Trajectories and Keyframes for Kinesthetic Teaching: A Human-Robot Interaction Perspective

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ABSTRACT

Kinesthetic teaching is an approach to providing demonstrations to a robot in Learning from Demonstration whereby a human physically guides a robot to perform a skill. In the common usage of kinesthetic teaching, the robot's trajectory during a demonstration is recorded from start to end. In this paper we consider an alternative, *keyframe demonstrations*, in which the human provides a sparse set of consecutive keyframes that can be connected to perform the skill. We present a user-study ($n = 34$) comparing the two approaches and highlighting their complementary nature. The study also tests and shows the potential benefits of iterative and adaptive versions of keyframe demonstrations. Finally, we introduce a hybrid method that combines trajectories and keyframes in a single demonstration.

Categories and Subject Descriptors

I.2.9 [**Artificial Intelligence**]: Robotics; H.1.2 [**Models and Principles**]: User/Machine Systems

General Terms

Experimentation, Design

Keywords

Learning from Interaction

1. INTRODUCTION

The goal of Learning from Demonstration (LfD) is to enable humans to program robot skills by showing successful examples [4]. There are various ways that this demonstration can take place. In this work we focus on "kinesthetic teaching" whereby a human teacher physically guides the robot in performing the skill, as in Fig. 1.

Kinesthetic teaching has several advantages for LfD. Since the teacher is directly manipulating the robot there is no correspondence problem and demonstrations are restricted to the kinematic limits (e.g. workspace, joint limits) of the robot. Moreover, extra hardware/instrumentation, such as motion capture or teleoperation devices, is not necessary.

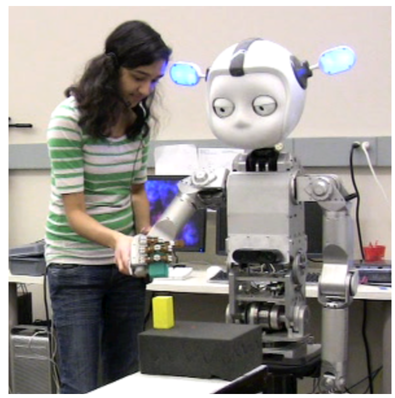


Figure 1: Simon interacting with a teacher.

While there has been much work on representations and learning algorithms, the usability of kinesthetic teaching has not been explored in depth. Kinesthetic teaching may be challenging for everyday users who do not have experience manipulating a robot arm with many degrees of freedom.

In many practical LfD applications (e.g., homes, schools, hospitals), the teacher will not be an expert in machine learning or robotics. Our research identifies challenges that everyday users face with common robot learning methods and investigate improvements to these methods to increase their effectiveness.

In the typical kinesthetic teaching interaction, and most LfD interactions, each demonstration is an entire state *trajectory*, which involves providing a continuous uninterrupted demonstration of the skill. In this paper, we explore the alternative of providing a sparse set of consecutive *keyframes* that achieve the skill when connected together. We present an experiment that compares these through quantitative measures, survey results and expert evaluations. We find that both are suitable to kinesthetic teaching from the user's perspective and both communicate different information. We also present two modified keyframe interactions and evaluate their utility. Based on our findings, we introduce a way to merge trajectory and keyframe demonstrations to take advantage of their complementary nature.

2. RELATED WORK

There are several methods for learning skills, which mostly fit into two groups: direct policy learning and cost/reward learning. Dynamical system approaches such as Stable Estimator of Dynamical Systems (SEDS) [13] and Dynamic Movement Primitives (DMP) [17] and mixture models (e.g. Gaussian Mixture Models as in [10]) fall into the former and inverse reinforcement learning (IRL) [1] or apprenticeship learning fall into the latter. These methods are designed for different skill types and all have their pros and cons. Apart from GMMs and DMPs, most methods require many training samples which is not suitable for a short-duration HRI study. However, DMPs and GMMs have either implicit or explicit time dependency. Most of the methods either cannot handle cyclic skills or they need to be reformulated. We chose GMMs as our skill learning algorithm for the following reasons: GMMs can be learned with a low-number of demonstrations, can be trained in interaction time, can handle cyclic skills as well as point to point skills, GMMs can be modified slightly to handle keyframe demonstrations (see Section 4.2.2), and the fact that we do not need temporal robustness (e.g. the robot will not be stopped in the middle of the motion) for our experiments.

In kinesthetic teaching, demonstrations are often represented as arm joint trajectories and/or end-effector path [9, 12]. Some also consider the position of the end-effector with respect to the target object of the skill [5, 11]. Typically start and end points of a demonstration are explicitly demarcated by the teacher. Most studies subsample the recorded data with a fixed rate [3, 5]. Demonstrations are often time warped such that a frame-by-frame correspondence can be established between multiple demonstrations [12].

Keyframes have been used extensively in the computer animation literature [16]. The animator creates important frames in a scene and the software fills in-between. In the LfD setting, an earlier work [15] utilizes via-points, which are similar to keyframes. These are extracted from continuous teacher demonstrations and updated to achieve the demonstrated skill. A recent approach is to only record keyframes and use them to learn a constraint manifold for the state space in a reinforcement learning setting [6]. In this paper we consider both trajectory and keyframe representations.

Human-robot interaction (HRI) has not been a focus of prior work on kinesthetic teaching, but there are a few examples. In [18], kinesthetic teaching is embedded within a dialog system that lets the user start/end demonstrations and trigger reproductions of the learned skill with verbal commands. A modification to the kinesthetic teaching interface is kinesthetic correction [7, 8], where the teacher corrects aspects of a learned skill in an incremental learning interaction by using a subset of joints in subsequent demonstrations. In another study [14], four types of force controllers that effect the response to users are evaluated for kinesthetic teaching. The study addressed human preferences on which controller was the most natural.

While various learning methods for kinesthetic teaching have been explored, there is a lack of studies with end-users testing the effectiveness of these techniques in terms of HRI. This is the focus of our work.

3. PLATFORM

Our robotic platform in this work is "Simon," an upper-torso humanoid social robot with two 7-DoF arms, two 4-DoF hands, and a socially expressive head and neck, including two 2-DoF ears with full RGB spectrum LEDs (Fig. 1). Simon is designed for face-to-face human-robot interaction. Simon's arms have compliant series-elastic actuators with stiffness that can be dynamically changed. We use *Microsoft Windows 7 Speech API* for speech recognition.

4. DEMONSTRATION METHODS

We explore three different ways for teachers to demonstrate skills: *trajectory demonstrations*, *keyframe demonstrations*, and *keyframe iterations*. In all three, users physically manipulate the robot's right arm, which is gravity compensated, to teach it skills (Fig.1). In this section we detail the implementation of each kinesthetic teaching mode.

4.1 Trajectory Demonstrations

4.1.1 Interaction

The teacher is informed that the robot will record all the movement they make with its right arm. The teacher initiates the demonstration by saying "New demonstration", moves the arm to make the robot perform the skill and finishes by saying "End of demonstration." This process is repeated to give as many demonstrations as the person desires. After a demonstration, the teacher can use the speech command "Can you perform the skill?" to have the robot perform the current state of the learned skill and adjust his/her demonstrations to attend to any errors.

4.1.2 Learning

Joint angle trajectories are recorded as the teacher moves the robot's arm to perform the skill. As mentioned previously, we use GMMs as our skill learning algorithm [10].

The data is subsampled in the time dimension to a constant length before being input to the learning algorithm. In our case, learning is done in an eight dimensional space (7 joint angles over time). First, we use the K-means algorithm with a constant k. The resulting clusters are used to calculate initial mean vectors and covariance matrices for the expectation-maximization (EM) algorithm. The EM algorithm is run to extract a Gaussian-Mixture Model (GMM) from the data. The resulting GMM has k sub-populations which is kept constant during our experiments. Gaussian-Mixture Regression (GMR) is used to generate a trajectory to perform the learned skill. The desired time dimension vector is given to GMR which in turn generates the joint positions. Note that the algorithm can learn from either a single or multiple demonstrations.

4.2 Keyframe Demonstrations

4.2.1 Interaction

The teacher is informed that the robot will only record the arm configuration when they say "Record frame", and it will not record any movements between these keyframes. The teacher can use the speech commands "New demonstration", "End of demonstration" and "Can you perform the skill?" in the same way as trajectory mode.

4.2.2 Learning

The resulting data from this interaction is a sparse trajectory of joint angles. If the teacher forgets to give keyframes for the start or the end position, these are added automatically. We generate time information for each keyframe using the inter-frame distance and a constant average velocity.

Learning is slightly different than the previous case, but the space is the same. Again K-means is the first step, but now the number k is chosen to be the maximum number of keyframes across all demonstrations provided for a skill. Then a GMM is learned in the same way as the trajectory version. To generate the skill, the GMM sub-population means are traversed by splining between them. We took such an approach since the GMM sub-population means obtained from the keyframe version will be of different nature than the ones obtained from the trajectory version. With keyframes, it is more likely to be a transition between two trajectory segments whereas with trajectories it is more likely to be a mid-point of a trajectory segment [10]. Thus, we need to control the velocity at each keyframe.

4.3 Keyframe Iterations

We implemented an augmented version of keyframe demonstrations, in which a new demonstration is an iteration of the current learned skill.

4.3.1 Interaction

In this mode, an initial demonstration is provided using keyframe demonstrations. Then the teacher can navigate through and edit the frames of this demonstration to create additional demonstrations. The teacher uses the speech command "Next frame", and "Previous frame" to navigate through the keyframe demonstration. At any keyframe, "Modify this frame" can be used to modify the arm configuration of the keyframe. "Add new frame" adds a new frame after the current frame. "Delete this frame" deletes the current frame. Also, the teacher can say "Play current demonstration" to see the modified demonstration before submitting it to the learning set. "Record this demonstration" submits the current demonstration to the learning set. As in the previous modes, the teacher can play the learned skill with "Can you perform the skill?"

4.3.2 Learning

Learning is the same as in keyframe demonstrations. We implemented iterations only for keyframes since implementing a similar extension for trajectory demonstrations is non-trivial. It is difficult to tie partial trajectories together. Moreover, speech commands might not give the necessary precision for navigating through a trajectory and modifying it. This is an interesting topic for future work.

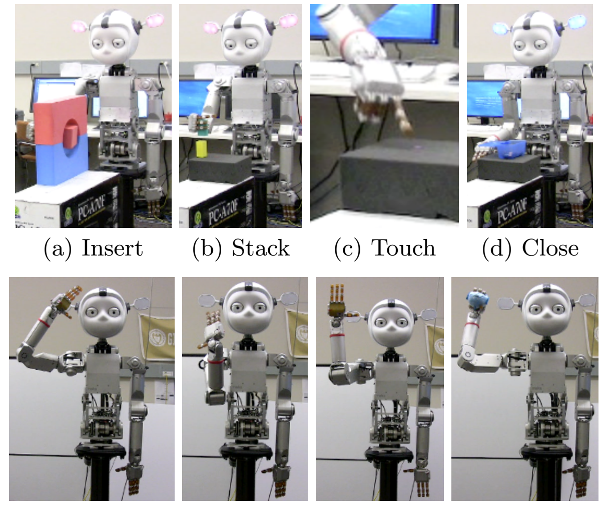
5. EXPERIMENTS

Our experiments address three research questions: (Q1) When everyday people teach the robot, what are the effects of each demonstration type? (Q2) Does the teaching method have any effect on learning different types of skills? (Q3) Can simple extensions to keyframe demonstrations (iteration and adaptation) increase performance/preference?

5.1 Experimental Design

5.1.1 Skills

We differentiate between two types of skills. *Goal-oriented* skills are related with achieving a particular world state (e.g., finger tip on a point while avoiding obstacles.) *Means-oriented* skills, on the other hand, include a gesture or communicative intent. We use four skills of each type, see Fig.2.



(a) Insert (b) Stack (c) Touch (d) Close
(e) Salute (f) Beckon (g) Raise (h) Throw

Figure 2: Goal-oriented (a-d) and means-oriented (e-h) skills.

The goal-oriented skills are as follows. (Fig. 2(a-d)). **Insert**: insert the block in hand through the hole without touching other blocks. **Stack**: stack the block in hand on top of another block on the table. **Touch**: touch a certain point with the finger tip. **Close**: close the lid of a box without moving it.

There is a single goal position per skill for the ease of the experiment. Multiple goal positions would prolong the experiment and our aim is not to analyze the generalization properties of the methods but rather to analyze the utility of the keyframe demonstrations from a user's perspective.

The means-oriented skills are as follows. (Fig. 2(e-h)). **Salute**: perform a soldier's salute. **Beckon**: perform a gesture asking someone to come closer. **Raise-hand**: raise the robot's hand as if it is asking for permission. **Throw**: perform a throwing gesture with a ball (without actually releasing the ball).

5.1.2 Conditions

Our experiment has four conditions, and we use a within-subject design. Three conditions correspond to the teaching methods in Sec.4. In addition, a fourth condition tests the effect of the initial demonstration in keyframe iterations.

- *Trajectory Demonstrations (TD):* Participants give one or more trajectory demonstrations for each skill.
- *Keyframe Demonstrations (KD):* Participants give one or more keyframe demonstrations for each skill.
- *Keyframe Iterations (KI):* Participants give keyframe iterations to teach the skills.
- *Keyframe Adaptation (KA):* Participants start with a predefined, slightly failing skill (e.g. touch is off by a few centimeters), instead of giving her/his own initial demonstration. They use the KI interaction to navigate and edit the frames to improve this skill.

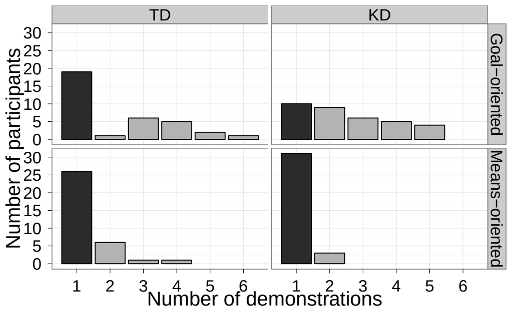


Figure 3: Histogram of number of demonstrations provided by participants in KD and TD conditions.

For Q1, effect of demonstration type, we compare TD and KD conditions. For Q2, learning of different skill types, we compare, *goal-oriented* and *means-oriented* skills in TD and KD conditions. For Q3, effect of extensions to keyframes, we first compare KD and KI, then compare KI and KA.

5.2 Experimental Protocol

The participants first teach the robot in the TD and KD conditions. The order of these two is counterbalanced. After these two conditions, KI and KA conditions followed. Thus the order was $(TD \mid KD) \rightarrow KI \rightarrow KA$. This ordering is to prevent biasing a participant in the KI condition with the predefined skill we use in the KA condition. We varied the type of skill taught to the robot across the TD and KD conditions, each participant taught one *means-oriented* skill, and one *goal-oriented* skill in these modes. Only *goal-oriented* skills were used in KI and KA conditions, to reduce experiment duration.

At the beginning of each condition, participants taught a *pointing* skill to the robot for familiarization with the condition. Participants were also allowed to move the robot's arm to practice before recording demonstrations.

5.3 Measures

We asked 7-point Likert-scale questions, administered after each condition, about *Feel*, *Naturalness*, *Ease*, and *Enjoyability*. We also asked open-ended questions after the first two conditions and at the end of the experiment.

Two different methods were used to measure the quality of the different types of learned skills. We evaluated the *goal-oriented* skills with three levels of success criteria, and the *means-oriented* skills with expert ratings.

The performance of goal-oriented skills were scored separately by the two of the authors, using three levels of success criteria Success-PartialSuccess-Fail. The scoring was based both on the recoded videos of the experiment and on the skill performances recreated on the robot. In the few cases where there was disagreement, the two coders revisited the example and reached a consensus on the scoring.

Unlike the goal-oriented skills, success for *means-oriented* skills is subjective. Therefore, we used expert ratings of the recreated movements to evaluate the performance. The experts, whose specialities are in computer animation, are asked to answer three 7-point Likert-scale questions for all means-oriented skills taught by all participants. The questions are about *appropriate emphasis*, *communicating intent*, and *closeness to perfection*.

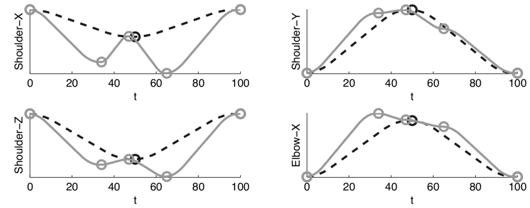


Figure 4: An example, in the KD condition, of forgetting obstacle avoidance keyframes in a first demonstrations (dashed line), and providing them in a second (solid line) while teaching the *Touch* skill.

We also measured the number of demonstrations, the number of keyframes, the time stamps for every event, and all trajectories of the joint movement during demonstrations.

6. RESULTS

We conducted a study with 34 participants (6 females, 28 males between the ages of 19-47), who were undergraduate and graduate Georgia Institute of Technology students with no previous machine learning and robotics experience. 22 of the participants taught Simon in all four conditions, while 12 only performed the first two conditions. The means-oriented skills were rated by two animation experts.

6.1 Trajectory vs Keyframe Demonstrations

First we compare the TD and KD experimental conditions, making five observations. [1]

6.1.1 *Single demonstrations are common*

Users were able to see what the robot has learned after each demonstration and either decide to move on or give another demonstration. Fig. 3 shows the number of demonstrations provided by participants in TD and KD. We see that teaching with a single demonstration was common in both modes. For goal-oriented skills, a larger portion of the participants provided a single demonstration in the TD condition than in the KD condition (19 versus 10). It was common in the KD condition to forget to provide keyframes that allow the robot to avoid obstacles while trying to achieve the goal. These frames were provided by participants in subsequent demonstrations after observing the performed skill colliding with obstacles (*e.g.* see Fig. 4). For means-oriented skills, teaching with a single demonstration was more common in the KD condition than in TD (31 versus 26).

6.1.2 *Trajectory demonstrations may be better at teaching goal skills in a single demonstration.*

Table 1 provides the distribution of participants according to the success of the goal-oriented skills they taught[2]. More participants achieved success in TD as opposed to KD (15 versus 5) when they taught with a single demonstration.

The large number of single demonstration instances is an artifact of our experimental design. The skills used in our experiments were chosen to be fairly easy to achieve, there was only a single goal location and participants were allowed to practice a particular skill before providing an actual

[1]We note that all of our observations reported in this section did not vary across particular skills.

[2]We treat success levels of skills as ordinal data.

Table 1: Number of participants who achieved different levels of success for goal-oriented skills.

Cond.	# of demo.	Success	Partial Success	Fail
TD	Single	15	4	1
	Multiple	1	5	8
	Total (%)	**16 (46)**	**9 (27)**	**9 (27)**
KD	Single	5	5	1
	Multiple	4	9	10
	Total (%)	**9 (27)**	**14 (41)**	**11 (32)**
KI	Single	4	0	2
	Multiple	6	4	6
	Total (%)	**10 (46)**	**4 (18)**	**8 (36)**
KA	Single	6	2	1
	Multiple	8	4	1
	Total (%)	**14 (64)**	**6 (27)**	**2 (9)**

Table 2: Expert ratings of means-oriented skills: Median and Coefficient of Dispersion

Cond.	Expert	*Emphasis*	*Intent*	*Perfection*
TD	1	5.5 (0.27)	5 (0.33)	5 (0.35)
	2	3 (0.29)	3.5 (0.38)	4 (0.3)
KD	1	6 (0.21)	6 (0.17)	6 (0.2)
	2	4 (0.21)	4 (0.24)	5 (0.22)
TD versus KD (Wilcox s.r. test)		Z=2679, p=0.10	Z=2677, p=0.11	Z=2796, p=0.03

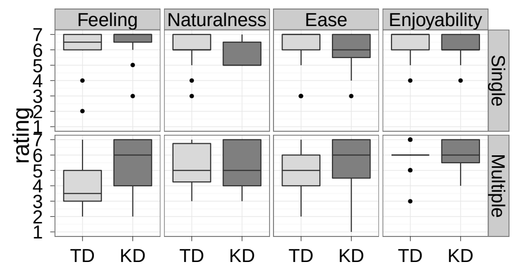


Figure 5: Subjective ratings of TD and KD conditions for goal-oriented skills separated by the number of demonstrations provided by the participant.

demonstration of the skill. We observed that this practice opportunity was used more in the TD condition, where people often practiced enough to be able to teach the skill in a single demonstration. To quantify this observation we analyzed the total movement of the arm during the practice sessions measured in the 7DOF joints space. We designate "minimal practice" to mean that movement in the practice session is less than 10% of average movement of all practice sessions. We observed that 17 practice sessions in the KD condition can be classified as minimal under this definition, while only 4 of the TD sessions are minimal. This supports our anecdotal observation that practice is more likely to be skipped in the KD condition.

Secondly, as mentioned earlier, participants often do not think of providing keyframes for obstacle avoidance in their first demonstrations. In some cases this does not effect skill success in terms of achieving the goal (*i.e.* partial success) and participants could be satisfied by this since they were not explicitly told to avoid collisions. A large portion of the participants who provided a single demonstration in the KD condition at least achieved partial success.

6.1.3 Keyframe demonstrations may result in preferable means-oriented skills

Table 2 summarizes the expert ratings for the means-oriented skills taught by participants. Both experts rated the means-oriented skills learned in KD condition higher in all three dimensions on average. The difference was only significant for *closeness to perfection*, and the difference is marginally significant when the three scales are averaged (Z=2740, p=0.06 on Wilcoxon signed rank test). This distinction is partly related to the difficulty of moving a 7-DOF arm smoothly in the TD condition.

6.1.4 Participants like both trajectory and keyframe

Analyzing participant's Likert responses, we found all ratings were biased towards higher values, and none of the measures showed a statistical difference between TD and KD (based on paired Wilcoxon signed rank tests). We observe that participants' ratings are correlated with their success in teaching the goal-oriented skills (r=.31, p<.001 in Spearman's rank correlation test, assuming Fail:1, Partial:2 and Success:3). As a result, when the participants are grouped into ones that provide a single demonstration and ones that provide multiple demonstrations, we find that participants who provided multiple demonstrations felt more comfortable with keyframe demonstrations (V=98, $p < 0.05$ in unpaired Wilcoxon signed-rank test). This difference is not seen in participants who provided single demonstrations.

6.1.5 Trajectory demonstrations require less time

Providing one demonstration in the TD condition took participants on average 19.34*sec* (SD=7.65), while it took 34.37*sec* (SD=12.79) in the KD condition. There are two reasons for this difference. First one is that participants could freely move the arm before providing a keyframe in the KD condition. Thus, they used more time during the demonstration to think about the next keyframe that they wanted to provide and adjust the arm for it. This is supported by the comparison of all arm movements in the KD condition between keyframes (which was recorded for reference) and arm movements in the trajectory demonstrations provided in the TD condition. We find that the average arm movement per demonstration per person in the TD condition is about 82% of that of the KD condition, although this difference is not statistically significant (t(112)=1.54, p=.13 on *t*-test). The second reason is that the overhead of the speech commands to record keyframes in the KD condition. Given that the average number of keyframes is 6.71 (see section 6.3) and assuming giving a record keyframe command takes a second, both reasons seem to be valid.

In the TD condition, since all movements are recorded, participants must constantly progress and cannot pause or adjust as in the KD condition. As mentioned earlier, one manifestation of this was a more thorough practice session prior to TD, as compared to KD. Additionally, while not shown in this experiment, we expect that TD has a higher mental workload than KD.

6.2 Goal- vs. Means-oriented Skills

6.2.1 *Different objective functions for each skill type*

As seen in Fig 3, a much larger fraction of participants provide a single demonstration for teaching means-oriented skills, in both TD and KD. Across both conditions, the average number of demonstrations provided for goal-oriented skills (2.37, SD=1.45) is significantly larger than the number of demonstrations provided for means-oriented skills (1.22, SD=0.53) (t(84)=6.18, p<0.001 on *t*-test). This highlights a fundamental difference between the skill types: while goal-oriented skills have a well defined objective function, means-oriented skills are subjective and under-specified. Means-oriented skills can vary a lot and were often satisfactory for the participants after a single demonstration.

Open ended questions in our survey reveal more about the difference in the objective functions for the two types of skills. We asked participants to indicate their criteria of success for each skill that they taught. We observe that 15 participants mentioned achieving the goal as their criteria for goal-oriented skills (*e.g.* "The action would most accurately meet its end goal", "Performing the task correctly", "Touching the point perfectly") while 11 participants mentioned at least one style-related criteria for means-oriented skills. 4 participants mentioned *naturalness* (*e.g.* "more fluid and natural performance", "how naturally Simon emulate the demonstration"), 4 participants mentioned *human-likeness* (*e.g.* "with human characteristics", "seeming less robot-like") and 6 participants mentioned *smoothness* (*e.g.* "how smooth and liquid the motion of the arm is", "more fluid motion", "no choppy movements").

6.2.2 *Characteristics of provided keyframes are different for each skill type*

The average distance between keyframes in the 7DOF joint space for goal-oriented skills is much smaller (around 47%) than the average distance for means-oriented skills (t(38)=-3.94, p<.001 on *t*-test). We hypothesize that participants are providing different types of keyframes within a single demonstration. For goal-oriented skills we see a distinction between keyframes that are instrumental to the goal of the skill, and the keyframes that lets the robot avoid obstacles. Similarly in means-oriented skills we see a distinction between keyframes that actually give the skill its meaning and make it recognizable and keyframes that are waypoints. Participants provide a large number of frames that are close to one another around the goal of goal-oriented skills. For means-oriented skills, they provide less frames that are separated by a larger distance. For both types of skills the waypoint keyframes or obstacle avoidance keyframes tend to be further apart. We do not observe a statistical difference in the average number of keyframes for goal-oriented skills (6.75, SD=1.89) and means-oriented skills (6.21, SD=2.17) (t(65)=1.11, p=.27 on *t*-test).

6.3 Keyframe demonstrations vs. Iterations

A larger fraction of the participants achieve success in the KI condition as compared to the KD condition (Table 1). Since we did not counter-balance the order of these two conditions, this difference partially involves the improvement that comes with more experience in teaching. However these

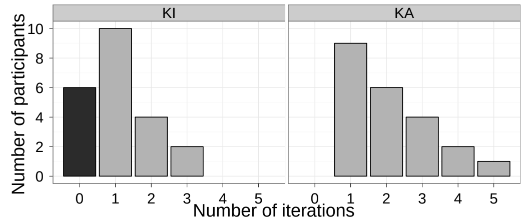


Figure 6: Histogram of number of iterations provided by participants in KI and KA conditions. For the KI condition "0" indicates the participants who only provided an initial demonstration and did not provide any iterations.

results show that the iteration process was effectively used by the participants, despite the increased number of commands and the complex interaction cycle. Note that 6 out of the 22 participants in the KI condition did not use the iteration process, *i.e.* they were satisfied the skill performance after the initial demonstrations, which is provided in exactly the same way as in the KD condition (Fig. 6). From the participants who used the iteration process, 10 participants provided a single iteration, however the iteration often involved several editing commands.

An interesting observation is that the number of keyframes in the demonstrations given by a participant varies less in the KI condition. The average number of keyframes provided within a demonstration for each participant is not very different in the KI (7.62, SD=1.48) and KD (6.71, SD=1.91) conditions. However the standard deviation in the number of provided keyframes across demonstrations of a participant seems larger in the KD condition (1.26, SD=0.94) as compared to the KI condition (0.46, SD=0.58). By starting from the previous learned skill, the iteration process limits the number of keyframes in the provided demonstrations which can be an advantage while learning from keyframe demonstrations if the initial demonstration is relatively good.

6.4 Effects of the Starting Skill for Iteration

The fraction of participants who achieve success is largest for the KA condition with 64% among all the others (TD: 46%, KD: 27%, KI: 46%, Table 1). As in the KI condition, experience in teaching the robot might be contributing to this improvement. However, this result indicates that an iterative process starting from a rough, often failing skill is potentially the best option in terms of achieving successful goal-oriented skills.

Our survey involved a question asking whether having a rough skill to start from in the KA condition made it easier or harder, or whether it did not matter in comparison with providing the initial demonstration themselves as in the KI condition. 12 participants responded that it made it easier, while 5 said "harder" and 5 said "did not matter".

7. DISCUSSION

7.1 Benefits of Demonstration Methods

The results of our experiment show that both trajectory and keyframe demonstrations are viable methods of interaction for kinesthetic teaching in LfD. Each has advantages and users seem positive towards both of them.

Trajectory demonstrations are clearly intuitive for a naïve user, and there is the benefit that many existing LfD methods are designed for learning skills from trajectory data. Trajectories allow complicated skills to be taught, and are particularly appropriate when speed information is a key component. However, it might be hard for users to manipulate a high-degree of freedom robot or sustain smooth trajectories over the course of a demonstration. In our experiment, this resulted in longer practice sessions for trajectory demonstrations, as well as means-oriented skills that achieved lower expert ratings.

Keyframe demonstrations are robust to these noisy and unintended motions during a demonstration. Their sparse nature result in a modular representation, which may be useful in generalizing a skill to new situations. For example, existing motion planning methods can easily be used to navigate between keyframes to execute salient aspects of the skill while avoiding obstacles. Additionally, it may be easier to deal with time alignment between multiple demonstrations.

A drawback of keyframes is the lack of timing information. We observed that some participants tried to achieve slower movements or stops by providing a large number of very close or overlapping keyframes. Several participants mentioned wanting speed related commands.

7.2 Skill Types and Demonstration Methods

Our experiment reveals the different nature of goal-oriented and means-oriented skills. The former is defined by *success* while the latter by *style*. Moreover, in the goal-oriented skills, only a portion of the skill's motion contributes to success whereas in means-oriented skills the entire motion contributes to the style.

People gave more demonstrations for goal-oriented skills. Since means-oriented skills can vary a lot, they were often satisfactory after a single demonstration. This was particularly true for keyframe demonstrations, since some users had a hard time manipulating the robot's arm, especially during the start of a skill. In goal-oriented skills, this usually did not impact task success (e.g. initial motion of the arm was not that important for pointing). However, this does have an impact when style is the objective. Thus, users often needed to correct the style by giving multiple demonstrations for the means-oriented skills in trajectory mode.

For goal-oriented skills, participants often gave multiple demonstrations due to the lack of fine control with keyframes, most notable being the timing (velocity) information. The robot often did not perform a skill as intended after the first demonstration in keyframe interactions, prompting users to improve the skill with more demonstrations.

We also observed that skill types have an effect of types of keyframes that are provided by the user. Waypoint keyframes are common in both of the skill types. Goal keyframes (keyframes that are closer together near a goal) and style keyframes (keyframes that are placed strategically to do the gesture, more apart) can clearly be seen respectively for goal-oriented and means-oriented skills.

7.3 Designing Keyframe Interactions

We explored different interaction mechanisms for a keyframe approach. Since keyframes temporally segment the demonstration, it is easy to apply an iterative interaction mechanism, and our experiment showed that people were able to use this to achieve greater skill success. We also saw that in an iterative interaction, people do not stray too far from their initial demonstration, thus emphasizing the importance of the starting skill. Our experiment showed that people were even able to use the iterative process to adapt a starting skill that was not their own, and many said that this made the teaching process easier.

As mentioned above, all keyframes are not equal, people think about them in different ways (e.g., goal frames, via points, etc.). A future extension would be to devise interaction mechanisms that are specific to each keyframe type. The distinction between these types of keyframes is important information for the underlying learning algorithm that human partners can easily provide.

7.4 A Hybrid Mode of Interaction

From this study, we found kinesthetic teaching is a viable method for teaching a humanoid robot, and that both keyframe and trajectory demonstrations have their advantages.

We think that the ability to provide both keyframe and trajectory information in the context of a single demonstration will be useful and intuitive for a variety of skills and even combination of skills (e.g. scooping and then serving). Hence, we are developing a new interface for LfD which merges trajectory and keyframe demonstrations in a single interaction. This *hybrid* interaction scheme allows the teacher to give both keyframes and trajectory segments in their demonstration (see in Figure 7). During a demonstration, the teacher can provide a keyframe by moving the arm to a desired position and saying "Go Here". At any point, the user can say "Like this" to initiate a trajectory demonstration and "That's it" to finish the segment. The teacher can combine these in any order resulting in four different kinds of demonstration: pure keyframe, single trajectory, segmented trajectory, and hybrid demonstrations.

We recently demonstrated this approach at the AAAI 2011 LfD challenge [2], on the PR2 robot, where anecdotal evidence[3] shows that this hybrid-mode was intuitive for conference goers. We have preliminary results with hybrid mode from a pilot study where three users tested the method in a scoop and pour task. These users gave positive comments about the interaction and their skills were successful.

We think the hybrid approach will give users more tools at their disposal to program robots in ways they find intuitive. Our future work will focus on the experimental validation of the hybrid mode of interaction, both with naïve and expert users and for LfD methods other than kinesthetic teaching.

7.5 Other Considerations

As mentioned previously, our aim was not to assess the generalization properties of the methods. One way to achieve generalization is to represent state as end-effector coordinates with respect to the goal. A more elaborate method is presented in [10]. This can be applied to trajectories, keyframes and hybrid demonstrations.

The presented tasks were simple but these interaction approaches may be even more beneficial for more complex tasks. For example in the case of a bi-manual LfD task, the user can position the arms individually and proceed with keyframes, which is usually impossible for trajectories.

[3] http://www.youtube.com/watch?v=Ng7SYetzkXI

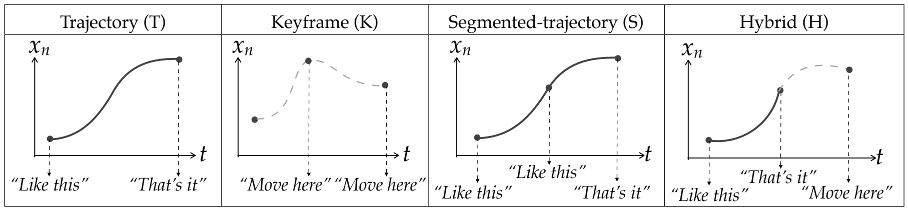


Figure 7: The possible interaction flows of the hybrid mode. The dots correspond to start/end points or keyframes, the solid lines to user demonstrated trajectories and the dashed lines to splines between keyframes.

8. CONCLUSIONS

We compared different methods of interaction for kinesthetic teaching in LfD with everyday people. Our study focused on the effects of different demonstrations, and we showed that trajectory and keyframe demonstrations have their relative advantages. We also explored different interaction schemes that a keyframe representation makes possible (iterations and adaption) and showed their success with human teachers. Finally, based on these observations, we introduced a hybrid mode of interaction in which the user can chain together keyframe and trajectory segments.

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