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Teaching Robots the Use of Human Tools from Demonstration with Non-Dexterous End-Effectors

Wenbin Li and Mario Fritz

Abstract— **Commercial, affordable and general-purpose robots like the PR-2, Baxter and UBR-1 robots can take over a wide range of tasks or assist human workers in a mixed human-robot environment. However, end-effectors on these robots are usually restricted to low-cost, non-dexterous grippers which constrains the application scenarios. We aim at increasing their range by teaching such robots the use of human tools by demonstration. We present a novel and compact model for the use of human tools and propose a dual-gripper strategy in replacement of the much less widely deployed dexterous hand for tool manipulation. Especially, we propose a hierarchical architecture to embed tool use in a learning from demonstration framework, learning temporal order for dual-arm coordination at higher level and Dynamic Movement Primitives at lower level for a multi-step execution. The approach is demonstrated and evaluated on a Baxter research robot for three human tools.**

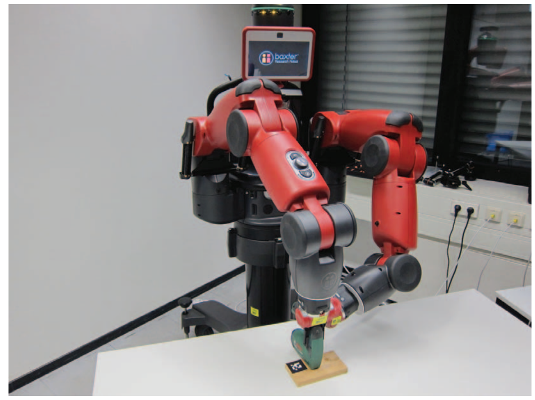

Fig. 1: Example of manipulating a human tool: Our approach enables the Baxter research robot to use an electric tacker.

I. INTRODUCTION

Humans use tools to extend their reach, to amplify their physical strength, and achieve many daily tasks, making tool use a very important aspect of human life. Being able to use tools is generally interpreted as a sign of intelligence. In contrast, even with the advent of commercial, affordable, general purpose robots, that start to penetrate human work places, their use cases are often restricted to simpler activities like pick-and-place actions. On the other hand, industrial robots use highly customized tools for much more sophisticated tasks like welding, cutting and painting and generally require experts to carefully script each step of a fixed procedure. We aim at narrowing this gap by exploring the possibility to teach affordable, general-purpose robots to use human tools in an easy way.

We envision a system that allows the end-users to intuitively and easily teach robots, which is key in facilitating wide spread deployment of robots into real world application. We approach this challenge by the *Learning from Demonstration (LfD)* framework [1], [2]: the robotic system observes a teacher's demonstration, automatically derives a representation of the activity and applies them to novel situation afterwards. One of the challenges of applying LfD to learning tool use is that manipulating a tool is generally a multiple-step process. It is non-trivial to separate the individual steps and properly model the stepwise operation. Building on recent work of *Dynamic Movement Primitives (DMPs)* [3], [4], we propose a formulation to embed tool use in a Learning from Demonstration framework.

Following the LfD framework, we need to encode the interaction patterns between the tools and human hands and transfer them to the robot's end-effectors. Dexterous hands featured on robots such as Honda's Asimo and NASA's Robonaut could follow this approach, since little changes are required to transfer the interaction pattern. Yet the hardware cost and limited deployment of these robots makes this approach less accessible. In contrast, the mechanical grippers equipped on low-cost robots are much more affordable and more widely deployed. Hence, we explore a strategy of utilizing dual-grippers to replace the dexterous hand for tool manipulation. We believe that this approach will significantly increase the range of tasks that can be performed by today's most widely deployed general purpose robots.

In the following, we first review related work about tool use and tool use in robotics and LfD and its applications. Then we discuss our novel approach to modeling tool use and express it in a LfD framework. We test and evaluate our approach on a Baxter research robot by learning and using three tools.

II. RELATED WORK

Early work on tool use in animals can be found in the work by Beck [5]. Yet until recently, there are few studies of autonomous robotic tool use. In [6], a behavior-grounded approach is proposed for tool representation by connecting the tool's affordance with feasible exploratory behaviors. While the idea is appealing, it is only tested in a simplified setting, i.e. like scoring with a hockey puck and different shapes of sticks. Kemp and Edsinger [7] address the modeling of the tool's tip as the task relevant feature. Later work [8] from the same group combines tip detection and tracking to model tool use, and test it on a brushing

Max Planck Institute for Informatics, Saarbruecken, Saarland, Germany {wenbinli,mfritz}@mpi-inf.mpg.de

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task. However, there are clearly more circumstances where the procedures of tool use are beyond the pure movement of tool tip including examples, like screwdriver and hot-glue gun used for tip detection in [7]. Our tool use model works with the similar type of tools and can tackle more complex instances by only using non-dexterous grippers.

There is a large body of work on LfD to program robots. Contrary to traditional approaches to robot control with domain dynamics and mathematically derived policies, LfD typically acquires the polices from demonstration, opening the policy development to non-robotics-experts. An overview of the topic can be found in [1], [2]. Among many approaches in LfD, DMPs [3] for motor skill learning is widely used due to its compactness and efficiency. Most related to our work, [9] demonstrated how to learn to pour water using DMPs and in [10] a variant of HMM and DMPs are applied for LfD to assembling an Ikea table. Our work also builds on a DMP formulation and explores extensions to model tool use.

Learning complex tasks with a single policy can be challenging. A common approach to handle this issue is to segment the complex task into multiple simpler sub-tasks where each sub-task can then be formulated in a established LfD framework. While it is appealing to automate the segmentation process and a number of attempts have been made towards this direction [11] [12] [13] [14], the unsupervised nature of these proposed methods cannot guarantee they will spot the exactly transition states which are often crucial to structured complex tasks. Hence in our work, we align different sub-tasks with the activation states' changes between the robot' arms and model each sub-task in a DMPs framework.

A line of relevant work are described in [15] [16] where the authors segmented tasks with Semantic Event Chain (SEC) by touching-nontouching relation. It is similar to our tool-tip model to decompose tool-use process by contact states, yet we aligned this with states' change between the dual-arm coordination, and together we present a efficient strategy for robot with dual-gripper to use human tools over dexterous hand.

III. METHODOLOGY

A. Compact Modeling of Human Tools

While there are various kinds of common tools, a large body of them can be characterized by interaction patterns between the world and a tool tip [17], [7]. The general process to operate such tools can be decomposed into three stages, including preparation, interaction and returning to standby as illustrated in Figure 2. In the *preparation* stage, the tool is moved to align the *tip* and the *action point* on the object. In the interaction stage, the tip of tool makes contact with the action point, triggering related mechanisms with respect to the functions of different tools. In the returning to standby stage, the tool tip is detached from the action point. This decomposition is consistent with the widely used definition of tool use from Beck [5], for example the preparation stage includes the requirement that "user is responsible for the proper and effective orientation of the tool" and the interaction stage is a compact representation for this type of tools as "an unattached environmental object to alter more efficiently the form, position, or condition of another object, another organism...".

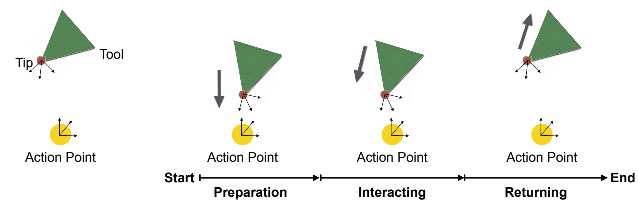


Fig. 2: Illustration of our tool-tip modeling where it decompose the process into three stages: preparation, interacting and returning. The arrow sketches the moving direction of the tool tip.

B. Robot Manipulation of Human Tools

Although industrial robots use tools, those tools are in general highly customized and the operating procedure is typically carefully scripted and fixed. There are various issues making programming a robot to manipulate human tools very challenging: (1) as discussed in related work, the process of manipulating a tool often goes beyond a single primitive movement. To construct a complete model for tool use, one approach is to apply the model-based approach built on the tool's affordance. Yet the modeling of affordance itself is non-trivial and often such modeling relies on the perception of the tool where the uncertainty of perception could bring about additional difficulties. (2) the design of human tools are usually optimized for human hands which are extremely dexterous. The most straightforward way to transfer the operating manner from human to robot would be a close and complete mapping of finger-palm movement to a dexterous hand end-effector on a robot like the NASA robonaut (Figure 3). Nevertheless such end-effectors are extremely expensive and not widely deployed to date.

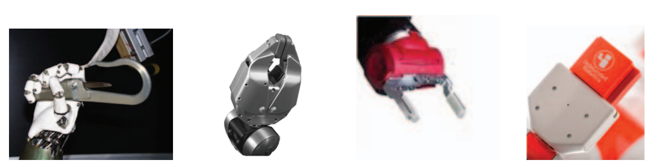


Fig. 3: End-effectors on different robots, from left to right: dexterous hand on NASA's robonaut, PR2's jaw gripper, Baxter's parallel plate gripper and UBR1 parallel jaw gripper

To cope with the aforementioned issues, we make carefully design choice for our method as follows:

1) Model-free Approach for Tool Use: Unlike the tool-specific affordance modeling as in the model-based approaches, we turn to a general, tool-agnostic paradigm for tool use modeling. With our tool-tip model, the action point P and the state of the tip T are tracked. Note we do not actually track the tip of the tool as in [7] but the end-effector with the tool under the assumption that the tool is held firmly by the end-effector with the same configuration. Hence the process of using a tool X is represented as sequence of state changes in time:

$$\text{ToolUse}_X := \{P, T\}_t$$

where t denotes time stamp for each state, P for the pose of the action point, T for the state of the end-effector, including the pose and other information like the closure of the gripper depending on the type of the end-effector.

2) Dual-Gripper Coordination for Complex Manipulation: With the rapid development in robotics, there is a trend that has supplied affordable robots to industry and research communities. Typical examples like the PR-2, Baxter and UBR-1 robot are equipped with reasonably low-cost grippers as shown in Figure 3. Although the much more expensive dexterous robot hands offer more flexibility, we can actually decouple the manipulation primitives and propose to achieve the complete operation using two arms with simple, non-dexterous grippers, i.e. with one gripper to hold the tool and the other to do additional operations, like pushing button. One such example is shown in Figure 4. Note that this can introduce additional step in the preparation phase like in the case of the electric tacker in Figure 4. While the first end-effector is holding the tacker, the second end-effector needs extra alignment step in order to finish the preparation stage.

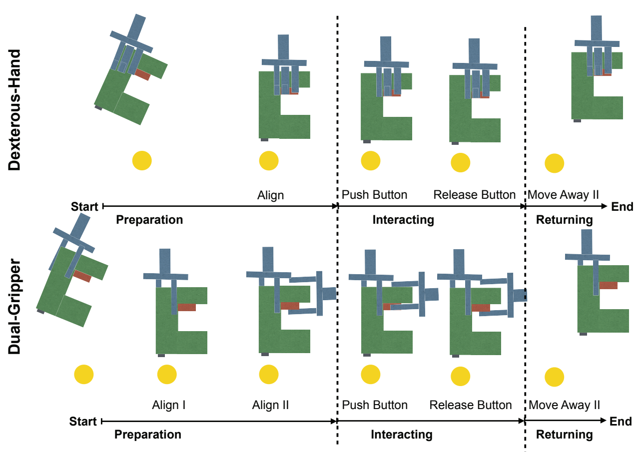


Fig. 4: Example of manipulating an electric tacker with dexterous hand and a dual-gripper.

Similar to the required coordination of different fingers in the dexterous hand system, the dual-gripper also needs proper coordination. This coordination reflects the temporal order in manipulations between different grippers which is essential to tool use and is typically asymmetric as discussed in [18], [19]. Yet explicit condition/event modeling as in [19] is not needed in our approach, as the temporal order between the two gripper can be included in the model-free formulation by replacing the single end-effector T with the gripper pair T_1, T_2. Hence we formalize the overall process as:

$$\text{Tool Use}_X := \{P, T_1, T_2\}_t$$

C. Learning Tool Use from Demonstration

We apply a hierarchical architecture to embed tool use in a learning from demonstration framework: on a higher level, temporal order for dual-arm coordination is learned and on the lower level, primitives are learned by constructing DMPs from exemplars. The pipeline is shown in Figure 5.

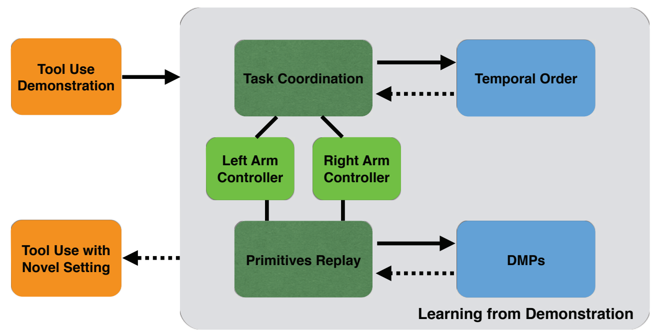


Fig. 5: Overview of our approach. The solid arrow denotes the learning process from demonstration while the dashed arrow for the process of replaying on novel task.

1) Temporal Segmentation for Manipulation Primitives: We teach the robot to learn the use of tools from kinesthetic demonstration, i.e. the teacher physically moves the robot's arm to perform manipulation as shown in Figure 6. In addition to the state of end-effectors T_1, T_2 and action point P, we track the activation state of each arm as S_1, S_2 respectively. The activated periods for each S_1, S_2 naturally segment the whole process into *Manipulation Primitive (MP)*:

$$\text{MP}_{S_i, \tau}, i \in \{1, 2\}$$

where τ denotes the temporal interval of the corresponded activated period for MP. S_1, S_2 together encode the temporal order of manipulative primitives between two arms. We assume only one arm is activated at a time. An example is shown in Figure 7. The MPs are in line with our tool use model shown in Figure 2 except for the part of additional alignment step introduced by the dual-gripper design.

2) DMPs for Manipulation Primitives: Dynamic Movement Primitives (DMPs) [3] describe the evolution of dynamical systems over time using a system of non-linear differential equations. In general it is nontrivial to represent the whole tool use process with a single DMP since it involves muti-stage operations, each with a distinct contraint between the stage-transition, yet we can encode the Manipulation Primitive at each stage with a DMP. In our study, we are only interested in the formulation for discrete movements

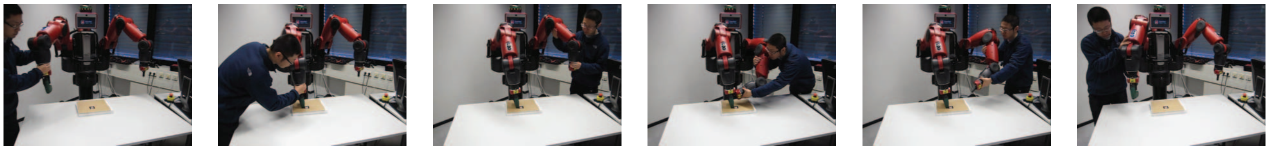


Fig. 6: Kinesthetic demonstration to use an electric tacker.

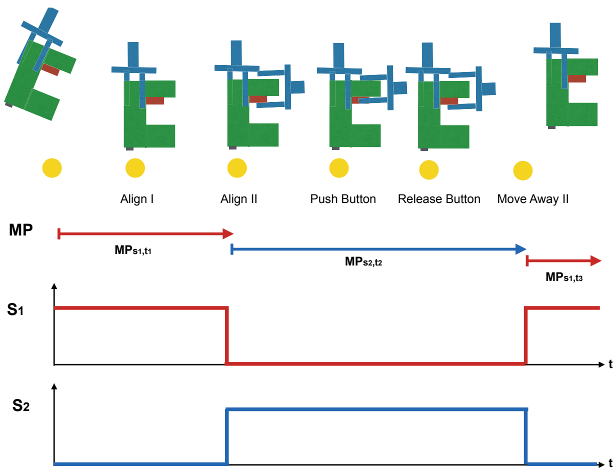


Fig. 7: An illustration of the LfD approach. S_1, S_2 represent the activated states for end-effector 1 and 2, MP for Manipulation Primitive.

and apply an improved version [4] formulated as follows:

$$\begin{aligned}\tau\dot{v} =& K(g-x) - Dv - K(g-x_0)s + Kf(s)\\ \tau\dot{x} =& v\\ \tau\dot{s} =& -\alpha s\end{aligned}$$

where x and v are the position and velocity of the system, x_0 and g are the start and goal position, τ is the temporal scaling factor, K is a spring constant, s a phase variable, and D a damping term. The non-linear function $f(s)$ defines the shape of the movement and is approximated by a weighted set of basis functions $\phi_i(s)$. Compared to the original DMPs formulation, it better adapts the movement to a new goal position by changing the goal parameter g [4]. We use Scott Niekum's DMP implementation [1], where $f(s) = \sum_{i=1}^{N} w_i \phi_i(s) s$ is approximated by the univariate Fourier basis [14] and the target function is formulated as:

$$f_{target}(s) = \frac{-K(g - x(s)) + D\dot{x}(s) + \tau\ddot{x}(s)}{g - x_0}.$$

Given a demonstration trajectory $\{x(t), \dot{x}(t), \ddot{x}(t)\}$, we can then learn a set of values for the weights w_i [3]. The spring and damping constants are set to ensure critical damping.

In the case of tool use, the goal positions $T = \{T_1, T_2\}$ of the two end-effectors are coded in the coordinate frame of the action point P and in order to execute the DMPs in a novel situation, the goals are then shifted based on the coordinate frame of the new action point P' as $T' = \{T_1', T_2'\}$ as shown in Figure 8. Let $M(i, T_i')_\tau$ be the model learned on the temporal interval τ for end-effector i over T' (recall the notation S_i for the activation signal for end-effector i) then the overall tool use process in LfD framework is defined as:

$$\text{ToolUse}_X := \{M(i, T_i')_\tau, S_i\}$$

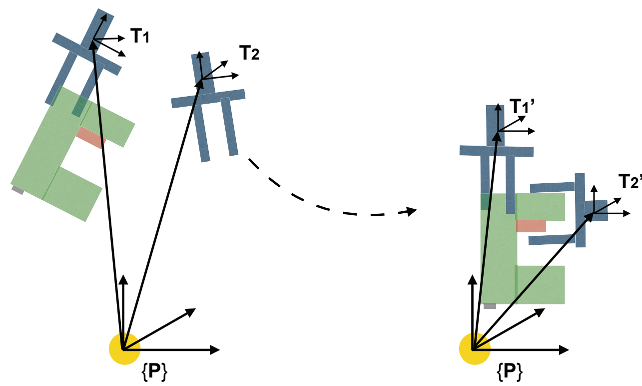
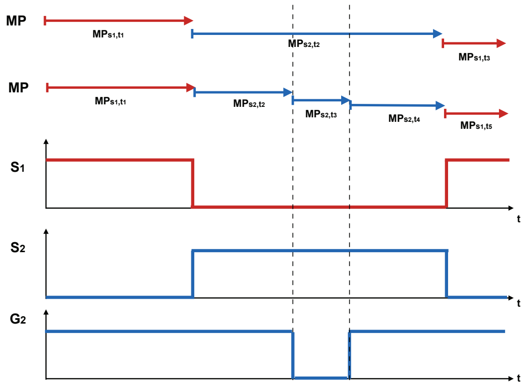


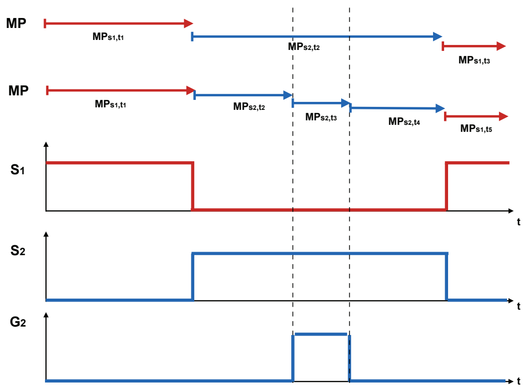
Fig. 8: The geometry of the tool use model. The trajectory of both end-effectors T_1, T_2 is tranformed into the coordinate system of the action point $\{P\}$, encoding the goal position $T' = \{T_1', T_2'\}$ in our tool use model.

Further, the second manipulation primitive that interacts with the tool has to be segmented into three primitives, i.e. 'before interaction', 'during interaction' and 'after interaction', in the case of using the tacker, these correspond to 'move the second end-effector to the button', 'push the button' and 'release the button $\rightarrow$ move away the second end-effector' (note the second primitive 'during interaction' is a trivial one since it only models how long the gripper opens or closes; we keep it as a constant in our experiments). This is due to the nature of the DMP model — DMPs allow the generalization of different paths between the starting and goal position. If it is applied to model the whole primitive from 'move the second end-effector' to 'move away the end-effector', there is no guarantee that the end-effector will be pushed at the same location relative to the tool as in the demonstration. In our settings, this segmentation is made by the identifying the state changes of the gripper during demonstration as shown in Figure 9, including two pattens, i.e. the gripper changes from 'close' to 'open' and from 'open' to 'close'.

[1] https://github.com/sniekum/dmp



(a) gripper changes from 'open' to 'close', then 'open'.



(b) gripper changes from 'close' to 'open', then 'close'

Fig. 9: Additional segmentation of maniuplation primitives introduced by the state changes of the gripper compared to the original segmentation shown in Figure 7. S_1, S_2 are the activation signal for end-effector $1, 2$, G_2 is the gripper's open/close state for end-effector 2.

IV. EXPERIMENTS

We implement our system in ROS [20] and test it on a Baxter research robot by learning to use three different tools: a tacker, a glue-pen and a drill as shown in Figure 10.

Example tasks are provided to the robot via kinesthetic demonstration, in which the teacher physically moves the robot's arm in zero-gravity mode to perform the task and uses the button on the cuff to set the closure of the grippers. On pushing the button on a arm, the recording begins, the teacher starts to move the same arm to perform manipulation. When the manipulation is done, the teacher presses again the button to pause the recording. To continue the manipulation with another hand and the recording, the teacher simply repeats the steps. The signals of arm activation and the grippers' state during the demonstration are recorded to segment the tool use process into sequential manipulation primitives, where each primitive is characterized by a starting pose, an ending pose of the actuated end-effector and the sequence of the poses during the primitive. The primitives are learned via the DMPs framework. These primitives and the sequencing of the primitives constitute the model for tool use.

At test time, the tool use model is replayed on novel configurations, generating a sequence of primitives, where each primitive's starting pose and ending pose are adjusted according to the action point. For both demonstration and test time, action points are tracked with AR tag as in [10] using an ASUS Xtion Pro Live sensor mounted on the robot.

Fig. 10: Tools used in our experiments, (left) an electric tacker, (middle), an electric drill and (right) a hot-glue pen.

A. Experiment 1: Learning to use a hot-glue pen

We first evaluated our system on learning to use a hot-glue pen. During the demonstration, the teacher moves one of the robot's arms holding the glue pen to the action point T, until there is only a small distance vertically between the tip and T. Then the other arm is moved to reach the button of the glue pen, and presses it with the gripper to release the hot glue. Afterwards, the arm pressed the button releases the gripper and returns to a neutral position. At test time, given an action point, the robot is required to (1) position the glue pen, (2) correctly press the button, (3) release button and (4) return to the neutral position. A failure case is counted whenever the robot fails to finish the whole process, for example, one arm fails to reach the button and hence cannot press it to use the tool. One successful run and corresponding signal sequences are shown in Figure 11.

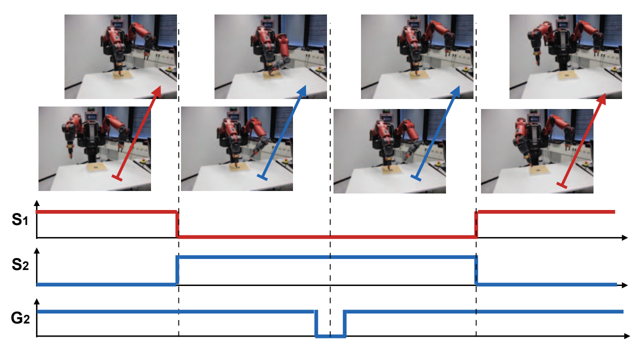


Fig. 11: Steps of robot using a gluepen after learning. S_1, S_2 are the activation signals for robot's arm $1, 2$, G_2 is the gripper's open/close state for arm 2.

B. Experiment 2: Learning to use an electric drill

Next, we evaluated our approach for an electric drill. Ideally, one would expect the tip of the drill to go into the contact surface, yet for the purpose of our experiments we refrain from penetrating the target. Thereby we make an alternative design for this experiment, similarly to the glue pen, we aim the tip of the drill to be correctly positioned right above the action point. At test time, given an action point, the robot is required to (1) position the drill, (2) correctly press the button, (3) release the button and (4) return to the neutral position. A failure case is counted when the robot fails to finish the whole process. One successful run and the corresponding signal sequences are shown in Figure 12.

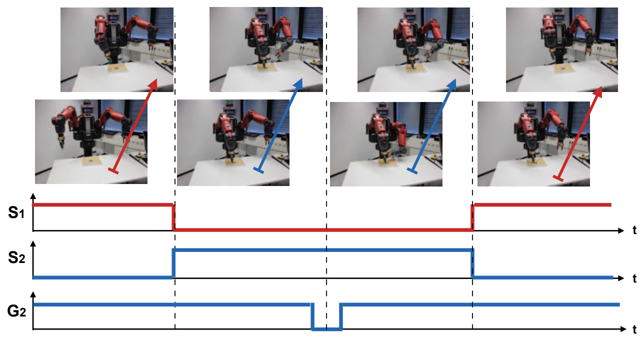


Fig. 12: Steps of robot using a drill after learning. S_1, S_2 are the activation signals for robot's arm $1, 2$, G_2 is the gripper's open/close state for arm 2.

C. Experiment 3: Learning to use an electric tacker

We also evaluate our approach for learning to use an electric tacker. During the demonstration, the teacher moves one of the robot's arms holding the tacker to the action point T. Then the other arm is moved to reach the button of the tacker, and press it with the gripper. Afterwards, the arm returns to a neutral position. A successful run requires the robot to (1) position the tacker, (2) correctly press the button, (3) release the button and (4) return to the neutral position. Whenever the robot fails to finish the whole process, a failure case is counted. Note that different from using the glue pen and the drill, the second gripper starts with the 'close' state and changes to 'open' state to press the button in this process for better maneuvering the tacker. One successful run and the corresponding signal sequences are shown in Figure 13.

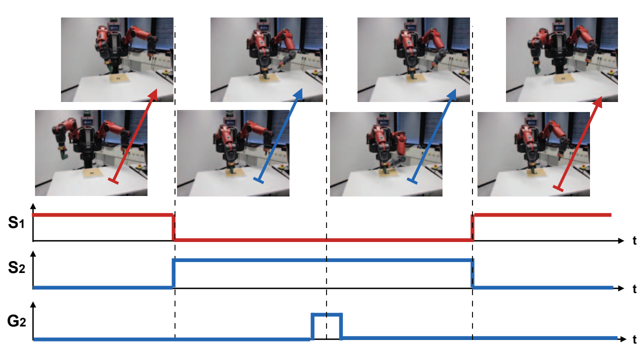


Fig. 13: Steps of robot using an electric tacker after learning. S_1, S_2 are the activation signals for robot's arm $1, 2$, G_2 is the gripper's open/close state for arm 2.

D. Evaluation

For all three tools we have tested 11 novel configurations together with the one seen in the demonstration as shown in Figure 14. The range of the configurations was chosen based on the reachable space of the robot holding the tool.

Fig. 14: Configuration tested in our experiment (top view of the robot), where the green dot denotes the position seen in the demonstration, blue dots for the novel locations.

As shown in Figure 15, alternatively to applying DMPs for each manipulation primitive, one can also use an end-to-end model from start to end position relative to the action point, then query the inverse kinematic solver for a plan. However, this approach tends to neglect the kinematic pattern, some of which reflect the physical constraint of the tool that can be crucial for the end-effector's operation. Two such failure cases of direct planning in contrast to the employment of DMPs are given in Figure 16.

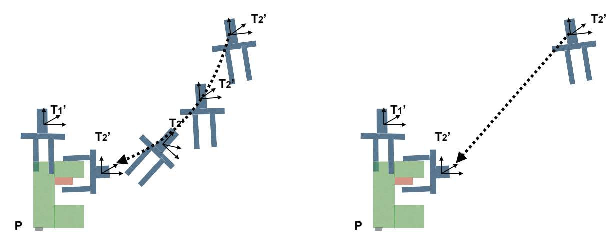


Fig. 15: Two different approaches for modeling the manipulation primitive: (left) trajectory modeling for the manipulation primitive where starting position, ending position and intermediate positions are included (right) end-to-end modeling for the manipulation primitive where only starting position and ending position are included.

A quantitative comparison of results for our sequential *Manipulation Primitives* with and without DMPs for individual primitives is shown in Table I. For simpler tasks, like the glue pen and tacker, sequential MPs with simple end-to-end modeling for each primitive achieves a reasonable success rate. Overall, DMPs significant improve the success rate for using all the three tools.

Fig. 16: Examples of failure cases for end-to-end modeling, (left) the second gripper fails to reach the proper position for the gluepen (right) the second gripper fails to reach proper position for the drill.

	Sequential MPs	Sequential MPs + DMPs
Glue-pen	66.7%(8/12)	100.0% (12/12)
Drill	33.3%(4/12)	66.7%(8/12)
Tacker	66.7%(8/12)	91.7% (11/12)

TABLE I: Success rate of tool use in our experiments

V. CONCLUSIONS

In this work, we first present a novel and compact model for using tools that can be described by a tip model. Then we explore a strategy of utilizing a dual-gripper approach for manipulating tools – motivated by the absence of dexterous hands on today's most widely deployed general purpose robots. Afterwards, we describe and formulate our hierarchical architecture to embed tool use in a learning from demonstration framework. At a high-level, we learn temporal orders for dual-arm coordination and at lower-level, we learn DMPs for manipulation primitives. The approach is tested and evaluated on a Baxter research robot. Learning and operation of three human tools, including an electric tacker, an electric drill and a hot-glue pen are shown.

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