Novel Interaction Strategies for Learning from Teleoperation

Baris Akgun, Kaushik Subramanian, Andrea L. Thomaz
Georgia Institute of Technology
College of Computing
801 Atlantic Dr., Atlanta, GA 30332
{bakgun3, ksubrama, athomaz}@cc.gatech.edu

Abstract

The field of robot Learning from Demonstration (LfD) makes use of several input modalities for demonstrations (teleoperation, kinesthetic teaching, marker- and vision-based motion tracking). In this paper we present two experiments aimed at identifying and overcoming challenges associated with using teleoperation as an input modality for LfD. Our first experiment compares kinesthetic teaching and teleoperation and highlights some inherent problems associated with teleoperation; specifically uncomfortable user interactions and inaccurate robot demonstrations. Our second experiment is focused on overcoming these problems and designing the teleoperation interaction to be more suitable for LfD. In previous work we have proposed a novel demonstration strategy using the concept of keyframes, where demonstrations are in the form of a discrete set of robot configurations (Akgun et al. 2012b). Keyframes can be naturally combined with continuous trajectory demonstrations to generate a hybrid strategy. We perform user studies to evaluate each of these demonstration strategies individually and show that keyframes are intuitive to the users and are particularly useful in providing noise-free demonstrations. We find that users prefer the hybrid strategy best for demonstrating tasks to a robot by teleoperation.

Introduction

In real world scenarios, it is not possible to pre-program robots with all the tasks they might need throughout their operational life. Learning from demonstration (LfD) is a paradigm in which robots are programmed by demonstrating successful executions of a task (Argall et al. 2009). We are interested in developing LfD systems that are suitable to be used by everyday people. There has been much work related to LfD algorithms and representations but usability of these with users who are unfamiliar with robotics and machine learning has not been explored in depth. We aim to identify the challenges that these methods pose to the user and propose solutions.

There are various means to show such demonstrations. We are particularly interested in *kinesthetic teaching*, in which the users manually guide the robot and *teleoperation*, in which they use a teleoperation device (see Figure 1). Both of these are desirable since they overcome the so-called "correspondence problem" and the resulting demonstrations are restricted to the kinematic limits (e.g. workspace, joint limits) of the robot. Moreover, extra hardware/instrumentation, such as motion capture devices, is not necessary.

(a) Kinesthetic Teaching (b) Teleoperation

Figure 1: Input modalities of interest for demonstrations

We first conduct a user study comparing kinesthetic teaching and teleoperation, to understand how natural and comfortable these input modalities are to different users and how they compare with each other. We find that people are partial towards kinesthetic interaction due to the small learning curve, ease of use and accuracy of demonstrations. However, teleoperation was still viewed positively.

Kinesthetic teaching requires that the robot and the user be co-located and that the user can manipulate the robot. This might not be possible if the robot is distant, the robot or the environment is dangerous or the scale of the robot does not permit it. This is when teleoperation becomes important, and leads to our follow-up experiment aimed at improving a teleoperation teaching interaction.

In previous work (Akgun et al. 2012b) we have proposed two novel interaction strategies to improve LfD, (1) *Keyframe demonstrations*, in which only the important robot configurations to complete the task are shown in sequence. (2) *Hybrid demonstrations*, the combination of trajectories and keyframes, allowing users to provide both keyframe and trajectory information in a single demonstration. The intuition is that keyframes are good for gross motions whereas trajectories are good for non-linear and complex portions of a task. In this work we show the particular benefit of these interaction strategies in a teleoperation setting.

Our second experiment studies the effect of different demonstration strategies on the LfD interaction, finding that people prefer keyframes-only over a trajectory-only interaction, and prefer the hybrid strategy over both.

We first describe, in Section , some work related to robot teleoperation and its application to LfD scenarios. We then detail the platform and tasks used in our experiments. In Section , we present the design and results of our first experiment on comparing kinesthetic and teleoperation input modalities. We then introduce of the keyframe-based demonstration strategies in Section and their evaluation in Section .

Related Work

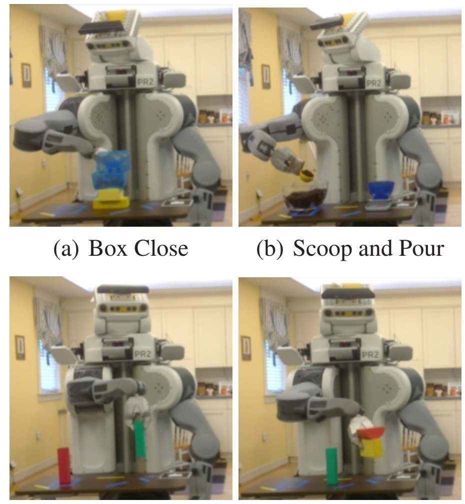
In LfD, demonstrations are often represented as arm joint trajectories and/or end-effector path (Calinon and Billard 2009). Some also consider the position of the end-effector with respect to the target object of the skill. Typically start and end points of a demonstration are explicitly demarcated by the teacher. Most studies subsample the recorded data with a fixed rate (Amor et al. 2009). Demonstrations are often time warped such that a frame-by-frame correspondence can be established between multiple demonstrations.

Keyframes have been used extensively in the computer animation literature (Parent 2002). The animator creates important frames in a scene and the software interpolates between them. In the LfD setting, an earlier work (Miyamoto et al. 1996) utilizes via-points (similar to keyframes) which are extracted from continuous teacher demonstrations and updated to achieve the demonstrated skill. A recent approach is to record keyframes and use them to learn a constraint manifold for the state space in a reinforcement learning setting (Bitzer, Howard, and Vijayakumar 2010). 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 (Weiss et al. 2009), kinesthetic teaching is embedded within a dialog system that lets the user start/end demonstrations and trigger reproductions of the learned skill with speech.

A modification to the kinesthetic teaching interface is kinesthetic correction (Calinon and Billard 2007a; 2007b), where the teacher corrects aspects of a learned skill in an incremental learning interaction by using a subset of joints in subsequent demonstrations.

The teleoperation concept has been around for more than 50 years, with the focus on dealing with delays, information loss, instabilities, operator noise, telepresence etc. (Hokayem and Spong 2006). However, there has also been some interest in LfD with teleoperation. An earlier work, which describes a skill learning method with HMMs for a manipulator, is presented in (Yang, Xu, and Chen 1993). Some other related work include (Peters and Campbell 2003) in which a space humanoid learns a "reach-grasp-release-recract" skill, (Lieberman and Breazeal 2004), which extends trajectory segmentation and time alignment from demonstrations obtained via a telemetry suit and (Howard and Park 2007), which injects haptic information to guide the user for better demonstrations. Whole body grasps for a simulated humanoid is learned in (Hsiao 2006) by forming template grasps demonstrations via "keyframes",



(a) Box Close (b) Scoop and Pour

(c) Stacking (d) Cup and Saucer

Figure 2: Tasks used in our experiments

which are the start/end points of a demonstration and the points of contact and loosing contact with the objects.

These methods do not explicitly concentrate on the user. Some of the existing usability studies for teleoperation, such as (Elton and Wayne 2011) which compares a novel hydraulic manipulator control interface with the traditional joint-by-joint control, concentrate on making task completion better/more efficient but do not consider learning.

Platform

We use the PR2 from Willow Garage and Sensable Phantom Omni® haptic device in our experiments. PR2's right arm is used which has 7 degrees-of-freedom (DOFs) and is passively gravity compensated. The teleoperation device has 6-DOFs, which is mapped to the end-effector of the robot. Force-feedback is disabled to eliminate lag and instabilities.

Experimental Tasks

We have a total of four main tasks for users to teach the robot, shown in Figure 2, all of which were designed such that they are achievable with all the interaction modalities and demonstration strategies. The tasks involve the use of a single arm of the robot.

- Box Close: The goal of this task is to move the robot arm such that it closes the lid of an open box.
- Scoop/Pour: A spoon is placed in the robot's gripper and the goal is to transfer as many coffee beans as possible from a big bowl to a nearby smaller bowl.
- Stacking: The goal of this task is to move the robot arm to grip a relatively slim block with a square cross-section and then place it on top of another similar block.
- Cup/Saucer: A hemispherical block is placed on another relatively thin rectangular block from its circular side. The top block falls if the arm moves too fast or the orientation

deviates. The aim is to transfer these blocks into a rectangular region by avoiding an obstacle.

We also have two practice tasks to help familiarize the user with the robot. One is called "Orient and Place". In this task, the robot holds an oblong prism and the goal is to make this fit within a gap of two blocks placed on the table. The gap is placed such that the user needs to both manipulate the position and orientation of the robot's end-effector. The other practice task is "Peg in Hole". In this task, a vertical slim block should be grasped, inserted through a horizontal hole, and then be placed back near its original position.

Experiment 1: Input Modalities

In our first experiment, we compare Kinesthetic Teaching (KT) and Teleoperation (TO) in an LfD setting with naïve users. The users are instructed to teach the PR2 robot a set of tasks such that it is able to efficiently execute them without any human intervention. The experiment is designed to provide insight into the characteristics of these two modalities and highlight the user's comfort and the robot's task accuracy in using these.

In kinesthetic teaching (KT), the user interacts with the robot by physically manipulating its end-effectors, as shown in Figure 1(a) and in teleoperation (TO), the user, with the help of the Phantom Omni haptic device, controls the robot's end effector from a distance. This interaction is shown in Figure 1(b). In order to demonstrate, the user provides a continuous trajectory of a task. We now briefly highlight the method used by the robot to learn them, followed by the experimental design and the results obtained.

LfD Method

When the user is demonstrating a particular task, the robot is recording every motion that the user exhibits. The robot, given a set of such task demonstrations, is required to process them and learn a generalized model of the task. In order to learn such a model, we choose a supervised learning approach based on Gaussian Mixture Models (GMMs). It has been previously used in similar LfD scenarios (Calinon, Guenter, and Billard 2007) and found to be very useful.

We choose GMMs as they can be learned with a small number of demonstrations, can be trained in interaction time and are adept at learning cyclic tasks as well as point to point tasks. In this method, the demonstrations are given to the learner in the form of time-stamped end-effector poses. These are first time-warped to ensure that each of them has a similar time scale. After this pre-processing step, k-means algorithm is run to cluster the data. The cluster means and covariances are used as the initial values for the Expectation-Maximization (EM) algorithm, which learns a GMM from the data. In our study, we used a constant number of clusters that was derived empirically (12 for Box Close and 18 for Scoop/Pour). The outputs of GMM are sub-population means and covariances which constitutes the model of the task. Given a time vector as an input, Gaussian Mixture Regression (GMR) is used on this model to extract a set of corresponding end-effector poses for the robot. These can then be executed by the robot in order to reproduce the task.

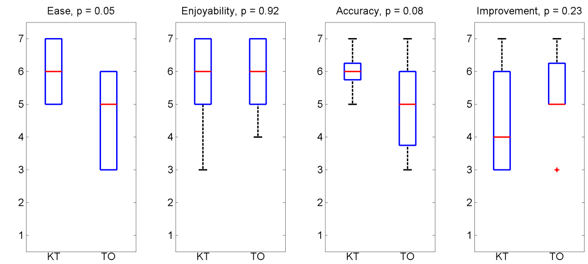


Figure 3: Box and whisker plots of survey replies for Experiment 1.

Experiment Design

To compare the KT and TO input modalities, we designed a within-subjects experiment where every participant taught two tasks, Box-Close and Scoop/Pour, to the robot in each of the modalities. We had 9 participants, 5 females and 4 males, all of whom were university students. Their ages were between 23 and 32 with a median of 25. None of the participants were experts in robotics or machine learning and none of them had prior experience with either modality.

We now describe the experimental scenario and highlight important aspects of the interaction. Each participant is first introduced to the robot. Then, based on a counterbalanced order, one of the input modalities is described to them. They have a short period of time to become familiar with the input modality and the robot by performing the "Orient and Place" task during the practice session. They are then asked to demonstrate one of the two experiment tasks (also counterbalanced). The user initiates the demonstration by saying "*New demonstration*", manipulates the arm to make the robot perform the task and finishes by saying "*End of demonstration*". The robot then learns a model of the task using GMMs and the user is given the option of reviewing what the robot has learned. The user, based on their assessment of robot performance, can decide to give another demonstration or move on to the next task. After teaching both tasks in the first modality, this protocol is repeated for the second modality. After completing the two tasks in the two input modalities, the user is asked to fill out a survey.

We asked the users to rate the *ease of use*, *enjoyability* and *accuracy* of the method and the extent to which they thought they would *improve at using the modality, given time* with a set of 7-point Likert-scale survey questions. We also asked an open-ended question to get the overall impression from the user. The question was phrased as "If you bought this robot to use at your house, which modality would you prefer and why?". In addition to the survey, we also compare KT and TO with respect to the task-oriented metrics: duration of demonstrations; and success of the learned task model.

Survey Results

We use Wilcoxon signed rank test to evaluate the survey (see Figure 3). A summary of the results obtained is given below.

Kinesthetic teaching was rated easier: The median answer to the ease-of-use-of-modality question was 6 for the KT case, whereas it was 5 for the TO case. Note that the answers are significantly different from one another ($p = 0.05$). We expected this result due to the fact that people are more accustomed to a kinesthetic type of teaching, i.e., it occurs naturally in human-human interactions. Moreover, with this interaction method, the users have more control over robot's joints, can more easily adjust their perspective to see more of the workspace and be more "situated".

Users enjoyed both methods: Both methods were rated highly on the enjoyability scale, thus we were unable to show a significant difference in enjoyability.

Users tend to think that they can give more accurate demonstrations with the kinesthetic teaching method: Although this is not significant, we can see a trend ($p = 0.077$).

Majority preferred kinesthetic: According to the open-ended question responses, a majority of participants (7 of 9) preferred KT over TO, with 6 users citing their reason being its "ease" of use.

Task Metrics

In addition to the survey results we look at task-specific success and demonstration durations. We define the end state of the Box Close task (Open or Closed) and the amount of coffee beans transferred for Scoop/Pour as the success metrics.

The Box Close task was completed successfully by almost all participants (except 1) using both modalities. In the Scoop/Pour task demonstrations, participants transferred more coffee beans with KT than TO ($p < 0.05$ in paired t-test). However we note that this is not always reflected in the learned tasks. There are two probable causes for this. First, users may provide subtle but useful assistance (e.g. rocking the spoon) during kinesthetic teaching since they are more accustomed to this form of interaction. However, these are smoothed out by learning. Second, an artifact of our experiment, we did not control the distribution of the coffee beans before executing the task. After a user demonstration, a dent is left in the distribution and the learned task will try to scoop from around the demonstrated region but will not get as many coffee beans due to the dent.

The participants were faster at providing demonstrations with Kinesthetic for Scoop/Pour ($p < 0.05$) than Teleoperation. For Box Close, people were faster on average but not significantly ($p = 0.09$). This is partly due to 2 outlier users who took some time to realize they needed to move some of the robot joints (shoulder joints) that were away from the end effector in KT modality. Overall KT leads to more successful demonstrations in a shorter amount of time.

We would like to highlight here that on observing the demonstrations given by the participants using teleoperation, we noticed the users frequently repositioning the robot arm to complete the task accurately. These characteristics affect the learned model as they are assumed to be part of the task demonstration. The robot, in its learned model, tends to replicate these extraneous movements. In real-world scenarios we would like to overcome this shortcoming.

New Demonstration Strategies

The results of the previous experiment showed us that there is a gap between Kinesthetic and Teleoperation in terms of usability in an LfD setting, with kinesthetic being easier to use and leading to more successful demonstrations. However, kinesthetic teaching requires that the robot and the user be co-located and that the user can manipulate the robot. This might not be possible if the robot is distant, the robot or the environment is dangerous or the scale of the robot does not permit it. Thus, we are interested in novel demonstration strategies aimed at improving a teleoperation teaching interaction. We explore two new ways to demonstrate tasks: *keyframe demonstrations* and *hybrid demonstrations*.

Keyframe Demonstrations

In Keyframe demonstrations (KF), the robot records only specific configurations (i.e. keyframes or poses) that are marked by the user. These configurations are stored as a sequential set of discrete end-effector configurations. In this strategy, the interaction proceeds as follows, the user initiates the demonstration by saying "New demonstration", moves the arm to specific configurations while making the robot perform the task and says "Record Pose" at each important point to record that configuration. The user finishes the task by saying "End of demonstration."

The resulting data from this interaction is a sparse trajectory (as opposed to a continuous trajectory used in Experiment 1). Given these sets of discrete points, the robot replays the demonstration by sequentially splining through each of them. An example of this is shown in Figure 4 under the title "keyframes". Importantly, we generate time information for the sparse trajectory by taking into account the distance between adjacent keyframes and assume a constant average velocity between them. In our implementation, if the user forgets to give keyframes for the start and/or the end position of a task demonstration, they are added automatically.

Learning is slightly different than the trajectory case, but the space is the same. Again k-means is run as the first step, but now the number k is chosen to be the maximum number of keyframes across all demonstrations provided for a task. Then a GMM is learned in the same way as the trajectory version. To generate the task, 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 (Calinon, Guenter, and Billard 2007).

Hybrid Demonstrations

In hybrid demonstrations (HY), the user is allowed to give both keyframes and trajectory segments in their demonstrations (illustrated in Figure 4). Trajectory segments are the same method used to provide demonstrations in Experiment 1. Starting and ending a demonstration and recording a keyframe is same as before. At any point, the user can say "Start Trajectory" to initiate a trajectory demonstration and "End Trajectory" to finish it. In the hybrid strategy, the user has the ability to mix and combine keyframes and trajectories in any manner. For example, a task could involve a se-

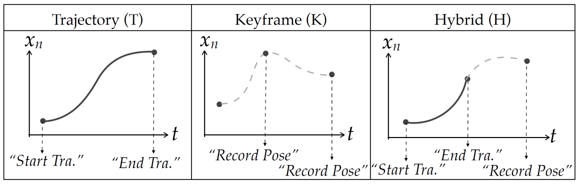


Figure 4: Left and middle columns depict the trajectory and keyframe strategies. All of the columns are possible demonstrations with the hybrid strategy. The dots correspond to start/end points or keyframes, the solid lines to user demonstrated trajectories and the dashed lines to splines between keyframes.

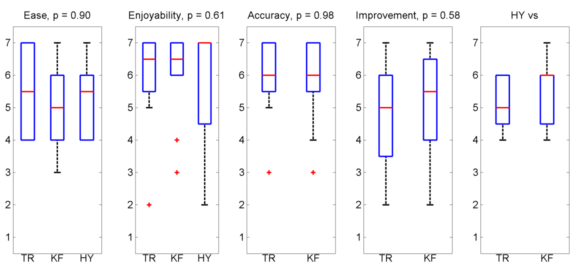


Figure 5: Results for choice questions on the survey for Experiment 2. The p-values are obtained with the Friedman's test when comparing all methods and the Wilcoxon signed rank test when comparing just TR and KF.

quence of 2 keyframes, 1 trajectory sequence and another 3 keyframes. For such a hybrid demonstration, the robot will replay the trajectory portions and keyframes as before and will transition between the two using splines.

We presented a method that can learn from hybrid demonstrations in (Akgun et al. 2012a). The main idea is to extract keyframes from trajectory segments (retaining velocity and acceleration information) and cluster all the keyframes together. Then spline between cluster centroids to generate the skill. The details are out-of-scope of this paper since the current study was done prior to the aforementioned paper.

Experiment 2: Improving Teleoperation with new Demonstration Strategies

In our second experiment we evaluate the various demonstration strategies described in the previous section in the context of improving teleoperation. We have two novel strategies (Keyframes(KF) and Hybrid(HY)), to complement the standard Trajectory demonstrations (TR). We hypothesize that the new strategies will enhance the user interaction with the teleoperation device both in terms of “ease of use” as well as providing better demonstrations. This experiment is setup to first compare the individual utility of keyframes and trajectory strategies and then compare them both against the hybrid strategy.

Experiment Design

We conducted a within-groups study where every participant did all the 3 strategies and performed all 4 tasks with potential task repetitions in the hybrid strategy. We had 12 participants, all male, from the campus community (different from the ones who participated in Experiment 1). Their ages were between 18 and 47 with a median of 21.5. Only one user was a first year Ph.D. student in the Robotics program. The others were not experts in any related field and none of them had used a teleoperation device before.

We used all the tasks mentioned in Section with a few differences. We made the Box Close task harder by requiring users to make the lid “click” (by pushing it down) after closing it. Since some of the tasks in this experiment require grasping, the users had the ability to close and open the robot gripper with verbal commands. Moreover, the robot makes a sound after each verbal command for confirmation.

We note that some tasks can be more efficiently solved using specific or a combination of strategies. For example, the stacking task can be better suited for demonstrations using the keyframe strategy as it requires only a set of linear translations, whereas the Cup/Saucer task requires the use of trajectories as they provide control over the speed of the arm. Without speed control, the hemispherical block has more tendency to fall down.

Each user demonstrates 2 tasks per strategy. The tasks differed across TR and KF. Then one task from TR and one task from KF is chosen for HY (e.g. (TO: T_1 T_2)→(KF: T_3 T_4)→(HY: T_1 T_4) where T_x denotes one of the four experimental tasks). We partially counterbalanced the strategy and the task order. Half of the experiments started with TR and the other half with KF. Note that there were $(3{\times}2){\times}12 = 72$ interactions which are distributed evenly among the related conditions (e.g. 24 per demo, 18 per task, 6 per demo and task combination).

The experiment starts with the participant getting introduced to the robot. Our experience from the previous study indicated that users needed more practice with the teleoperation modality. We added a short session of “free form” practice before beginning the experiment in which users moved the arm around freely and were asked to put the end-effector in various canonical configurations (e.g. horizontal, vertical). They performed the Orient and Place task after this to complete the practise session.

After the practice session, they are introduced to one of the strategies (either KF or TR, picked from a counterbalanced order). They are familiarized with the strategy using the Peg in Hole task. They are then asked to demonstrate two of the four tasks (also counterbalanced) using the instructions specific to that strategy. Once completed, they repeat the same procedure for the other modality using the remaining two tasks. The user is then asked to complete a survey based on these two strategies. They are introduced to the hybrid strategy afterwards and asked to demonstrate two of the four tasks, one from each modality. Then, the user completes the last survey with questions on the hybrid strategy.

Using data gathered from the above protocol, we compare the three demonstration strategies based on the survey results (Likert scale questions and open-ended responses) as well as characterizations of the demonstrations data provided with the different strategies.

Survey Results for Keyframe, Trajectory, and Hybrid

In Figure 5, we present the results of our survey questions.[1] None of the replies are statistically significant between the strategies, so we cannot draw any differential conclusions. There was positive bias in people's answers across all the strategies. For example, all of them were rated enjoyable, with medians being close to the upper limit. This is in part due to the novelty effect of interacting with a humanoid robot, but the positive bias also indicates that our interaction strategies were acceptable to the participants.

Participants subjectively reported that all of the interactions were easy. However, this was not our observation. It is difficult to manipulate a robot with a teleoperation device, and people clearly struggled at times. Nevertheless, the perceived ease is a positive for teleoperation and the interaction methods and shows that the participants were comfortable with the design and use of these strategies.

Users also thought that the methods were accurate. This is interesting since the keyframe method does not seem intuitive at first, but it received very similar perceived accuracy ratings compared with the more intuitive trajectory method. The improvement results indicate that the users think that they could do better with more experience, which is especially true for such a teleoperation scenario.

Open-ended Responses on Keyframe vs. Trajectory

In an open-ended response question, we asked people to directly compare keyframes and trajectories.

In their responses, 9 out of 12 users preferred keyframes over the trajectories mode. Six of the participants who chose keyframes mentioned giving more "efficient" demonstrations and "not recording any mistakes". Two of the users admitted that they were not very proficient with the teleoperation device and felt more comfortable with the keyframe mode. All three users who chose trajectory mode complained about "having to give many poses" with the keyframe strategy; showing some concern for the loss of information with keyframes.

Analysis of Keyframe vs. Trajectory Demonstrations

The average number of keyframes per task was 10.25 ($\sigma = 3.77$). Table 1 shows the mean and the standard deviation of distance covered and the average time taken to complete a task in each of the modes. There seems to be an inverse relationship between the time taken and the distance covered. We first analyze these metrics between trajectories and keyframes. We see a significant difference for the demonstration duration ($t(23) = -2.67, p = 0.014$) and a significant difference for distance traveled by the robot end-effector between trajectories and keyframes ($t(23) = 4.80, p < 10^{-4}$). The latter result is due to the fact that the robot moves nearly in a straight line between keyframes but trajectories include the unnecessary motions of the user.

[1]Only two of the questions were asked for HY. This was to shorten the survey to minimize fatigue. Also, since we did not counterbalance HY, it is biased, people inherently improved and became more accurate by the time they completed this.

Table 1: Mean (and standard deviation) of demonstration duration (in seconds) and distance (in meters).

	Trajectory	Keyframes	Hybrid
Dur.	50.69 (26.26)	72.45 (30.36)	59.84 (31.13)
Dist.	3.65 (1.46)	2.12 (0.26)	3.08 (1.3)

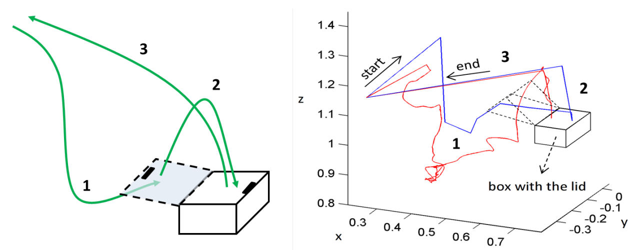


Figure 6: Comparison of Trajectory (Red) and Keyframe Demonstrations (Blue). The left image shows a desirable trajectory for closing the box lid.

These results indicate that the participants spent more time positioning the arm and thinking about the positions. This in turn resulted in a good selection of keyframes as the arm completed the task by traversing a smaller distance, making it more efficient.

We would like to point out that the accuracy of the trajectories as perceived by the participants and as obtained by the quantitative measures can be misleading as the participants were more interested in task completion rather than providing clean and noise free demonstrations. The trajectories had hand jitter and unnecessary motions that would be very hard to learn from. However, on reviewing the demonstrations obtained in the keyframe mode, we find that they were noise free (i.e. little or no unnecessary keyframes) which is much better suited for input to a learning algorithm. This attribute is highlighted in Figure 6, showing an example keyframe and trajectory demonstration of the Box Close task.

Additionally some tasks were hard to perform using the keyframe mode. For example, the Scoop/Pour task and the Cup/Saucer required fine control as well as speed control of the arm. We can therefore say that the keyframe mode was not sufficient to solve all the tasks efficiently.

Survey and Open-ended Responses on Hybrid mode

On comparing hybrid with the other two techniques, the results were encouraging. Figure 5 shows that hybrid is rated easy and enjoyable. People not only thought it to be a valuable addition to the interaction modes, many participants were able to figure out efficient ways to combine keyframes and trajectories. The last column of figure 5 is people's response to questions asking them to rate how much they prefer the HY method over the TR and KF. People were positive towards the hybrid mode with a median of 5 for HY vs TR and median of 6 for HY vs KF and all users were at least neutral (4) towards HY.

Our second open choice survey question was designed to compare the hybrid mode with the other two modes and provide reasons for their choices. 11 of the participants thought hybrid was a valuable addition and they preferred it over keyframes and trajectory modes. We would like to highlight two characteristics mentioned by the participants in the survey question. 6 of the participants preferred the Hybrid mode due to the efficiency of the interaction and 5 of the participants highlighted the ability for precise control. Specifically several mentioned how it is easier to demonstrate gross motions using keyframes and fine motions using trajectories. One user mentioned "a combination keyframes and trajectories" would be a valuable addition before being informed about the hybrid strategy.

Analysis of Hybrid mode Demonstrations

In our final analysis of the hybrid strategy, we highlight some of the choices the participants made, specifically how they choose keyframes and trajectories depending on the type of task. We observed that the keyframe mode was primarily used for gross motions from location A to B, for linear motions or when only the end point mattered. The trajectory mode was primarily used when the task required non-linear motions or fine control over the speed. An example scoop and pour demonstration can be seen in figure 7. It can be seen that scooping and pouring is done with trajectories and going from one bowl to the other with keyframes.

We analyze the choices of the users in the hybrid mode for specific tasks.

- In the Cup/Saucer task, 5 out of 6 participants that did this task with hybrid used the trajectory mode to move the cup because it gave them more control over the speed.
- In the Scoop/Pour task, $5/6$ used trajectory for scooping, $2/6$ for transferring, and $5/6$ for pouring.
- In the Close the Lid task, $3/6$ users moved under the lid with the keyframe method and all of them used trajectory mode to close the lid. 1 of the users then used the keyframe method to push the lid to its place.
- In the Stack the Block task, 4 people used keyframes to move to the first block, 2 to go to the next and 3 to stack. Among the users, one of them did this task with only keyframes, which is arguably the best option.

In general, we observed that people tried to take advantage of keyframes and trajectories wherever appropriate. Participants show a trend of choosing trajectory for fine control and keyframes for gross motion. We argue that with more practice, users can develop even better strategies to more efficiently achieve the tasks with the hybrid strategy.

Discussion

Our first experiment showed that users preferred kinesthetic teaching over teleoperation as it is more intuitive and more situated. They were still positive towards teleoperation. The

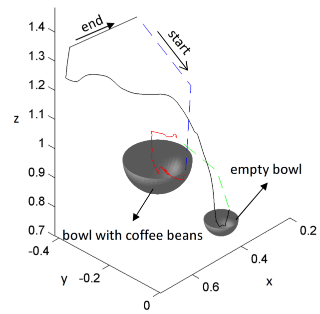


Figure 7: An example hybrid demonstration for the scoop and pour task. Dashed lines represent keyframe portions and continuous lines represent trajectory portions. Different colors correspond to different demonstration segments.

users did not have any previous experience with the PR2 robot nor have they ever had any experience with a teleoperation device. This makes the already steep learning curve of teleoperation even steeper. Taking this into account, we were able to show that within the span of an hour, the users were becoming better at using the teleoperation device and were able to demonstrate the tasks relatively well.

Our introduction of keyframes and the hybrid strategy made the LfD interaction with teleoperation more suitable. Participants quickly figured out the concept of keyframes and learned how and when to provide them. It took users a couple iterations of looking at the robot replay their demonstrations at most to understand the steps necessary to correct the position of the keyframes. We can see that the time taken for providing keyframes was greater than trajectories, shown in Table 1. We attribute this to two reasons; one, the users spent time to think where the poses must be given and to position the robot accurately and two, they spent time saying the phrase "Record Pose" and waiting for the robot to confirm. This in fact supported our hypothesis that users were ready to spend that extra time in providing keyframes because the robot demonstrations were less prone to noise.

Furthermore some participants, with continued interactions, were able to gain insight into the properties of keyframes as envisioned by us. Specifically, they were able to understand that keyframes assume constant speed between them and therefore do not encode any velocity related information. Two participants mentioned that "keyframes are not good when speed control is required". This only goes to show how naive users using a few interactions were able to grasp the details of the interaction strategies.

Given these characteristics of the participants in our study, we highlight an aspect that was common to most of the users. Our results indicate that the users concentrated more on task completion rather than providing good demonstrations, although they were encouraged to give smooth demonstrations. They perceived the robot being accurate during the replays, however their trajectories often contained noisy, unnecessary and imprecise portions which makes learning difficult. We believe that this was an artifact of not showing the participants the learned model. Thus, integrating this work with online learning is planned for future work.

Conclusions

We found that teleoperation is harder than kinesthetic teaching for naïve users of LfD. Users found the kinesthetic modality to be more comfortable and better suited to provide accurate demonstrations. We presented two novel demonstration strategies for teleoperation to make it easier to provide "good" demonstrations and compared these against the traditional trajectory method. Our first strategy was based on keyframes that helps to avoid errors and noise in trajectories. Experiments with participants show that this interaction strategy is much better suited for learning from teleoperation. Additionally, we combine the keyframes with continuous trajectories in a hybrid manner. This combination provides a suitable and intuitive interface to efficiently solve most tasks.

A link with a video of the key contributions of our work can be found at `http://www.cc.gatech.edu/social-machines/video/KLfD-Teleop-AAAI-FSS12.mov`

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