Effects of low level changes in motion on human perception of robots

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***Abstract*—This paper examines the effects of varying low level motion profiles on human perceptions of robots. We define two kinds of motion profiles, linear (constant velocity) and a more lifelike sigmoid (nearly constant acceleration). We use the robot Keepon in a simple card game where volunteers teach the robot how to play. We use participant responses to a questionnaire to quantitatively analyze the effects of the motion profiles. A 2x2 design is used to compare the effects of the motion profile with variations of the learning rate of the robot. We hypothesized that the sigmoid robots would be considered more lifelike and suspected that they would also perform better in other areas. Our 24-participant study indicated that motion profiles can have significant effects on human perceptions of robots. Our data indicate that sigmoid robots are perceived to be more lifelike, likeable and intelligent than their linear counterparts. This is more pronounced in less intelligent robots, i.e., the slower learning case. For example, the slow-sigmoid robots were perceived to learn almost twice as fast as the slow-linear robots.**

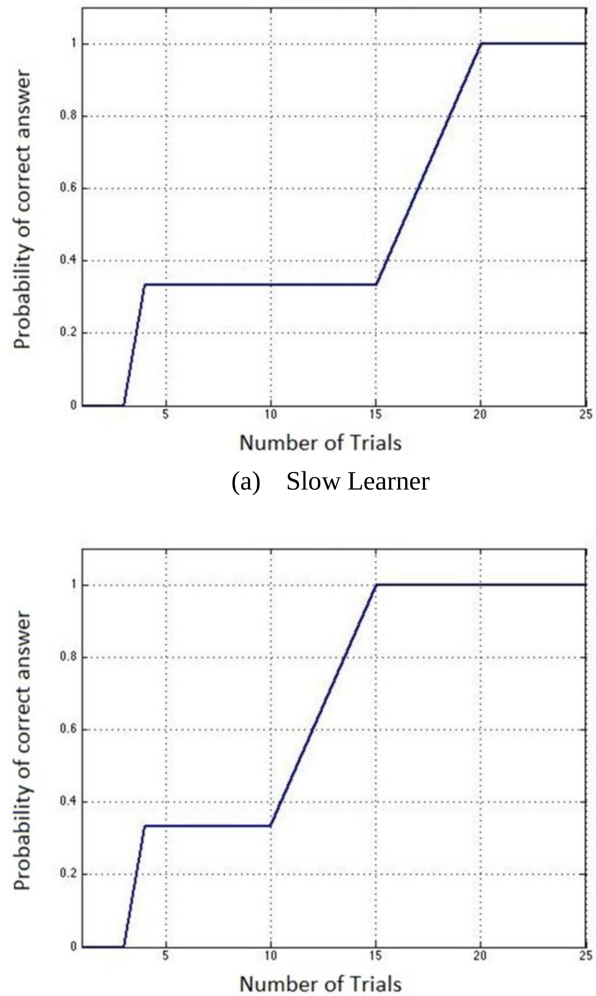
***Index Terms*—Keepon, robot motion, social robotics**

I. Introduction

HUMAN perception of robot intelligence may be affected by many factors, ranging from actual variation in task performance to subtle changes in robot behavior. Exploring the effects of subtle robot behavioral changes can help us understand how to design more effective social robots [1].

The present study considers the effects of low-level motion changes on the perception of the robot. Rather than change the overall high-level behaviors of the robot, we decided to vary the low-level velocity profiles of every robot action between two conditions. The displacement versus time plots for the two velocity profiles can be seen in Figure 1.

In the linear condition, every robot movement is performed with a constant velocity. The sigmoid motion is modeled instead after a typical human motion profile. Human motions, such as those of the upper limb during reaching experiments, commonly exhibit a parabolic velocity profile [2]. The movements start out slowly, accelerate to a peak speed, and then slow down as the limb approaches the target position. The sigmoid motion condition was chosen to exhibit similar characteristics.



(a) Slow Learner

(b) Fast Learner

Figure 1: Probability curves for slow and fast learners

Given its similarity to human movements, we hypothesize that the robot using the sigmoid motion condition will be perceived as more lifelike. We also hypothesize that the robot with the sigmoid motion may be perceived more positively in other ways, such as viewing the robot as more intelligent.

II. Method

A. Participants

There were 24 participants, all current graduate students from Yale University, of whom 8 are currently studying Engineering or Computer Science. The participants reported their experience in robotics on a 7 point scale (with 1 being "no experience" and 7 being "extensive experience"), resulting in a mean of 2.2 (SD 1.6).

B. Apparatus

The participants interacted with the robot by means of a simple card game, where each card had an integer value printed on it. During each trial, the participant presented the robot with three cards. The participant's objective was to teach the robot to always choose the card with the maximum number.

TABLE I
2X2 Plan for Game

	Sigmoid	**Linear**
Fast	Fast-sigmoid	Fast-linear
Slow	Slow-sigmoid	Slow-linear

4 types of robots, based on two motion profiles, and two learning rates

Each participant was exposed to one "type" of robot as seen in Table I. The robots were programmed with two different learning rates, "fast" and "slow". The fast robot learned the game approximately 5 trials earlier than the slow robot, based on a probability curve. In the beginning, the robot had a 1 in 3 chance of getting the answer correct, which slowly increased over time, until it had "learned" the game, at which point it got the answer correct with probability 1. The sequences of correct and incorrect trials for the slow and fast learners were pre-generated and identical for all subjects.

The amount of time taken for a motion was also identical for sigmoid and linear motions, thus ensuring that the only difference between the two was the motion profile, and not overall speed.

Software

The coding work consists of two main parts. First, we implement a fundamental move action which lets the Keepon move from the current position to some target position. A Boolean flag determines the motion profile (linear or sigmoid) that the action operates under.

For each movement, we specify the total amount of time to complete the action and the length of one time slot, which results from a division of the total amount.

For the linear case, the Keepon moves the same distance within each time slot; for the sigmoid motion, its movement follows a scaled sigmoid function to make sure that it adheres to the following description: it moves slowly at the beginning, picking up speed, reaches a peak velocity, then slows down as it approaches the target position, finally coming to a halt.

We also implement multiple high-level actions, including looking at the subject, looking at the cards, and choosing a card, all based on the basic move action. Their corresponding motion profiles and durations are dictated by those of their underlying move actions.

The second major block of code involves the creation of a wireless control system for the robot. We implemented a client-server based architecture over TCP to facilitate remote control of the Keepon. The server side is directly connected to the Keepon and constantly processes incoming instructions from the client side and controls the Keepon based on them. The client side has a graphical user interface from which the experimenter can issue instructions to the remote Keepon server.

Questionnaire

At the end of the experiment, each participant was given a questionnaire. We designed the questions on the basis of the suggestions provided by [3]. The questionnaire consisted of a number of behavioral questions, rated on a 7-point scale:

1. Have you worked / played with robots before?
2. How well did the robot respond to emotional cues?
3. How lifelike was the robot?
4. Would you want to teach this robot a more difficult game?
5. How intelligent do you think the robot was?
6. How likeable did you think the robot was?

The questionnaire also asked the participant to estimate the amount of time it took the robot to learn the game, as well as the number of tries it took to so.

C. Procedure

Each subject was led into the room and instructed to sit down in front of the Keepon. A standard script explaining the procedure was then read to each subject. The full script can be found in Appendix A.

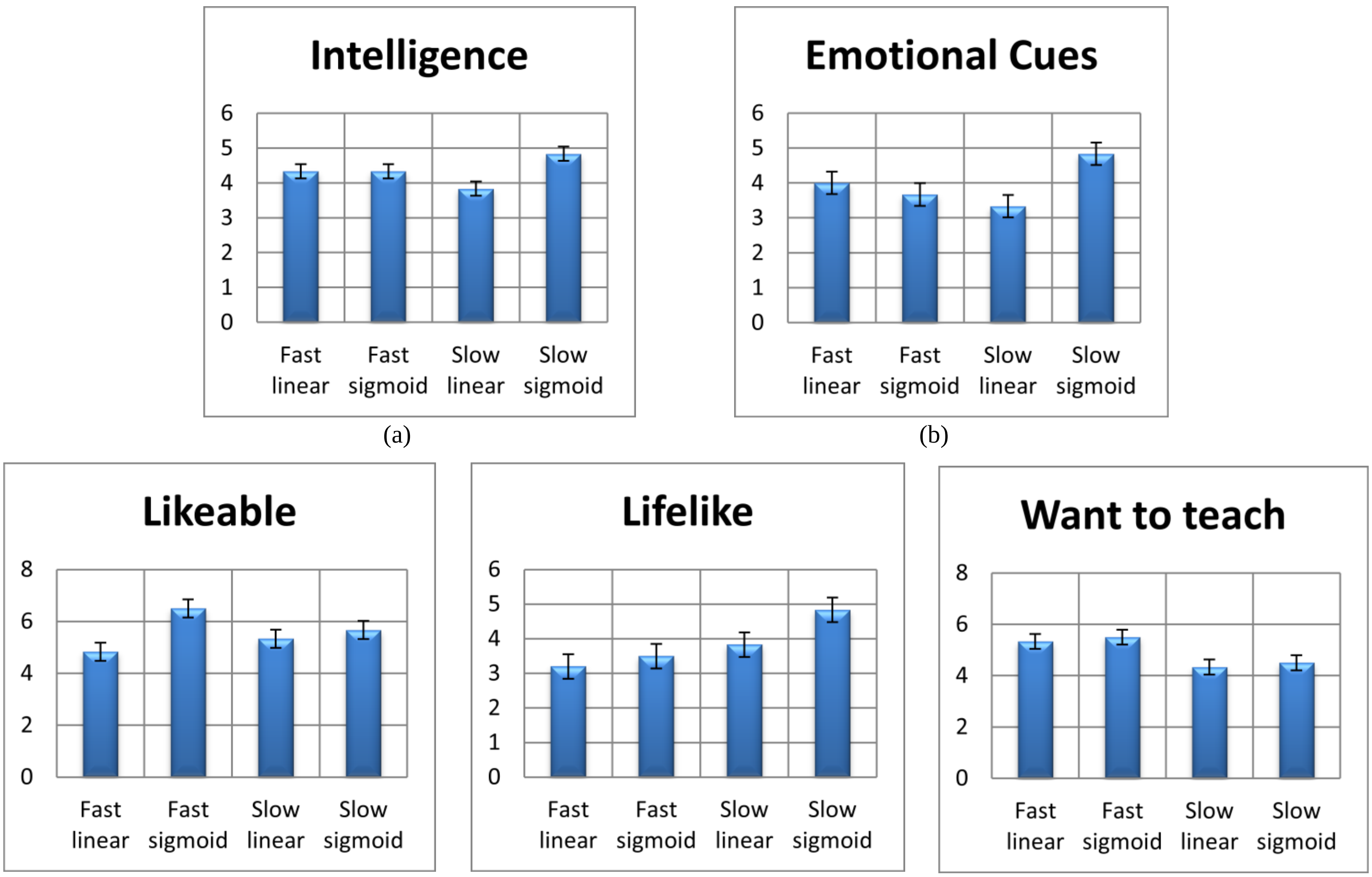
After the script was read, the experimenter took any questions from the subject, trying their best to only repeat specific phrases from the script to answer the questions. After answering any questions, the experimenter left the room, causing the subject to start the experiment. The subject was told that they were teaching a simple card game to the Keepon using verbal feedback after each trial. The subjects started each trial by placing three cards from the deck in front of the Keepon. After the cards were placed, the Keepon looked at each of the cards, performed a brief thinking motion, and then selected a card by leaning towards it. The subject then gave verbal feedback to the Keepon and discarded the three cards. When all initial 75 cards were discarded, the subject exited the room to find the experimenter outside.

The experimenter then gave the subject a brief survey to fill out. After the subject filled out the survey, the experimenter instructed the subject to provide their best guess for a specific time and number of trials after which the Keepon had learned the game. Additional instructions were provided as necessary when it was found that subject did not understand the specific

TABLE II
MEANS OF PARTICIPANT RESPONSES

	Emotional	Lifelike	Want to teach	Intelligent	Likeable	Perceived time	Perceived # tries
Fast linear	4.00	3.20	5.33	4.33	4.83	7.33	14.58
Fast sigmoid	3.67	3.50	5.50	4.33	6.50	6.17	14.33
Slow linear	3.33	3.83	4.33	3.83	5.33	10.67	21.33
Slow sigmoid	4.83	4.83	4.50	4.83	5.67	5.67	15.67

"Emotional" refers to "response to emotional cues". The fields "Emotional", "Lifelike", "Want to teach", "Intelligent" and "Likeable" were all measured on a 7-point scale. Perceived time was measured in minutes. The survey question relating to "previous experience with robots" is excluded from this table.



(c) (d) (e)

All of the above scores were reported on a seven point scale, with 1 being the most negative response, and 7 being the most positive response. The error bars indicate standard error. The survey question relating to "previous experience with robots" is excluded from this figure.

Figure 2: Participant Responses

type of response desired for a question. After the subject completed the survey, the experiment was complete.

III. RESULTS

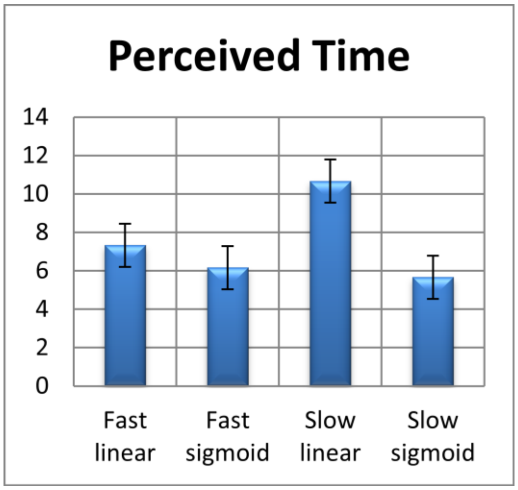
We hypothesized that the change from linear to sigmoid would improve the participant's opinion of the robot, so we compared the means of the scores reported across the four cases, paying special attention to how the scores for the "fast" and "slow" robots changed as we varied the motion profile.

Interestingly, the differences between the linear and sigmoid varieties were more noticeable and consistent than those between the fast and slow learners (see Table II).

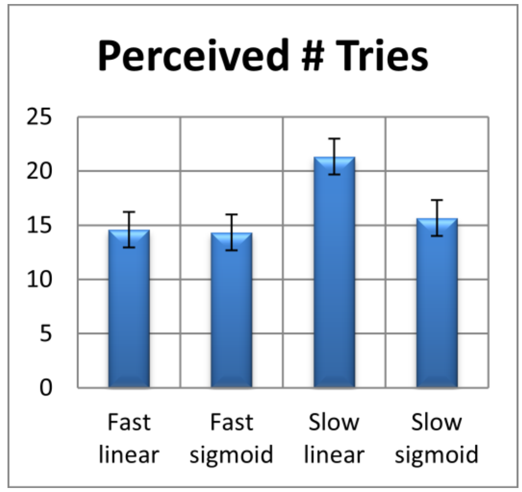
The levels of intelligence reported did not vary significantly for the fast cases, but there was a significant gap between the slow-linear and slow-sigmoid cases (Fig. 2a).

When reporting the robot's response to emotional cues, participants scored the slow-sigmoid robot much higher than the slow-linear robot (p=0.03, see Fig. 2b). The scores for the fast versions did not differ significantly.

The sigmoid versions were considered to be more likeable



(a)



(b)

Perceived time was measured in minutes. The error bars indicate standard error.

Figure 3: Participants' perceptions of time

than their linear counterparts (Fig. 2c). The change from sigmoid to linear for the fast case was much greater than the same change for the slow case (p=0.02 for fast-linear and fast-sigmoid).

Again, the sigmoid robots were consistently considered to be more lifelike (Fig. 2d). The slow-sigmoid performed much better than the fast-linear (p=0.05). The difference was far more pronounced for the slow cases.

When asked about their desire to teach the robot a more difficult game, the participants who were exposed to the fast robots consistently responded more positively than those exposed to the slow robots (Fig. 2e). There was no noticeable difference between the linear and sigmoid cases.

The perceived time taken was significantly higher for the linear cases, compared to the sigmoid (Fig. 3a). The gap between the slow-linear and slow-sigmoid was more prominent (p=0.046) than between the fast cases. The same pattern is observable in the number of tries perceived (Fig. 3b) – the fast robots have similar performance, while the slow-sigmoid performs significantly better than the slow-linear (p=0.042).

IV. Discussion

The data reported by the participants supports our main hypothesis that sigmoid movements are better (more intelligent, lifelike, likeable, etc.) than linear movements.

The data also indicates that this difference becomes more pronounced in less intelligent robots – essentially, the more intelligent a robot is, the less effect its motion profile will have on human perceptions of its intelligence.

The other likely explanation for the greater differences between the slow learning cases is this: since the fast robot learned quickly, subjects may have paid less attention to it after it started giving correct responses. This could result in the motion profile difference having a weaker effect in the fast learning case, since the subjects focused on the robot for a shorter duration.

The slow-sigmoid robot performed better than the fast-linear robot across the board, except for the scores related to the participants' perceptions of time. This makes sense, since the actual learning time would be expected to have a greater effect on survey questions directly related to the amount of time the robot took to learn the task.

Although we hypothesized that the sigmoid robot would produce generally better scores than the linear robot, we didn't have a clear explanation for this in all cases. We did expect the observed difference in the perceptions of how lifelike the robot is, since it makes sense that more human-like sigmoid motion profiles would be perceived as more lifelike.

However, in other cases, while clear effects are present, the reasons are not as clear. The robot was perceived as learning in about half the time and about five less trials on average in the slow sigmoid case, when compared with the slow linear case. This may suggest that the subjects enjoyed interacting or were more engaged with the slow sigmoid robot than with the linear one, since they perceived time as passing more quickly when interacting with the robot [4].

V. Conclusion

In this paper we look at the effects of linear (constant velocity) and sigmoid (constant acceleration/deceleration) motion on human perceptions of robots. The results of our study indicate that sigmoid motions are considered to be more lifelike, likeable, intelligent, and respond better to emotional cues than linear motions. The data also indicate that the effects of linear vs. sigmoid motions are more pronounced in less intelligent robots. The effect of merely varying the motion profile for the slow robots was comparably large or larger than that caused by actually using fast robots (which successfully learn the game approximately 5 trials earlier than the slow ones).

APPENDIX

Appendix A: Script

I'm going to explain the procedure for the experiment.

The robot you see in front of you is called "Keepon" – you'll be teaching the Keepon to play a simple card game.

During each trial, you will draw three cards from the deck and place them face up on the three rectangular spaces on the mat in front of you (don't spend too much time positioning the cards exactly within the rectangles – an approximate fit will work). Once you're ready, say "I'm ready". The Keepon will look at each of the three cards and then choose a card, by looking at it and gesturing.

The Keepon will initially choose randomly, because it doesn't know the rules of the game. The Keepon will learn the rules based on your verbal feedback after it selects the card. After each trial, please tell the Keepon whether it has chosen correctly. Please try your best to speak clearly and naturally. Note that the Keepon may take some time to adjust to your voice, so please be patient during the first few trials.

Upon hearing your reply, the Keepon will move back to its original position, and bob its head to indicate that the trial is over and that it's ready for the next set of cards.

At the end of each trial, move the three used cards and place them face down in a separate discard pile. Then draw three more cards from the deck for the next trial. The experiment ends when all cards in the initial deck have been placed in the discard pile.

We have selected a set of simple games for the Keepon to try to learn. Each subject is given a specific rule to teach the Keepon. For you, we have selected the "maximum value" rule - that is, your job will be to teach the Keepon to select the face up card with the highest number.

Please note that your interactions will be recorded for future evaluation. This experiment is voluntary, and you may stop at any time.

I will now leave the room. Once I have left, please start the experiment by drawing the first three cards. When the last three cards have been discarded, the experiment is complete, and you should come find me (I'll be just outside the door).

Thank you.

(The participant completes the experiment)

You will now complete a brief survey about this study.

ACKNOWLEDGMENT

We thank Prof. Brian Scassellati and Henny Admoni for their guidance throughout this study.

CONTRIBUTION OF TEAM MEMBERS

Because the work was pretty evenly divided throughout the project, it is difficult to elaborate on the specific work that the authors have done without getting down to pretty low level details. Ian played a slightly smaller role in the code development because he was unable to type much due to RSI issues. He was still present for the meetings but did not type code directly. Fei controlled the robot during the experiments, while Debayan and Ian traded off managing the subjects and briefing them on the experimental procedure. Debayan did more of the work on typing the presentation slides after they had been planned as a team, while Fei and Ian worked on clipping and editing the video. The paper writing and any other final work was evenly split between group members.

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