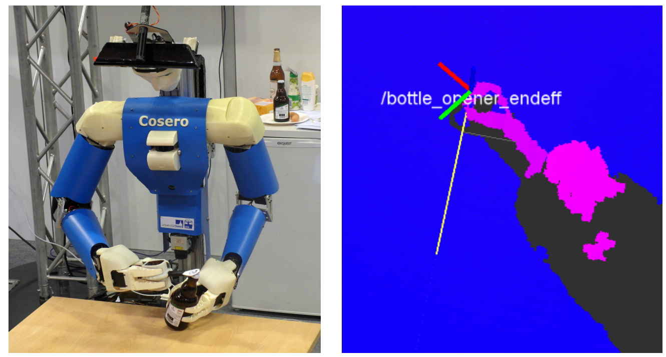

Fig. 1. Opening a bottle with a bottle opener tool. Our robot Cosero perceives the cap of the bottle and the tip of the tool (right).

For our robot, we implemented several examples of tool-use that integrate perception and control. Tools used by humans are specifically designed for the human body. Hence, we also propose to adapt the tools themselves to the robot body by equipping them with special handles that can provide the necessary stability for the grasp. We propose a variety of RGB-D perception approaches that allow for segmenting tools, estimating their tips, and tracking their pose. We also establish shape correspondences between similar tools to transfer tool-use skills from one tool to another.

II. RELATED WORK

In industrial robotics, robot end-effectors are specialized tools for performing tasks such as picking, welding, painting, etc. Typically, the motion of the robot is carefully scripted, and repeatability is based on the movement precision of the mechanism. Adaptation to small perturbations is often costly to implement, e.g., to treat material variations or to control the quality of a weld. Special sensors and perception methods are used that need to be tightly integrated with the motion control of the robot. The tool is specifically designed and rigidly attached to the robot in order to precisely know the tool position on the robot. Tool changers allow the robot to exchange the tool during a task, but such tool changers are carefully designed to provide the precision of a rigidly attached tool.

In our scenario, such a precise attachment is not possible. We aim at a multi-purpose robot that can work on a variety of tasks with its arms and grippers that not only involve tool-use. The resulting imprecision needs to be handled through perception and control of the tool. Furthermore, the workspace is not limited at a single place, but the tasks require mobility between locations, e.g., in a home environment. Hence, the robot also needs perception and control methods to align towards the objects that are relevant to a task.

Kemp and Edsinger [1] observe that many tools used by humans share the common feature that the tool end-effector is at the tip of a prominent, elongated structure. The authors detect and estimate the tool tip location relative to the robot gripper. The robot moves the tool in its hand in front of its RGB camera. Initial hypotheses about the location of the tool-tip are found in edges with largest optical flow. The hypotheses are accumulated in a multi-scale voting process to find position and extent of the tool tip. To use the tool, the robot kinematics is extended with the estimated 3D location of the tool tip, and the tip is visually servoed. The authors demonstrate that the tip of tools such as bottles or feather dusters can be estimated and that the tips can be controlled in the image. Our work also includes tool tip perception and control and integrates these into tool-use behavior. For grasping tools in a purposeful way, we propose to perceive the tools in RGB-D images using 3D models of the objects.

Kresse et al. [2] propose RGB-D perception approaches that analyze the position, orientation, and other geometric features of more complex tools such as a spatula or a spoon. Such features may include the edges of a spatula or the lowest position and upward orientation of the concavity in a spoon. Kinematic controllers align these features with the affected object. In addition, the impact of the tool with the affected object is detected. To this end, observation models are trained from time-series data of joint-torque sensors in the robot fingers. Kresse et al. report on results for visual inspection, impact estimation, and tool alignment. Grasping the tool or how to adapt the tool to the robot kinematics is not detailed as in our work.

Within the DARPA ARM program, Hoffmann et al. [3] developed tool-use of a drill and a pencil. For compensating the uncertain grasp posture of the tool in the hand of the robot, their approach visually inspects the tool to find its tip. The visual perception method segments the tool coarsely from the background in 3D using dense stereo-reconstructed depth. The segmentation is refined based on contours in the stereo images using a level-set method. The farthest point within the segment from the robot hand is interpreted as the tool tip. For using a pencil, a model of the tactile feedback desired during the task is trained. The robot is controlled to reproduce the feedback. While we also devise means to detect the tip of tools, we investigate perception for grasping tools and bimanual tool-use strategies.

Some approaches also learn the function of tools, i.e. their affordances. Nishide et al. [4] link the visual appearance of a tool with the observed dynamics during tool motion using recurrent neural networks. The trained models are used to recognize tool function and to reproduce motions with the tools. The tools in this work are I-, L-, and T-shaped hooks. Stoytchev [5] considers similar tools and learns their effect on objects through exploration. The effect of actions for each tool is maintained in affordance tables. Once trained, the robot is demonstrated to extend its reach with the tools to move an object on a surface. Tikhanoff et al. [6] also let a humanoid iCub robot move tools in front of its cameras to perceive the tool tip. The robot learns the effects of the tools on objects through exploration. In this work, also I-, L-, and T-shaped tools are employed. Instead of the learning of affordances, our work focusses on perception and control strategies to implement the use of complex tools in single and dual-arm tasks.

Fig. 2. The cognitive service robot *Cosero*. Left: Cosero hands over an object during RoboCup German Open 2014. Right: Cosero grasps a bottle.

Our approach to tool-use skill transfer can be seen as a variant of learning from demonstration. Recently, Schulman et al. [7] proposed an approach in which motion trajectories are transferred between shape variants of objects. They primarily demonstrate tying knots in rope and suturing, but also show examples for folding shirts, picking up plates, and opening a bottle. Their non-rigid registration method is a variant of the thin plate spline robust point matching (TPS-RPM) algorithm. We develop an efficient deformable registration method based on the coherent point drift method (CPD [8]) to align RGB-D images efficiently and accurately. We demonstrate bimanual tool-use, and propose to select tool end-effectors as reference frames for the example trajectory where it is appropriate. Grasp poses and tool end-effector frames are transformed between example and new object.

III. SYSTEM OVERVIEW

A. Robot Hardware

We designed our service robot Cosero [9] to cover a wide range of tasks in indoor environments (see Fig. 2). It has been equipped with a flexible torso and two anthropomorphic arms that provide human-like reach. A linear actuator moves the whole upper body up and down, allowing the robot to grasp objects from a wide range of heights—even from the floor. Its anthropomorphic upper body is mounted on a base with narrow footprint and omnidirectional driving capabilities. By this, the robot can maneuver through narrow passages that are typically found in indoor environments, and it is not limited in its mobile manipulation capabilities by holonomic constraints. The human-like appearance of our robots also supports intuitive interaction of human users with the robot.

The grippers of our robot consist of two pairs of Festo FinGripper fingers on rotary joints (see Fig. 2). The fingers are made from lightweight, deformable plastics material. When the gripper is closed on an object, the bionic fin ray structure adapts the finger shape to the object surface. By

Fig. 3. Object pose tracking. We train multi-view 3D models of objects using multi-resolution surfel maps. We estimate the pose of objects in RGB-D images through real-time registration towards the model. We apply object tracking, for instance, to track the model (upper right) of a watering can for approaching and grasping it.

this, the contact surface between fingers and object increases significantly, compared to a rigid mechanical structure. A thin layer of anti-skidding material on the fingers establishes a robust grip on objects. Having two fingers on each side of the gripper supports grasps stable for torques in the direction of the fingers and for forces in the direction between opponent fingers.

For perceiving its environment, we equipped the robot with multimodal sensors. Multiple laser scanners on the ground, on top of the mobile base, and in the torso measure objects, persons, or obstacles for navigation purposes. We use a Microsoft Kinect RGB-D camera in the head to perceive objects and persons in 3D.

B. Mobile Manipulation

1) Motion Control: We implemented omnidirectional driving for the mobile base of our robots. We control the 7-DoF arms using differential inverse kinematics with redundancy resolution. The arms also support compliant control in task-space [10].

2) Navigation: Our robots navigate in indoor environments on horizontal surfaces using a 2D laser scanner on the mobile base as main sensor. We acquire 2D occupancy maps of the environment using simultaneous localization and mapping (gMapping, [11]). The robots localize in these 2D maps using Monte Carlo localization [12]. They navigate to goal poses by planning obstacle-free paths in the environment map, extracting waypoints, and following them. For obstacle-free driving, we incorporate 3D measurements of the laser range sensors in ego-centric obstacle grid maps. Efficient local planning finds steering commands in these maps that implement safe driving on planned paths.

3) Scene Segmentation: A basic building block for mobile manipulation is scene segmentation into support planes and objects on these surfaces. Our plane segmentation algorithm rapidly estimates normals from the depth images of the RGB-D camera and fits a horizontal plane through the point cloud using these normals through RANSAC. All points above the plane are classified as potentially belonging to objects. The remaining points are segmented by Euclidean distance, subsuming all points within the same segment that are within a range threshold.

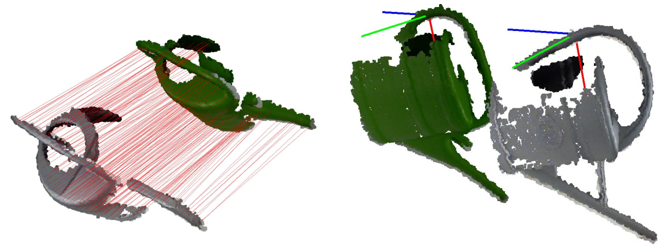

Fig. 4. We estimate shape correspondences (left) and local transformations (right) between objects using deformable registration.

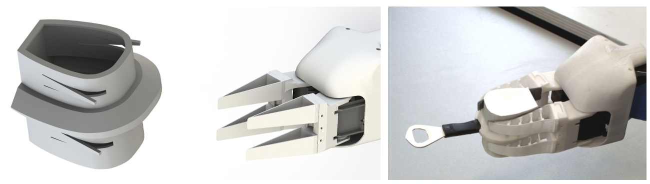

Fig. 5. Tool Adapters. We designed special adapters for tools to establish stable grasps that resist forces and torques in any direction. Left: Adapter. Center: Gripper design. Right: Grasp on the bottle opener.

4) 6-DoF Object Tracking: We track objects using multi-resolution surfel maps (MRSMaps, [13]). Fig. 3 illustrates our tracking approach with an example.

In MRSMaps, RGB-D measurements are represented in an octree in which the voxels store the Gaussian distribution of the points falling into the voxel. In addition to shape, we also model the distribution of color. The maps allow for storing RGB-D measurements from multiple view points which enables the modeling of objects. Such object models are acquired with a view-based SLAM approach.

Our MRSMaps also come with an efficient RGB-D registration method which we use for tracking the pose of objects in RGB-D images. The pose of the tracker can be initialized to a rough estimate using our planar segmentation approach.

5) Deformable Registration: We propose a multi-resolution extension to the coherent point drift (CPD [8]) method to efficiently perform deformable registration between dense RGB-D point clouds (see Fig. 4, left). Instead of processing the dense point clouds of the RGB-D images directly with CPD, we utilize MRSMaps to perform deformable registration on a compressed measurement representation. The method recovers a smooth displacement field which maps the surface points between both point clouds. It can be used to establish shape correspondences between a partial view on an object in a current image and a MRSMap object model. From the displacement field, the local frame transformation (i.e., 6-DoF rotation and translation) at a point on the deformed surface can be estimated. By this, we can determine, how poses such as grasps or tool end-effectors change by the deformation between objects. Further details on our deformable registration method can be found in [14].

IV. TOOL-USE STRATEGIES

A. Tool Adapters

For a firm grip on tools, we designed 3D-printed tool adapters matching the four-finger grippers of Cosero (Fig. 5).

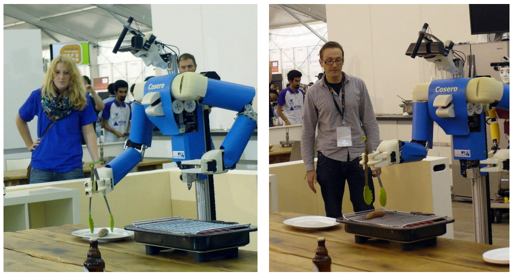

Fig. 6. Grasping sausages from a barbecue with a pair of tongs. Our robot Cosero perceives position and orientation of the sausages in RGB-D images.

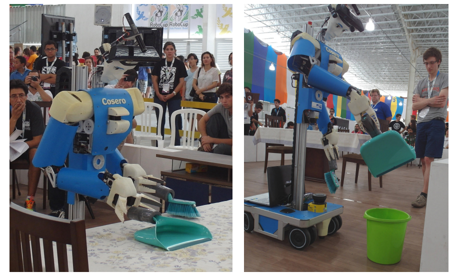

Fig. 7. Sweeping dust using a pan and a brush. Our robot Cosero estimates the pose of the dust pan and the brush to grasp them (left). It pours the content of the dust pan into a dust bin (right).

When the gripper closes on the adapter, the fingers bend around the shape of the adapter and establish form closure. The ridge on the center of the adapter fits into the space between the fingers. It fixates the adapter for exerting torques in pitch direction. For some tools such as pairs of tongs, the opening of the gripper is also used to operate the tool. To create form closure with the fingers at various opening angles, the adapters have flat springs for each finger.

B. Using a Pair of Tongs

When grasping sausages from a barbecue, the robot should not directly grasp with its grippers. Instead it should use an adequate tool to keep the food clean and to keep the grippers clear of the hot barbecue (see Fig. 6).

We segment the sausages from a plate or the barbecue using plane segmentation and adapt the grasping motion to the position and orientation of the sausages. We exploit that the height of the barbecue or the plates on the plane is known and discard points of these support objects. The remaining points are clustered by Euclidean distance. We then estimate the principal axes of the segments and compare length (first principal axis) and width (second principal axis) with the expected size of the sausages. If these measures are within specific ranges, the segment is classified as a sausage. Position and orientation of the sausage are directly obtained from the mean and principal axes of the segment points.

In this task, the perception of the tip of the tongs is not required. We observed that the passive positioning through the interface between the tool adapter and the robot gripper provides sufficient accuracy.

A parametrized motion primitive uses position and orientation of the closest sausage to pick it up with the tongs. The robot holds the tool above the table, and the objects on the table at all times during the demonstrations, such that collisions with these objects are avoided.

Further steps are necessary to fully implement the demonstration of picking up sausages from one location such as the plate and placing it at another one, e.g., on the barbecue. Before approaching the objects in an accurate way, the robot drives roughly in front of the known location of the objects. This is either implemented using navigation in an allocentric map of the environment, or by relative driving from one object to the next along the table.

For accurate alignment, the robot detects the barbecue or the plate that it needs to approach using plane segmentation in the RGB-D camera. During the alignment it tracks the objects in real-time, for which we implemented two alternative methods. The first method is to track the mean position of the object segments. We also support the tracking of the 6-DoF pose of objects using multi-resolution surfel maps, if the robot needs to orient itself directly towards the object.

C. Sweeping Up Dust

For sweeping up dust with a brush and a pan, the robot manipulates two tools simultaneously. Both objects have to be moved in a purposeful way to sweep the dust onto the pan: the pan is being moved under the dust, while the brush sweeps the dust. For grasping the tools, the robot approaches dust brush and pan on a horizontal surface. It registers MRSMap object models to the segments of the objects and executes predefined grasps relative to the objects. Before sweeping the dust up, we position the mobile base towards the dust, such that it is reachable with the tools. The heap of dust could be tracked in various ways. We implemented tracking with a 2D laser range scanner that is mounted on our robot shortly above the floor. As soon as the dust is at a predefined location, both arms perform a synchronized sweeping motion.

D. Bottle Opening

Opening a capped bottle with a bottle-opening tool is challenging, since the opening tool must be accurately placed onto the cap. Simple open-loop control is not feasible for this task due to several sources of imprecisions. Firstly, an exact calibration between the robot sensors and end effector may not be known. Also, the pose of the tool in the gripper or the manipulated object cannot be assumed to be known precisely. We therefore implemented perception of the tips of the tool and the manipulated object using the head-mounted RGB-D camera (see Fig. 1). During manipulation, our robot looks at the tool and the manipulated object, segments the objects from the surrounding using our efficient segmentation method (see Sec. III-B.3), and detects the endings of the objects in the segments.

We detect the tip of the opening tool in-hand by segmenting points in the depth image from the planar background. We select the segment closest to the position of the robot gripper and track for the farthest position from the gripper along its forward direction. The cap of the bottle in the other

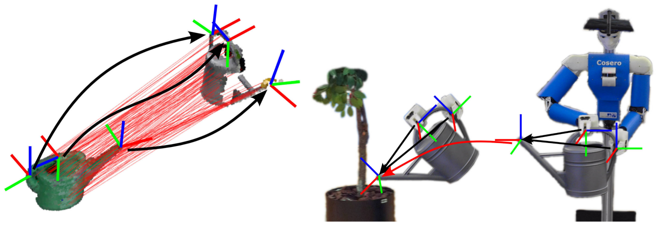

Fig. 8. Tool-use skill transfer. The skill is described by grasp poses and motions of the tool end-effector relative to the affected object. Once these poses are known for a new instance of a tool, the skill can be transferred.

gripper is found in a similar way: within the segment closest to the gripper, we search for the highest point. Since we know the size of the opening tool and the bottle, we can verify the found positions using position intervals. This also allows for identifying, if the bottle-opening motion succeeded, or if the bottle has already been opened before.

For opening the bottle, the robot first grasps the bottle and the tool with its both arms. It holds both objects close to each other above a horizontal surface. In order to stabilize the motion of the bottle, it touches the horizontal surface with its bottom. The robot perceives the tip of the tool and the cap of the bottle and determines the final approach motion from the difference between the detected positions.

E. Watering Plants

For watering a plant with a watering can, our robot controls the motion of the can with two arms (see Fig. 9). For grasping a previously known watering can, the robot approaches the can using 6-DoF object tracking and grasps the can at predefined poses. Water is poured into a plant by moving the tool end-effector in a predetermined way through synchronized motion of the arms.

Preprogramming such a tool-use skill for every shape variation of watering cans is not desirable. We propose to use our deformable registration method to transfer the skill for a specific shape instance to different cans. The skill of using the watering can is described by grasp poses relative to the object surface and motion trajectories of the can spout (see Fig. 8). To transfer this skill to a new variant of cans, we segment the new can from its support plane and establish shape correspondences to the object model of the known can. We estimate local frame transformations of the grasp poses and the tool end-effector of the known can towards the observed can. The robot executes the transformed grasps to pick up the new can. For watering a plant, the robot moves the can end-effector frame relative to the plant in the same way as for the modeled can. This constrains the motion of the arms to keep the relative position of the transformed grasp poses to the transformed tool end-effector pose.

V. RESULTS

We publicly demonstrated tool-use skill transfer based on our deformable registration approach during the Open Challenge at RoboCup 2013 in Eindhoven, Netherlands. The jury chose one of two unknown cans, while the skill was pretrained for a third instance of cans. Cosero successfully transferred the tool-use skill and executed it.

The grasping of sausages with a pair of tongs has been publicly demonstrated during the finals of RoboCup 2013 in Eindhoven, Netherlands, and RoboCup German Open 2014 in Magdeburg, Germany. In Eindhoven, Cosero received the tongs through object hand-over from a team member. The robot coarsely drove behind the barbecue that was placed on a table by navigating in the environment map. It tracked the 6-DoF pose of the barbecue using MRSMaps to accurately position itself relative to the barbecue. Cosero drove to the right along the table to approach a plate with two raw sausages. It picked one of the sausages with the tongs (Sec. IV-B) and drove back to the barbecue, on which it placed the sausages with the tool.

While the sausage was grilled, Cosero handed the tongs back to fetch and open a beer. It drove to a shelf with the bottle opener tool and grasped it. With the tool in hand, it drove to the place of the beer bottle and grasped it with the other hand from a table. It approached the table and executed the bottle opening skill described in Sec. IV-D. Note that the bottle has been used before such that the cap was slightly loosened but still locked onto the bottle. It placed the bottle opener on the table and delivered the beer to a jury member. Afterwards, it received the tongs again. Cosero drove back to the barbecue to grasp the sausage and to place it on a clean plate which was placed left of the barbecue. This part of the demonstration could not be finished within the 10 min duration allotted to the finals.

In the finals of German Open 2014, Cosero repeated the use of the tongs and the bottle opener. This time, we put the sausage on the grill in advance such that the task of Cosero was to pick it from the barbecue and place it on a plate which was located on a tray. The sausage was brought to one of the jury members on the tray. Before picking the sausage from the barbecue and delivering it, Cosero opened a bottle of beer with the bottle opener tool, which it also kindly delivered. Opening the bottle was also part of the Open Challenge demonstration at RoboCup 2014 in Brazil.

In the finals at RoboCup 2014, Cosero also performed the sweeping of dust. It grasped a dust pan and a brush in order to clean some dirt from the floor using the approach in Sec. IV-C. Unfortunately, the dirt detection failed. The robot executed the cleaning motion and continued by pouring out the contents of the dust pan into the dust bin. It placed the tools back on a table and continued with the next part of the demonstration.

The demonstrations convinced the juries which consisted of team leaders, members of the executive committee of the league, and representatives of the media, science, and industry. Our team won the competitions of RoboCup 2013 in Eindhoven and German Open 2014 in Magdeburg, continuing our series of first places at international and German RoboCup competitions since 2011.

Fig. 9. Watering a plant. We specified bimanual grasp poses, the can end-effector, and the motion of the end-effector for watering a plant with a specific instance of cans. To transfer this skill to new cans, Cosero uses deformable registration to efficiently align the can in its current RGB-D image with the known can. Based on the shape correspondences, Cosero transfers grasp poses and tool end-effector motion to the new can.

VI. CONCLUSIONS AND LESSONS LEARNED

In this paper, we detailed our approaches to tool-use by an anthropomorphic service robot. We developed various perception and control methods to implement several examples of tool-use.

We proposed perception methods that we use as building blocks for tool-use. We segment scenes at high frame-rate into support surfaces and objects. To pick up tools with specific grasp poses, we align RGB-D measurements on the object with a 3D model using multi-resolution surfel maps (MRSMaps). Within the depth image, we find the tip of a tool by exploiting prior knowledge how the tool was grasped. Through deformable registration of MRSMaps, we transfer tool-use skills to differently shaped instances of the same category of tools.

Our perception methods can be flexibly used in a variety of tool-use scenarios. Clearly, there is plenty of research ahead to eventually reach human-level performance in this task. Perception clearly depends on the sensors used. The RGB-D sensors used so far are limited in measurement quality with respect to depth noise, resolution, and quantization, which influences the type of perceivable tools. Touch and force-torque sensing would provide complementary information on the interface between the robot and the tool, or the tool and the affected object. Such sensing would also allow for capturing dynamical properties of the task. The modeling and perception of physical properties such as weight, stability, friction, and elasticities would increase the range of possible tool-use tasks. While not necessary for many tool-use tasks, the perception of the internal state of objects, e.g., the fluid level in a bottle, can also be useful.

An interesting insight is that robots can be supplied with tools that are designed for their robot body instead of the human one. Clearly, the difference between the tools may disappear with the approximation of robot hardware capabilities to those of the human body. One aspect that needs to be considered in more detail in future work is how to bring the tool into a purposeful posture within the gripper. To this end, regrasping strategies could be tightly integrated with the perception of the tool in-hand.

An open research question is how to best describe tool-use skills and objects, such that this knowledge can be used as prior experience for the use of different types of tools. Closely related also is how robots can learn and improve such tool-use knowledge from own experience.

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