IDENTIFYING FEATURES OF LEGIBLE MANIPULATION PATHS

by

MIN ZHAO

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ABSTRACT OF THE THESIS

Identifying features of legible manipulation paths

By MIN ZHAO

Dissertation Director:

Professor Kostas Bekris

This work performs an experimental study on the legibility of paths executed by a manipulation arm available on a Baxter robot. In this context, legibility is defined as the ability of people to effectively predict the target of the arm's motion. Paths that are legible can improve the collaboration of robots with humans since they allow people to intuitively understand the robot's intentions. Each experimental trial in this study reproduces manipulator motions to one of many targets in front of the robot. An appropriate experimental setup was developed in order to collect the responses of people in terms of the perceived robot's target during the execution of a trajectory by Baxter. The objective of the experimental setup was to minimize the cognitive load of the human subjects during the collection of data. The extensive experimental data provide insights into the features of motion that make certain paths more legible for humans than other paths. For instance, motions where the end-effector is oriented towards the intended target appear to be better in terms of legibility than alternatives.

Key words: Human robot interaction, Legible paths, Manipulator, Co-robots

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1. General Introduction

1.1. Human-Robot Interaction

Human-Robot interaction (HRI) focuses the interaction processes between human and robot. Before becoming as a research topic, Human-robot interaction as an idea had been pointed out by Isaac Asimov (1941) in his short fiction story. He stated three laws of Robotics: "(1) A robot may not injure a human being or, through inaction, allow a human being to come to harm; (2) A robot must obey any orders given to it by human beings, except where such orders would conflict with the First Law; (3) A robot must protect its own existence as long as such protection does not conflict with the First or Second Law". Namely, an interaction between human and robot should be a safe interaction. As the robot and human beings getting closer, the risks that human beings are harmed by the robot could increase. For descent of years, in order to avoid such risks, human beings and robots were separated and not allowed to share the same workspace.

Recently, the increasing availability of low-cost, compliant and human-friendly manipulators allows robots, such as Rethink Robotics' Baxter [1], to be placed in close proximity to human workers. Unlike traditional automation systems, which needed to be kept in cages, these compliant robots can share a common workspace with human workers. A clear benefit of this close proximity is the opportunity for cooperation between a human worker and an assistive robot. One important task for robots is to move items that humans cannot reach. For example, robots may deliver food or water to a person who cannot move due to age or disability. Another example is warehouse-based robots. The warehouse-based robots navigate within the warehouse, find the product and transport it back to a human operator. In all situations involving assistive robots and human beings, there are two main directions to make the interaction safe and human-friendly: (1) Robot can better understand humans' intention and then provides appropriate actions; and (2) human beings can easily understand robots' intention and response appropriately. The first direction requires the cognitive models and theory of mind of human beings. The second direction requires the better design of robot's actions. It is useful for that the robot to be programmed human-friendly so that people can interpret the robot's action accurately. For example, if a robot brings a cup of water to a person, the person should be able to interpret the robot's actions so as to make a proper response about when and where to reach the cup. Accurate and timely interpretation of robots' action will allow people to make better use of robots, and further improve the software design of robots to provide more useful interactions. The current study focused on the second direction, and examined how human beings perceive robot's intention by just observing its actions.

1.2. Related Work

1.2.1. Legible Motion

In order to make a robot play an assistive role efficiently, it is important that the human is able to easily and quickly understand the robot's intentions by just observing its actions. Ideally, this understanding will come in an intuitive manner, similar to how humans are innately able to communicate with one another non-verbally when working in close quarters. When interacting with humans, robot has to adopt legible behavior, which contains crucial social cues and expresses robot's intention [22, 23]. Legible motion plans are an important part of making the robot understandable by human co-workers intuitively. In this context, the legibility of a motion corresponds to whether human subjects can realize the actual target out of many possible choices from the arm movement. Legibility could be improved from varies of aspects, such as improving the safety by increasing the distance between human and robot [23], increasing the visibility of all parts of the robot [23], minimizing the cost of reaching of human beings [23], explicitly expressing the intention of the robot by making the robot looking at the target [24], etc.

Previous work has emphasized the importance of anticipatory motion [2]. The robot's actions could be easily and quickly interpreted by human being observers by using alarms, such as symbol, noise, particular social representative components, at early stage of the motion. It has also been indicated that legible, anticipatory motion greatly assists in collaborative tasks.

Research has also focused on exploiting the repeatability of common collaborative tasks to generate anthropomorphic motions [3]. There has been work on creating metrics that can reproduce motion plans to be more human-like [4]. Another philosophy in generating motion plans has been learning by demonstration. Motions, that are demonstrated by human teachers, are used to build the policy for the robot to map its state to an appropriate motion [5, 6]. This line of work leverages anthropomorphic motions. The legibility problem, however, does not necessarily correspond to the capability of a robot to reproduce human-like motion, but how a human perceives the robot's motion.

This crucial motivation has resulted in recent important efforts in identifying aspects of and generating legible robot motion [7, 8], which have inspired and influenced the current work. The legible motion was defined as the motion that enables an observer to quickly and confidently infer the correct goal (action-to-goal), while the predictable motion was defined as the motion that matches what an observer would expect, given the goal (goal-to-action). In particular, these efforts have resulted in a formalization of robot motion legibility, and approaches for autonomously generating legible robotic motion plans. They stated that the legibility motion generator should always find the maximum probability among candidate goals along the paths from the start location to the target. And there is a trust region that constraint legible motion to make it understandable. They listed numbers of factors that could influence the understanding of legible trajectories, such as ambiguity, scale, timing, numbers of possible goals, and obstacle. Further work by the authors along this line has focused on distinguishing between predictability and legibility. Researchers tried to compare the legible motion and the predictable motion in a two-target situation. Predictable motion was defined as the motion that matches what an observer would expect, given the goal (goal-to-action), which appears as lower cost, less surprise and more efficient trajectories. In the corresponding experimental process the focus was on discriminating the legibility of motion using a simulated point robot, video recordings of a robot, and human actors that can potentially reach two goals in an otherwise uncluttered workspace. They found subjects tend to make correct estimations faster and more confident with legible motion than predictable motion, particularly for the simulated point robot. Familiarization [9] has been shown to improve predictability when coupled with learning.

1.2.2. Human Motion

Human beings are good at interpreting actions and relative intentions of other moving agents in their environment. This ability is developed during the first fourteen months of a person's life [10]. During daily life, there are usually two action interpretation processes [11]:

1. Action-to-Goal inference, in which people try to predict the result of the action based on the information accumulated during the action's execution.

2. Goal-to-Action inference, in which people try to predict a type of action that could achieve a determined goal.

The focus of legibility is on understanding action-to-goal inference, namely how humans interpret the observed actions and then discover the underlying intention [7]. Adults, young children, and even infants are able to selectively focus on the key components of the behavior of others, which is relative to their intention. In psychophysical experiments the human hand was discovered to play a crucial role during interpreting and sharing actions and intentions of people with others [12, 13]. Previous psychological studies show that between nine months and twelve months, infants develop a perceptual link between pointing to the target object and the target, itself. They understand that pointing is an object-oriented action [13]. These results motivate the focus of this study on features related to the robot's end-effector.

1.3. Current Study – Perceiving the action of the robot

The goal of the current study was to identify the key features of robotic motion for manipulators that contribute to their legibility. Five different types of trajectories were generated to cover a variety of discriminant legibility features. Some of the features correspond to arm policies, such as the shortest path in the configuration space, and other correspond to “hand", i.e., end-effector, policies, such as the orientation of the end-effector relative to the target. A human-robot face-to-face experiment was setup to examine how human perceive the goal of the robot by observing its arm action. In the experiment, trajectories were executed by two seven degrees-of-freedom manipulation arms that were mounted on a Baxter robot. The arms moved towards grasping multiple targets, which were positioned linearly in front of the robot. As the manipulator moves, human subjects observed the robot and reported their belief regarding the intended target of the arm. An appropriate experimental setup was developed in order to collect these responses, so as to minimize the cognitive load of the human subjects and achieve good accuracy.

The experimental results show that the legibility of different trajectories was indeed different and consistent across different targets. Motions which allowed the end-effector to point towards the intended target and move along a straight line in the workspace result in enhanced legibility. The learning effect was also examined by repeat testing trajectories.

The long term objective of identifying these legibility characteristics is the design of motion planners that incorporate these features into the planning process so as to automatically generate legible motion, and thus co-robots, which can generate legible motion plans, can more effectively collaborate with humans.

2. Generating Different Manipulator Paths

Two main factors were considered as key features of the legible trajectories for a dual arm manipulator, i.e., a Baxter robot by Rethink Robotics. One is the path from the start position to the target location (arm policy). The other is the orientation of the end-effector (hand policy). For the path from the start position to the target location, there are four arm policies considered in this study:

1. Shortest path in configuration space (i.e., minimizing change in joint angles),

2. Overhead motion frequently appearing in “pick and place" paths,

3. Shortest, straight-line path for the end-effector in workspace, and

4. “Curved" path for the end-effector in the workspace to exaggerate intent (see Fig. 1a).

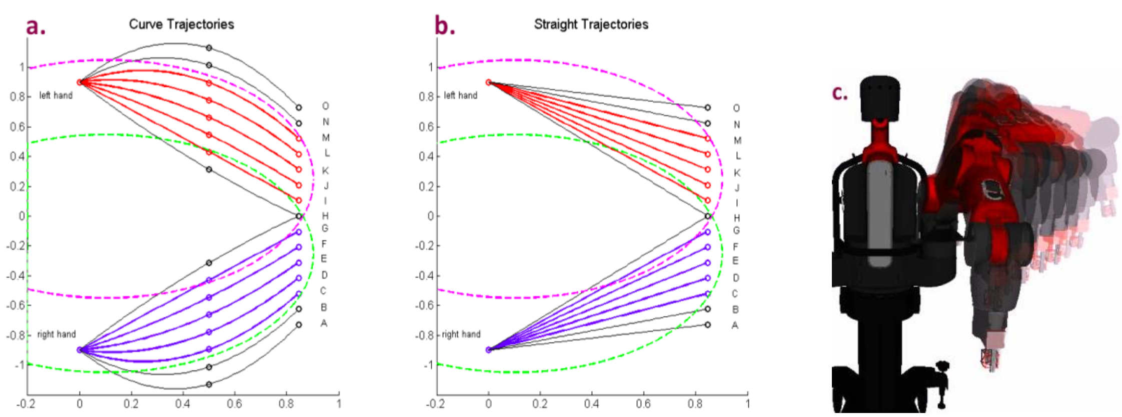

Figure 1. Left(a) : “curve" and Center(b): “straight" paths seen from above. The points on the left side of each plot represent the starting position for the left (red) and right (blue) end-effector. The lines show paths to reachable targets. Each hand has its own reachable region (green curve for right; purple curve for left hand). Right(c): one of the “overhead" paths in simulation [14]. The end-effector remains vertical and points downward.

And there were two possible hand orientations (potential hand policies):

1. Hand goes immediately to final joint position (e.g., overhead grasp) and stays there for the duration of the motion, and

2. Hand points toward the goal in the workspace at all times. The pointing feature of these paths can be seen as a symbol generating anticipation of the motion [2].

By combining the above mentioned policies and pruning incompatible combinations, five different classes of path were considered in the experimental study:

1. “Shortest" path: This was the shortest path in the configuration space computed on an asymptotically near-optimal version [15, 16] of a probabilistic roadmap [17] in the Open Motion Planning Library [18]. This class was resulted from arm policy 1 (Fig. 2a) and immediately provided a path for the hand as well.

2. “Overhead Down" path: Similar to paths employed for pick-and-place tasks by Baxter robots in industrial settings, where the end-effector moved in a position over the target and points downwards throughout the motion (see Fig. 1c). This class was resulted from the combination of arm policy 2 and hand policy 1 (fig. 2b).

3. “Straight" path: The robot moved its end effector along a linear path from the initial position to the target object while the end effector pointed towards the target (see Fig. 1b). This class was resulted from the combination of arm policy 3 and hand policy 2. (Fig. 2c)

4. “Straight Down" path: The robot moves its end effector along a linear path from the initial position to the target object while the end effector remains in a vertical orientation pointing down. This class was resulted from the combination of arm policy 3 with hand policy 1. (Fig. 2d)

5. “Curved" path: The robot moves its end effector along an exaggerated curved path while pointing at the target. This class is inspired by ideas in previous work towards

generating legible paths [7] (see Fig. 1a). This class was resulted from the combination of arm policy 4 combined with hand policy 2. (Fig. 2e)

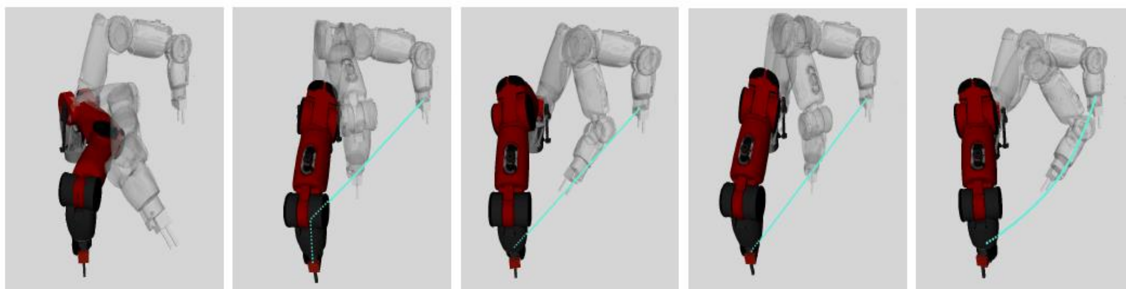

Figure 2. Left to right: 1: Shortest C-space path, 2: Overhead down, 3: Straight pointing to target, 4: Straight down, 5: Exaggerated \curved" motion pointing to target

Both hands were tested in the experiment, so trajectories were generated for both hands of the robot. For each arm and for every type of trajectory, a fixed start position that was raised from the at-rest position of Baxter is used. It helped in terms of target reachability. The targets are placed evenly along a line on a table in the manipulator's reachable workspace (see Fig. 1a, b). For each target, one unique trajectory was generated for each trajectory class. Left hand can only reach 5 targets on the left side, while right hand can only reach 5 targets on the right side (see Fig. 1a, b, for reachable range of each hand). The left 5 possible targets were not overlapped with the 5 ones on the right. In total, there were 50 unique trajectories generated in the preparing process.

The above set of trajectories was designed to avoid confounding the effects of hand policies with the effects of arm policy, while keeping the total number of trajectories to a reasonable number so as to be able to finish testing and as well to extract useful conclusions. Note that there are two types of trajectories that are sharing the same arm policy (straight-line for the end effector in the workspace) but are different in terms of the employed hand policy. There are also two control classes, reflecting standard manipulation strategies (“shortest" and “overhead down" trajectories). In this way, the relative importance of these features can be discovered by comparing the time it takes for human subjects to realize the motion's target.

To ensure that for all classes there is ample time for subjects to give feed- back about their belief of targets, all trajectories in this study are scaled to be performed in 8 seconds.

3. Human Robot Interaction Experiment

A human-robot-interaction experiment was run in order to examine human's perception and interpretation of the robot's intention by observing robot's actions.

3.1. Methods

3.1.1. Subjects

Thirty subjects were tested. All of them were paid volunteers. All subjects had normal vision, hearing condition and were naïve as to the purpose of the experiments. The procedures were all approved by of the Rutgers University Institutional Review Board for the Protection of human subjects.

3.1.2. Design

There were 5 different types of trajectories (see details in section 2). The trajectories were stored and played back during the trials in order to ensure that artifacts from the random sampling in our motion planning do not cause discrepancies between trials of the same class to the same target. Moreover, the overhead of planning for the execution for the trajectories was avoided by generating the trajectories once and replaying them. For each of the workspace constrained paths, MathWorks' MATLAB [19] is used to perform linear interpolation among a series of points in the workspace. Then, the MoveIt! Package [20] with a KDL kinematics solver [21] and an OMPL [18] implementation of a PRM* variant is used to plan trajectories between the interpolated points. The final trajectories can be played on the robot using the Baxter RSDK [1].

Both hands (left and right) of the robot were tested. The experimental setup is designed to effectively record the responses of subjects' belief about the target of trajectories executed by the robot. A requirement was that both the targets and the robot were within the view of the subjects. The subjects also had a clear view of the entire motion of the robot manipulators. For studying legibility, the subject must be able to pay attention to the motion of the robot without distractions. Minimizing the cognitive load of the subject during the experiment involves minimizing distractions as well as making the data recording interface intuitive and effortless. In order to achieve this, an efficient recording mechanism is desired, which is both accurate in recording the responses and easy to assemble. The recording interface should also be resilient enough to withstand repeated experimental trials. The experimental setup consists of a Baxter robot, a workstation, a table with 15 colored cups, and a pointing device (Fig. 3). Among the cups, the 10, that can be reached by the robot from its starting position with all 5 types of trajectories, were designated as potential targets.

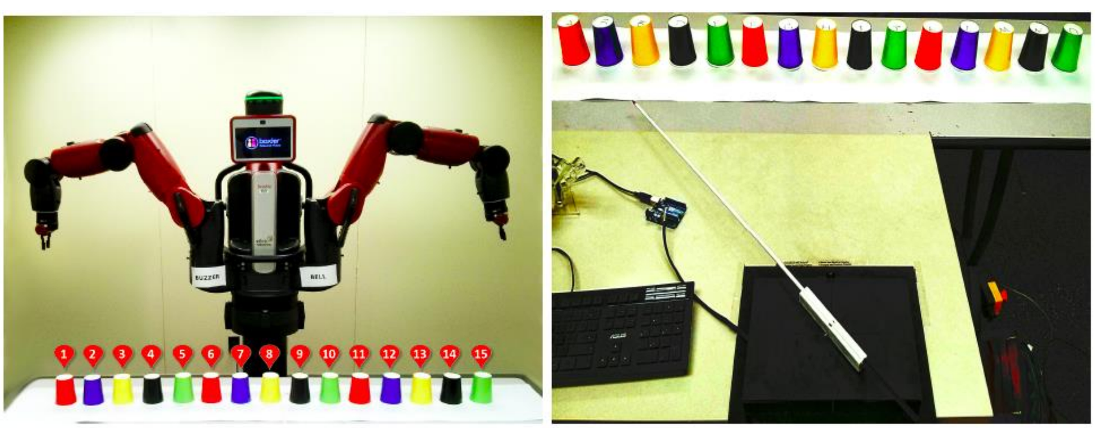

Figure 3. (left) The start position of the trajectories on the Baxter robot during the experimental setup. (right) A view of the pointing device from the subject's perspective.

A pointing device was designed to better record subjects' responses. The pointing device is fixed to the spindle of a linear potentiometer. The edges of the resistive track are then connected to the 5 volt and ground pins of an Arduino device and the wiper to an analog input pin. An Arduino device sketch then performs the necessary calculations to extrapolate from the wiper voltage the position along the line of targets at which the ray of the pointer will intersect. This distance is then forwarded to the Arduino's USB port.

3.1.3. Procedure

During the experiment, Subjects were seated around 150 cm in front of the Robot. There was a table located between the subject and the Robot. 15 colored cups were placed on the table.

For each trial, subjects pressed the "space" key on the keyboard placed beside them to start the trial. Once the trial started, they heard either a "Bell" sound to indicate the left arm would move, or a "Buzz" sound to indicate the right arm would move. The sounds alert the subject regarding which are they should direct their attention toward. Then the robot played the trajectory from its starting position to a selected target, which has been scaled to run in 8 seconds. Subjects were asked to continuously guess which cup was the target that the robot was trying to reach, from the beginning of the trial to the point when they were very confident with their estimations. Subjects used the pointer in the pointing device located in front of them to indicate their belief of the target of the robot's motion. The position of the pointing device was then recorded in a log together with the target number and the class of the trajectory. The pointer position was recorded till the end of the trajectory (8s). After the robot reached the target, the robot's arm returned to a start position which is common to all the trajectories. Then the subject was shown the number of trials that haven been completed, and was prompted to press any on the keyboard to continue the next trial.

Each subject was tested in 3 blocks. Each block contained 50 trials. For each subject, three random permutations of the 50 recorded trajectories were generated using a python script. There were 50 different recorded trajectories (2 hands * 5 possible targets for each hand * 5 different trajectory classes), thus each playback trajectory was played one time and only one time in each block. The trajectories of each permutation are then executed in order, recording a log of the trajectory filename and pointer position, with time-stamps, captured from the Arduino during the playback of each trajectory. In this manner it is possible to ensure even coverage among the classes and targets while minimizing the chance of subjects guessing the target through means other than visual perception of the robot's motion.

After each block of 50 trials, which forms a permutation of the full set of trajectories, the subject was given a mandatory two minutes break. These breaks allowed the subject to rest, and to maintain attention on the perception task. Each subjects participated in the experiment only once, in order to compare the perception of base legibility of the paths and the learning effects among subjects.

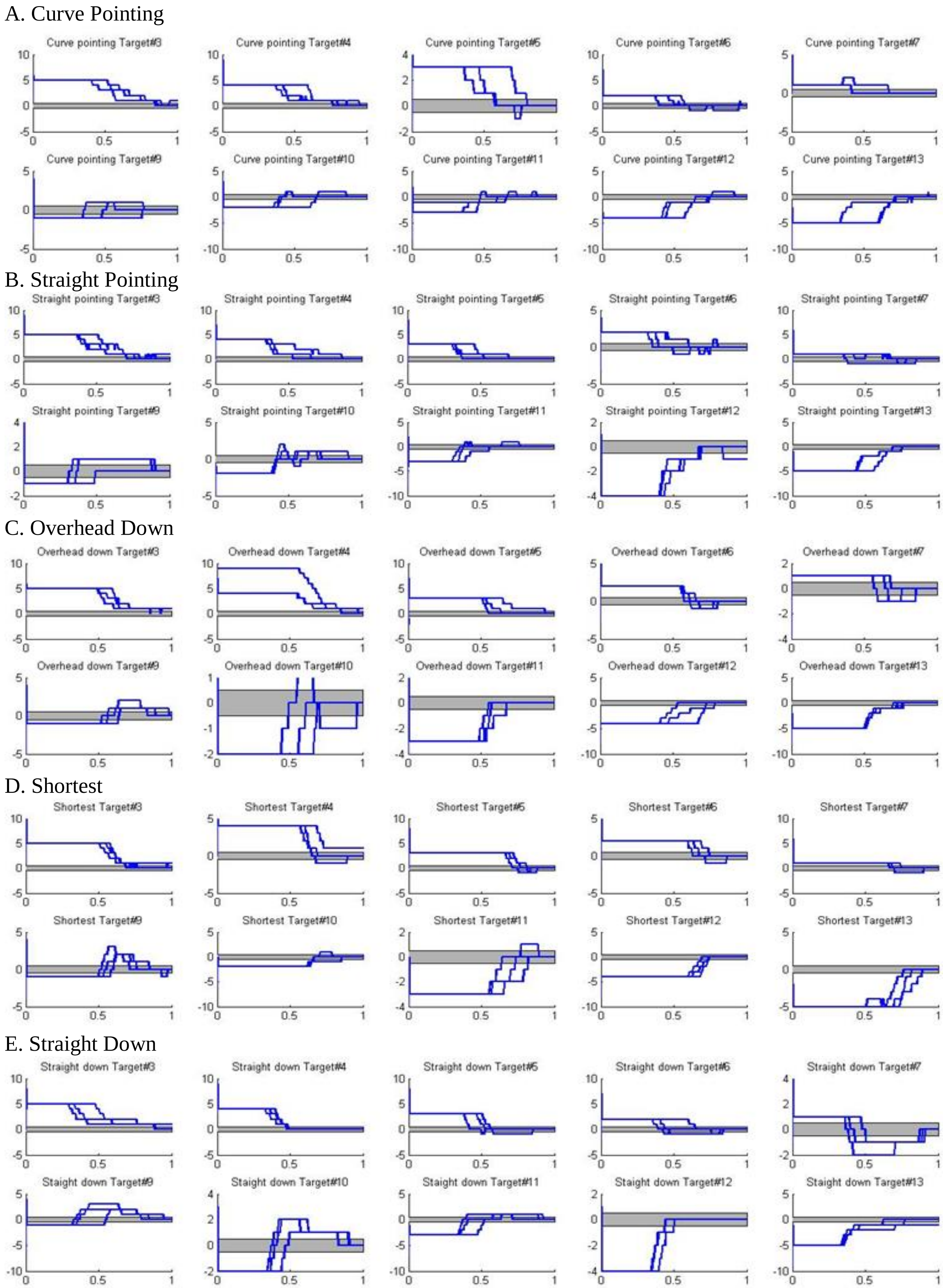

Figure 4. Examples of pointer traces for randomly selected individual subject. Grey represents target area.

3.2. Results

The pointer can only be moved in one dimension – in horizontal direction. For each trial, the horizontal positions of the pointer were recorded from the beginning to the end of the trial. The pointer position was averaged in a 160ms window, so that there were 50 position points along 8s trajectory length. Fig. 4 shows the examples of pointer traces for a randomly selected individual subject. It includes the example of traces for each individual trial. Grey areas represent the correct target area. Three traces were from three blocks that subject ran.

3.2.1. Predicted Target over time

The root mean square of the distance between the pointer and the correct target reflects the subject's prediction of the target as time passed. It is averaged across trials within subjects, and then across all subjects. Fig. 5 shows the root mean square was varied for different types of trajectories at the beginning and converged to the correct target location in the end over a normalized time scale. The convergence was fast during the middle range of trials (0.3-0.7) for all trajectories. The predictions for the shortest trajectory were further away from the correct target than for the other types of trajectories, which was consistent with the results of root mean square.

The pointer velocities (Fig. 6) which was how fast subjects moved the pointer, were peaked at the middle (.4-.6) range of trials. It again shows that the shortest type was different from the other four. These results suggest that the subjects might not able to predict the target during the early parts of the shortest trajectories as well as the other types. Frequently during the shortest paths, the end-effector was overshooting the target and then returning back to it, which complicated the interpretations of the motion even close to the completion of the path.

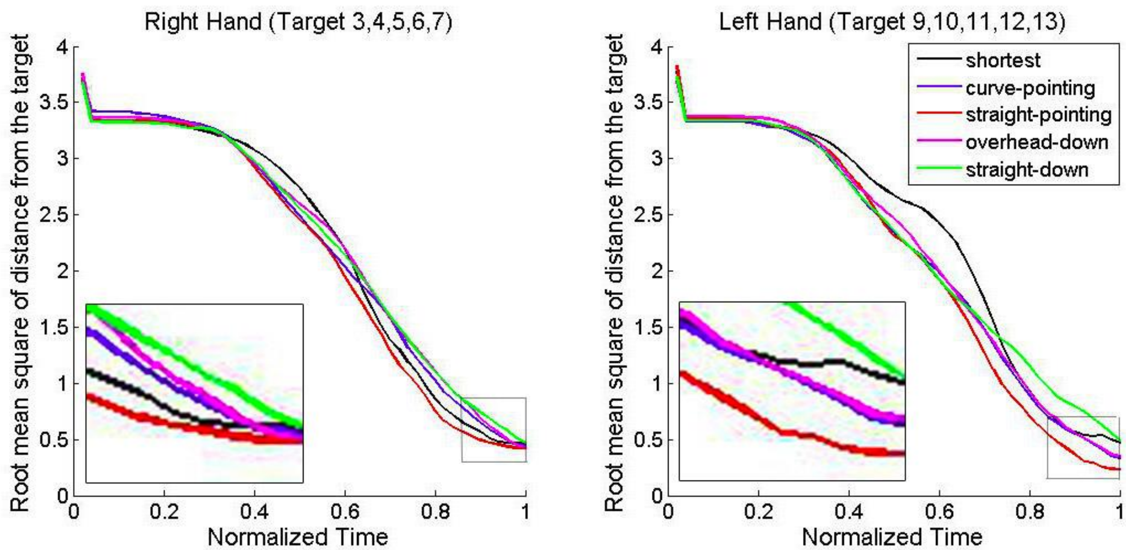

Figure 5. Root mean square of distance from the target along the normalized time scale for five types of trajectories: shortest (black), curve-pointing (blue), straight-pointing (red), overhead-down (pink) and straight-down (green).

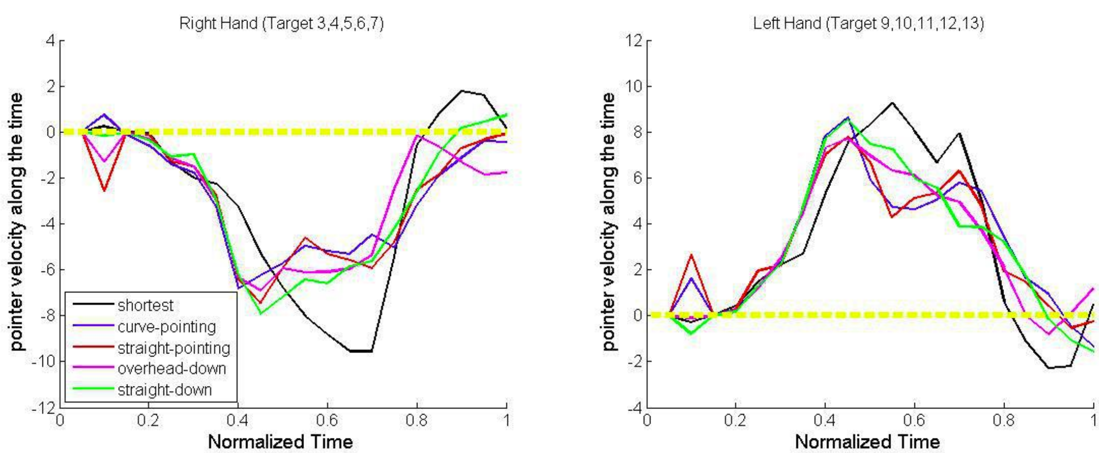

Figure 6. Pointer velocity along the normalized time scale for five types of trajectories: shortest (black), curve-pointing (blue), straight-pointing (red), overhead-down (pink) and straight-down (green).

3.2.1. Reaction Time

In order to compare different types of trajectories in more detail, we further examine the reaction time of subjects' response. Reaction time is the time duration from the start of the trial to the point subjects made a corresponding decision. Fig. 7 plots three types of reaction time (RT):

(1) RT of converging to the range within 2 cups away from the target (Fig. 7a), which happened at the beginning of trials;

(2) RT to converging to the range within 1 cup away from the target (Fig. 7b), which happened at the middle range of trials; and

(3) RT to converging to the target itself (Fig. 7c), which happened at the late part of trials.

Data from three blocks were presented in the order from left column to right column. In general, the straight-pointing type (red bars) was always the best. The curve-pointing (blue bars) was the second best. And the shortest type (grey bars) was worst, especially when converging to large error range (2 cups away, or 1 cup away from the target). One-way ANOVA test shows that there were significant difference among different types of trajectories for all groups (Table 1, F scores and p values).

First, let's just look at the block 1 (plots on the leftmost column), in which every trajectory was first presented to subjects. The performance to the shortest (grey bars) type was always the worst when converging to all types of error range. The disadvantage of the shortest type was obviously when converging into relative large error range (2 cups or 1 cup away from the target). Pairwise comparison shows that it is significantly longer than the other four types (Table 1). This disadvantage decreased when approaching to the correct target finally. It suggests that the confusion of the shortest type usually appeared as the early stage of the trajectories.

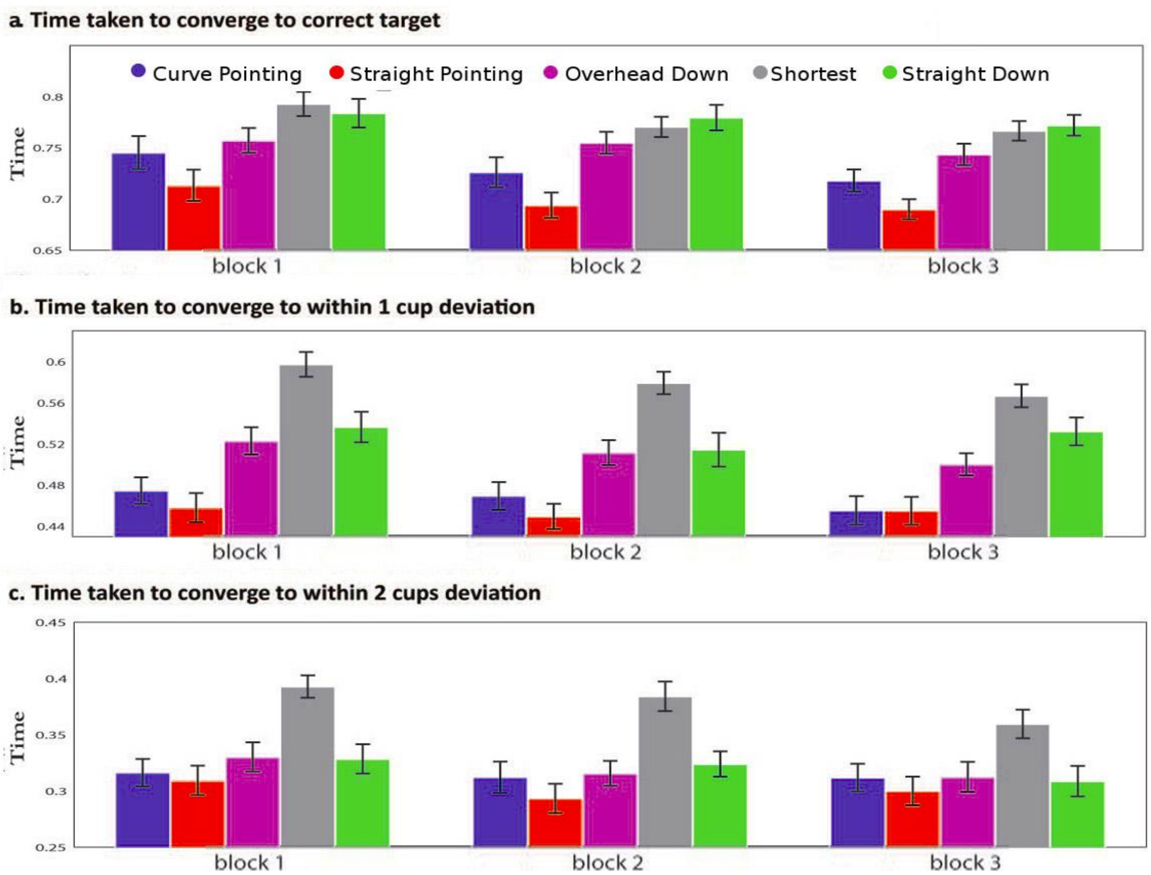

Figure 7. Reaction time (RT): the time converging to (a) the correct target; (b) 1 cup away from the correct target; (c) 2 cups away from the correct target. There were five different types of trajectories: curve-pointing (blue), straight-pointing (red), overhead-down (pink), shortest (gray) and straight-down (green). There were three blocks of 50 trajectories in order: block 1 (left), block 2 (middle) and block 3 (right). The error bars represent -/+ 1 standard deviation error.

The reaction time for the straight-pointing type (red bars) was significantly shorter than the others when converging to the range 1 cup away from the target and to the target, and it is marginally shorter than the others when converging to the range 2 cups away from the target. The curve-pointing was always longer than the straight-pointing but shorter than the rest three. It means that the straight-pointing is the best, and the curve-pointing is the second best among all five types. The easiness of understanding the straight-pointing and the curve-pointing trajectories could be due to the fact that end-effector (robot's hand) was always pointing to the target. The end effector (the hand) was previously reported as an important cue in understanding others' intention [12, 13, 10]. The advantages of the end-effector pointing to the target were strongest when converging to the range 1 cup away from the target. It suggests that the characteristics of curve-pointing and straight-pointing helps people understand the intention of the robot by converging to the smaller error range more quickly.

Table 1. One-Way ANOVA analysis for RT of 2 cups away, 1 cup away and pointing to the target for each block. In each cell, the values in the first row are the F-score (p-value). The second row lists all pairwise types which are significantly different from each other from post-hoc test (1- Curve-pointing; 2- Straight-pointing; 3-Overhead-down; 4- Shortest; 5- Straight-down).

	Block 1	**Block 2**	**Block 3**
target	5.2 (<.01) 2-4; 2-5	8.34 (<.001) 1-5; 2-3; 2-4; 2-5	11.37 (<.001) 1-4; 1-5; 2-3; 2-4; 2-5
1 cup	16.74 (<.001) 1-4; 1-5; 2-3; 2-4; 2-5; 3-4; 5-4	14.38 (<.001) 1-4; 2-3; 2-4; 2-5; 3-4; 5-4	14.91 (<.001) 1-4; 1-5; 2-4; 2-5; 3-4
2 cups	7.3 (<.001) 1-4; 2-4; 3-4; 5-4	7.61 (<.001) 1-4; 2-4; 3-4; 5-4	3.3 (=.013) 2-4; 5-4

The "curve-pointing" did not perform as well as the "straight-pointing", which was surprising given the conclusion of previous studies [7]. It could be due to the difference between two targets setting in previous studies and multiple and crowded targets setting in the current experiment. With multiple targets in a crowded environment, the curve path was more likely to confuse people, rather than providing legibility information.

The overhead-down was the third most legible trajectory and it was better than the straight-down. It also makes sense, because whenever the overhead-down trajectories reached to the top of the cup, subjects know the answer for sure. While the straight-down was still on the way to the top of the cup at the same time point. This leads to the performance as similar reaction time when converging to 2 cups or 1 cup away from the target between these two types of trajectories, and shorter RT for the overhead-down when converging to the correct target.

3.2.3. Learning Effect

As we mentioned in the Method section, three blocks were tested for each subject. In each block, every trajectory was randomly run and only run once. Fig. 8 shows that the time converging to the target was decreased across blocks, which means subjects did learn trajectories. The learning effect is larger from block 1 to block 2, than from block 2 to block 3. This could be because subjects were already well trained before entering into block 2 and might get tired in block 3. Learning effect also varies among different types of trajectories. The shortest type shows greater learning effect than the others in all convergence situations (Fig. 8a,b,c). These results suggest that the shortest type was the hardest one to be interpreted at the early stage, but it can be learned by more training. Nevertheless, the learning does not allow it to reach the legibility level of alternatives such as the “straight-pointing” path. Additionally, the learning effect also appeared as less variance in later blocks (block 2 and 3).

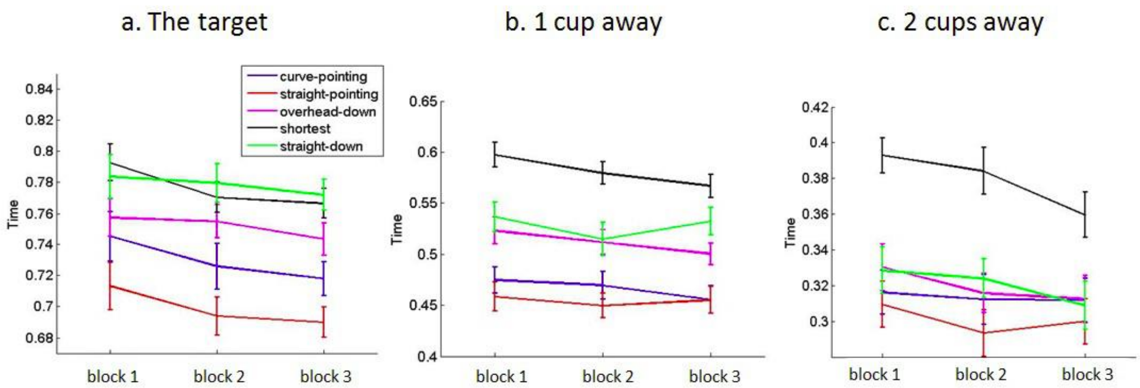

Figure 8. Learning effects reflected in reaction time, the time converging to (a) the correct target; (b) within 1 cup deviation from the true target; (c) within 2 cups of the true target. There were five different types of trajectories: curve-pointing (blue), straight-pointing (red), overhead-down (pink), shortest (black) and straight-down (green). The error bars represent -/+ 1 standard deviation error.

3.2.4. Performance for each cup

The understanding of different types of trajectories was also related to the location of the target. In order to better analysis different trajectories, we further examined performance (mean position and pointer velocity along the time) for different cups. Fig. 9 shows the mean distance from the target for each cup and Fig. 10 shows the pointer velocity for each cup.

Comparing to cups located on edge of the target set (i.e. 3, 4, 12, 13), for cups located near to the center (i.e., 6, 7, 9, 10), the mean distance from the target was more easily to across 0 level to the opposite direction (Fig. 9). As the subjects typically begin with the pointing device centered, this suggests that subjects were more likely to overshoot the target. The overshoot could be due to many reasons. For example, when moving the pointer, people are more likely to move it fast and in a large range to roughly approaching to the target, and then move it carefully and precisely to hit the target. So that, the overshoots happened more likely for center items, in which cases, the first step of movements took the pointer over the target. The starting position of the robot is nearer the edge cups than the center cups. The overshooting could indicate that they are following the arm rather than predicting the target accurately. Subjects were more likely to overshoot the target for the shortest type. As we mentioned in above, during the shortest trajectories, the end-effector was overshooting the target and then returning back to it. The traces here illustrated subjects' corresponding reactions. The trajectories with the lowest reaction times also demonstrate the least overshooting.

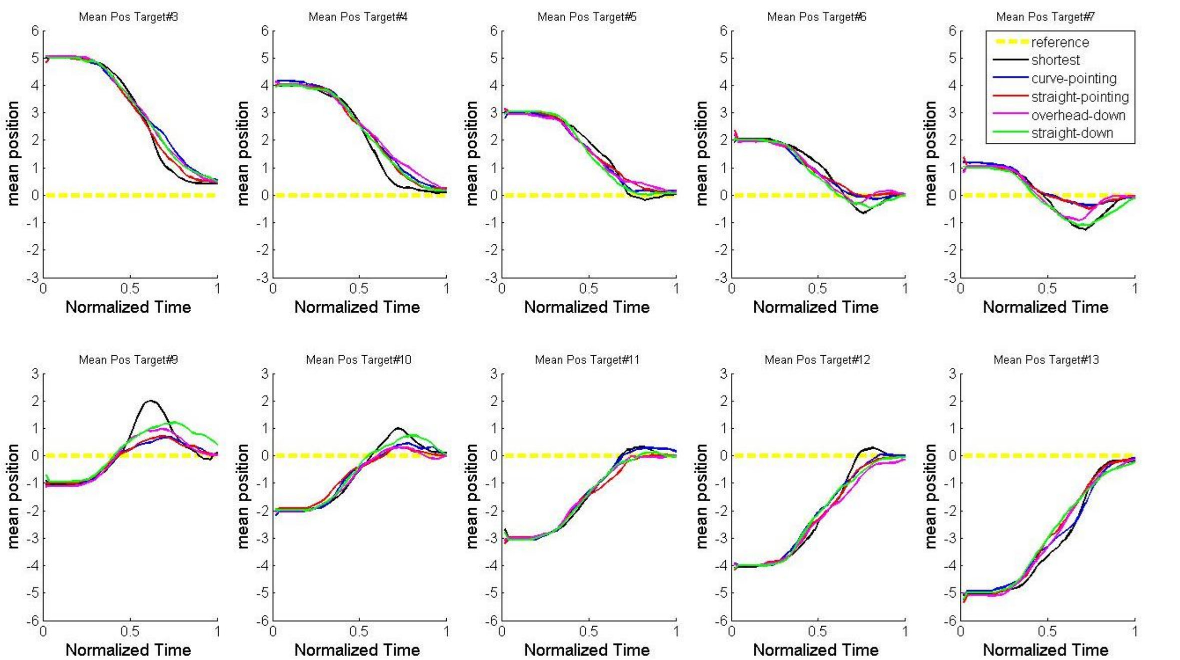

Figure 9. Mean distance from target along normalized time scale for each cup (cup No. labeled on the top of each plot). Five types of trajectories: shortest (black), curve-pointing (blue), straight-pointing (red), overhead-down (pink) and straight-down (green).

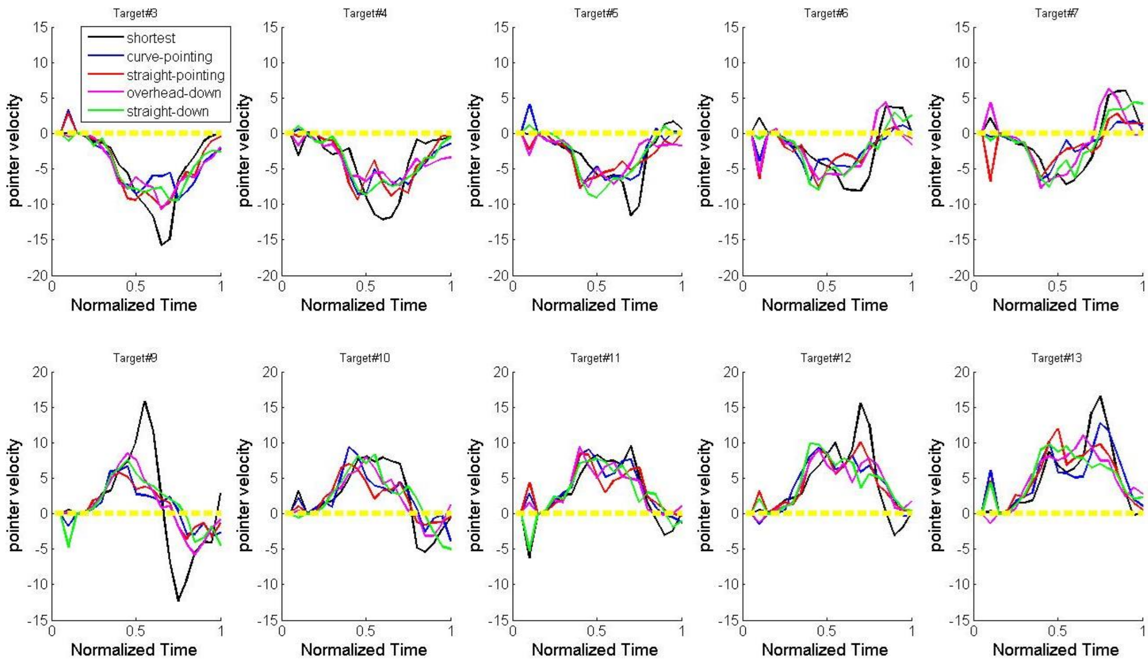

Figure 10. Pointer velocity along the normalized time scale for each cup (cup No. labeled on the top of each plot). Five types of trajectories: shortest (black), curve-pointing (blue), straight-pointing (red), overhead-down (pink) and straight-down (green).

The mean position (Fig. 11-13) and the pointer speed (Fig. 14-16) were examined in each block separately, in order to see whether there was any adjustment of strategies across blocks. It shows that the patterns of three blocks were similar. Fig. 11- 13 plots the mean position of the pointer away from the correct target along the normalized time scale in block 1 (Fig. 11), block 2 (Fig. 12) and block 3 (Fig. 13). Each plot represents one target. There were five types of trajectories: Shortest (black), curve-pointing (blue), straight-point (red), overhead down (pink) and straight-down (green). Each lines were averaged the performance of 30 subjects. The yellow dash line represents the correct target. It shows that the overshoot phenomena did not reduce in later block. The comparison across three blocks suggests the occurrence of overshoot might not due to the unawareness of the possible target range for each arm. Fig. 14- 16 plots the mean position of the pointer away from the correct target along the normalized time scale in block 1 (Fig. 14), block 2 (Fig. 15) and block 3 (Fig. 16). Each plot represents one target. There were five types of trajectories: Shortest (black), curve-pointing (blue), straight-point (red), overhead down (pink) and straight-down (green). Each lines were averaged the performance of 30 subjects. The yellow dash line represents 0 level. In all blocks, subjects tent to move the pointer slow at the beginning, fast in the middle and then slow again when approaching to the end. Subjects adjusted the pointer more frequently in block 3 than in block 1, which appears as more serrated shapes on velocity plots, especially for the shortest type.

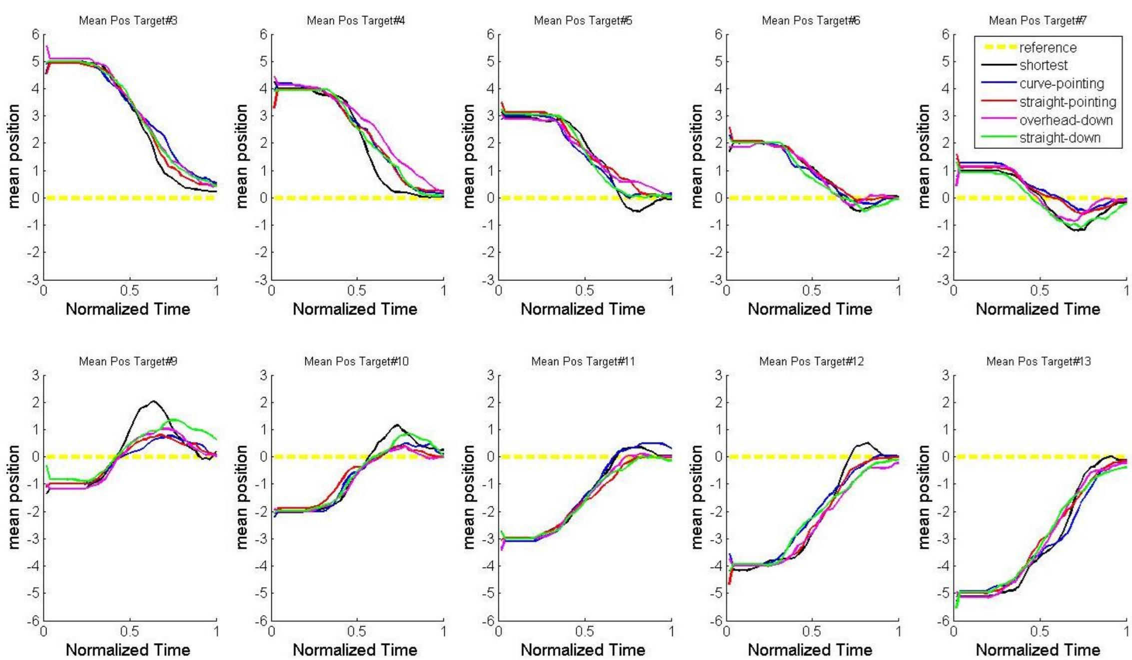

Figure 11. Mean distance from target along normalized time scale for each cup (cup No. labeled on the top of each plot) in block 1.

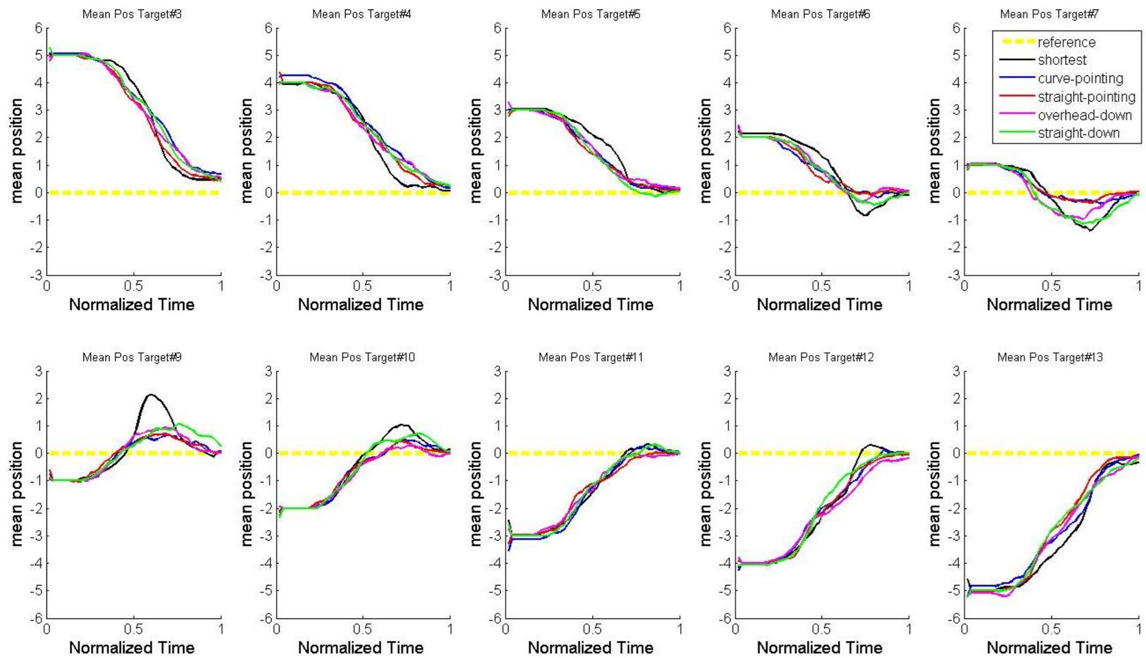

Figure 12. Mean distance from target along normalized time scale for each cup (cup No. labeled on the top of each plot) in block 2.

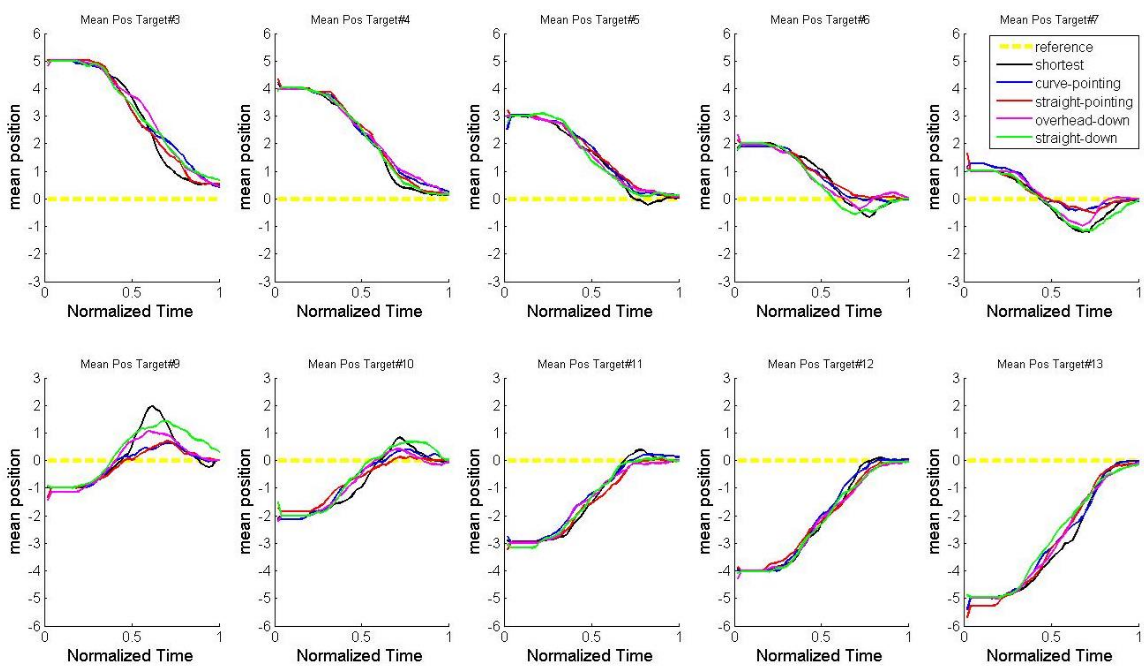

Figure 13. Mean distance from target along normalized time scale for each cup (cup No. labeled on the top of each plot) in block 3.

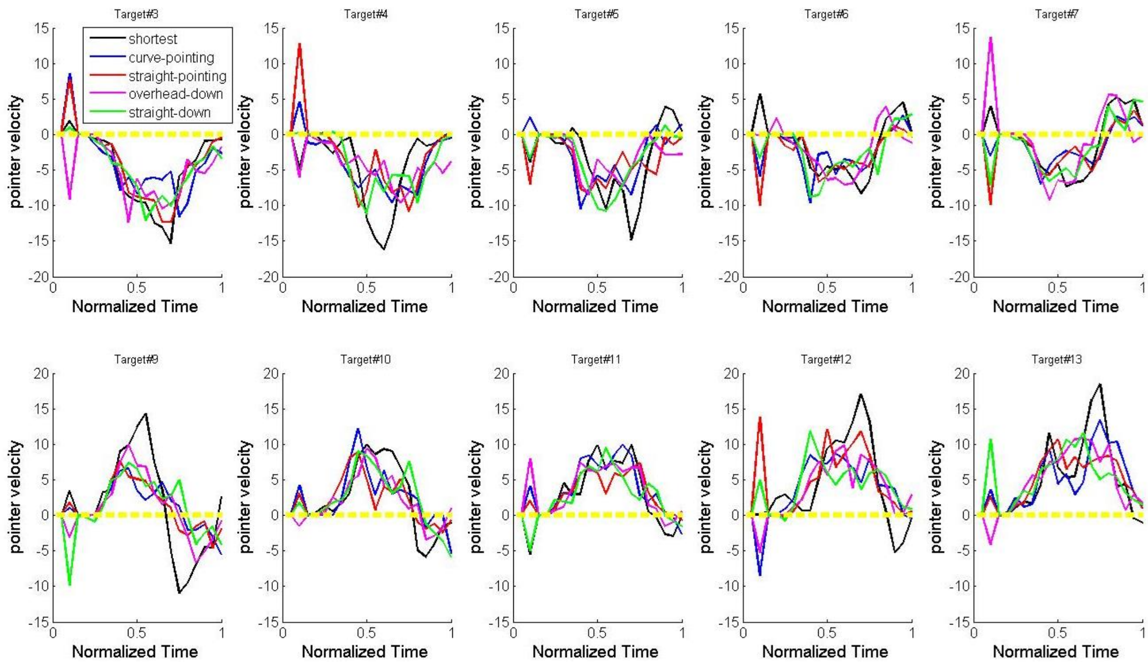

Figure 14. Pointer velocity along the normalized time scale for each cup (cup No. labeled on the top of each plot) in block 1.

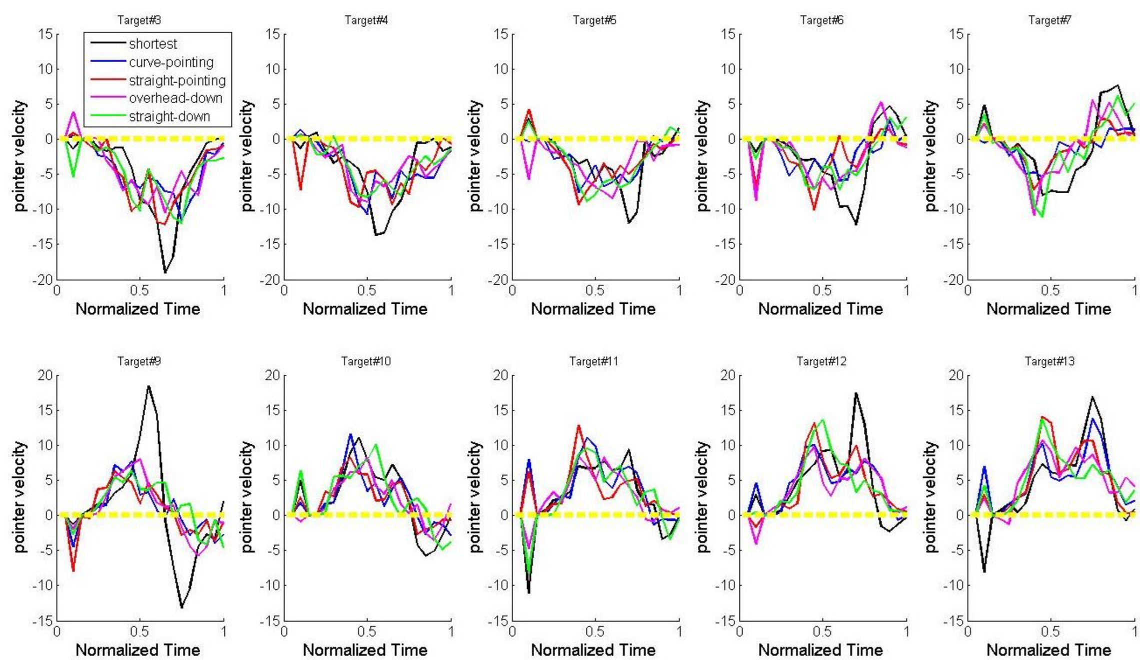

Figure 15. Pointer velocity along the normalized time scale for each cup (cup No. labeled on the top of each plot) in block 2.

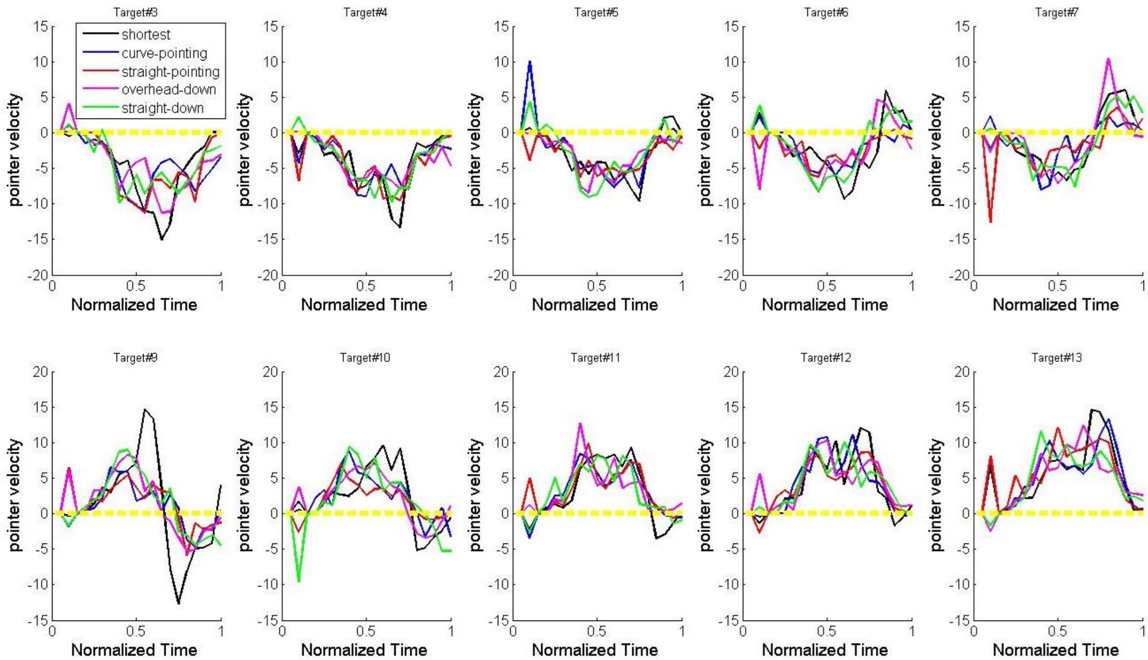

Figure 16. Pointer velocity along the normalized time scale for each cup (cup No. labeled on the top of each plot) in block 3.

Given the above results, we could conclude several points. In general, the straight-pointing was the easiest to be understood, the curve-pointing was the second best, and the shortest type was the hardest one. The advantage of the straight-pointing and the curve-pointing is most probably due to the fact that the end-effector was always pointing to the target. This claim can be confirmed by the results that the straight-down was way behind the straight-pointing, through both of them followed the same straight paths.

The advantages of legibility were previously reported, that the legible trajectories should be responded faster and interpreted more accurately [7]. This was partially supported by our results – the curve-pointing (legible trajectories) was the second, better than the rest three (illegible trajectories). However, the fact that the straight-pointing type was better than the curve-pointing type is different from previous findings – legible trajectories should be better than the predictable ones. This difference might be due to multiple targets we used instead of just two targets in the previous studies.

The disadvantage of the shortest type appears as slow convergence – it took more time to approaching a certain error range compared to the other types. The overhead-down was better than straight-down when converging to the target, but these two were not different when converging to the location 2 cups or 1 cup from the target. It is also make sense that subjects could know the target for sure when the hand moved to the top of the cup, while at the same time point, the straight-down motion was still away from the target.

The learning effect exists, however, varies for different types of trajectories. The general learning benefit appears as less variance in block 2 and 3. Three types – shortest, curve-pointing and straight-pointing – could be learned across blocks, while the overhead-down and the straight-down were barely learned across blocks. However, even though the shortest type can be learned, it still cannot beat the other four types of trajectories. In another words, we could not simple use the most efficient actions (in terms of joints movements) and expect people could learn such actions.

4. Discussion

The current study, based on the previous legible motion work, aimed to examine the features of legibility of robot's motion in a multiple targets environment. Such a crowed workspace was more similar to the natural working environment. The experiment with settings as natural environment might provide more valuable information which could be directly applied in real human robot collaboration. Two features of legibility were considered – arm path and hand orientation. Five different classes of trajectories were generated based on these two features. It shows that the most efficient class of trajectories (human could interpret it easily and quickly) is the ones that the robot's arm moving straightly from start position to the target while the hand always pointing to the target.

This study partially supports previous findings regarding the legibility of robot motion [7], i.e., different types of paths can have highly divergent levels legibility. Shortest C-space paths, frequently the focus of the motion planning literature, can be poor choices in terms of legibility. Similarly, paths that are currently used for pick-and-place tasks in industrial setups (e.g., "overhead") also appear not to be intuitively interpreted. Paths that focus on the orientation of the end-effector seem to be advantageous in terms of legibility, since they exhibited the best performance in target estimation (high accuracy and less convergence time).

It was different from previous findings that "straight-pointing" types were more legible relative to "curve-pointing" paths. The idea behind the "curve-pointing" paths is that legibility may increase by exaggerating the arms' motion so that it moves away from unintended targets (Fig. 1a). The difference seems to be due to the presence of multiple targets in the current work. When there were only two possible targets, exaggerating the motion in one direction can significantly assist in identifying the target. However, such exaggeration can be confusing in the case of multiple targets, or in cluttered workspaces. This study is intended to inform legibility in such cluttered environments.

A significant observation was the importance of the end-effector's orientation relative to the target. It was hypothesized that humans might pay particular attention to the pose and orientation of a robotic end-effector, similar to the way they respond to humans' hands. The experimental results confirmed this hypothesis. It would be worthwhile to incorporate the maintenance of such end effector orientations into the cost functions of motion planners in the future.

A question that needs to be answered is whether it is worthwhile to consider legibility of robotic motion planning paths, as opposed to relying on learning ability of human observers. There was a learning effect when the subjects repeat observed the same trajectories. The benefit primarily appears as reduced variance during repetitions of the same trajectories and varies across types of trajectories. Three types of paths, shortest, curve-pointing and straight-pointing, could be learned across blocks, while the overhead-down and the straight-down did not exhibit significant learning behavior. Although the learning effect existed, the benefit of the learning might not be able to override the advantage of the legible information, which was supported by the fact that the performance of the shortest type was improved in later blocks, but still not as good as the performance of other types.

Note that in the experiment the subjects witnessed the same path to a target 3 times in three blocks rather than 3 variations of the same type of path to the same target.

Certain planners, such as sampling-based ones, can vary in the repeatability of their solutions. It is not necessarily the case that similar degrees of learning would occur for the general case of repeated exposure to motions plans generated from such motion planners. Furthermore, in this study the initial condition was always the same. When a robot needs to plan on the y and transition from one task to another, the human subject will not be exposed to the same exact trajectories repetitively. It is interesting to consider the effects of legibility in the context of trajectories that have different initial conditions.

During the experimental study, there was a transition from a web-based UI in the pilot trials, to the physical pointer feedback device used in gathering the data included here. This change decreased the cognitive load placed on human subjects by the data collection interface and resulted in a reduction between the best-performing and worst-performing path classes relative to the pilot study. A human co-worker in a collaborative setting is likely to have additional mental demands beyond the robot interaction. While minimizing the cognitive load might clarify the effects of legible features, such distractions might exaggerate the legibility of robot motions. An interesting line of future research is to analyze the effect of cognitive load on legibility.

Initial pilot trials also used trajectories which varied in duration. Increasing duration of trajectory execution gives the subject more time to recognize the legible features of the motion. However, it is not clear whether the effect persists if the trajectory duration keeps on increasing. Unnaturally slow trajectories might obfuscate the features that contribute to legibility. A scope for future work would be to understand the effects of the duration and speed of trajectories on legibility consistent among different types of trajectory.

The overshoot phenomenon occurred for the items located in the center area, but not for edge area. It could be due to the habit of moving pointer – moving fast and not precisely at the beginning in order to bring the pointer near to the target, and then moving precisely to approaching to the target. It also could be due to the unawareness of subjects about the possible range of targets for each hand. Analysis on the performance (both positions and velocity of the pointer) for each block shows the occurrence of overshoot did not reduce by training. However, it might require more trials for further analyze each individual case.

Future experiments could involve the random placement of targets over a two-dimensional subspace, the presence of obstacles, as well as stopping the motion of the arm half-way towards the target and asking the user to guess the intended target. The longer-term objective is the definition of appropriate motion planners that generate highly-legible paths. It appears that such planners and accompanying cost metrics need to be reasoning for the orientation of the end-effector and its workspace path. This line of work can eventually lead to robots that use time-efficient paths when they operate in a dark factory floor and automatically switch to humanly-legible but less efficient paths when people enter their workspace and collaborate.

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