The Paths We Pick Together: A Behavioral Dynamics Algorithm for an HRI Pick-and-Place Task

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ABSTRACT

Behavioral dynamics models provide an observationally grounded basis for HRI algorithms and provide another tool for creating robust, natural, and interpretable HRI systems. Here, an HRI pick-and-place algorithm was implemented based on a behavioral dynamics model of human decision-making dynamics in an interpersonal pick-and-place task. Participants were able to complete the HRI pick-and-place task, we provide comparisons to HHI pick-and-place results.

ACM Reference format:
M. Lamb, R. Mayr, T. Lorenz, A.A. Minai, and M.J. Richardson. 2018. The Paths We Pick Together: A Behavioral Dynamics Algorithm for an HRI Pick-and-Place Task. In *HRI'18 Companion: Conference on ACM/IEEE International Conference on Human-Robot Interaction, March 5-8, 2018, Chicago, IL, USA*. ACM, NY, NY, USA, 2 pages. DOI: https://doi.org/10.1145/3173386.3177022

1 INTRODUCTION

Humans can interact and coordinate seamlessly with other humans. For this reason, research on human-human interaction (HHI) and coordination plays an important role in the development of new human-robot interaction (HRI) technologies and algorithms. According to the behavioral dynamics approach, behaviors and interaction patterns emerge from the dynamics of the interacting systems composed of two humans or a human and a robot that are embedded in a task space which can be modeled using differential equation models. The current work shows the application of a pick-and-place algorithm derived from a behavioral dynamics approach to HHI [1–5] in an HRI context.

1.1 Pick and Place Task

We implemented a modified version of a joint pick-and-place paradigm introduced in previous HHI studies [4], [6]. Data from this HHI task was used to validate the results from the current HRI study. Each trial has two task phases: First, the co-actors decide who will pick up a presented object and second, the agent with the object must choose to either pass the object to the co-actor for placing it at a target or decide to do it alone. The task and task space were presented to the participant on an interactive projection table (see Figure 1). At any given point in the task, there is exactly one object (green circle) to be picked up and one specified target (red circle) location. Objects can be picked up by moving a wireless motion tracking sensor (Polhemus Liberty) over the object location and the trial ends when the object has been moved to the target location.

Figure 1: Kinova Mico² arm and interactive table setup. Participants were positioned at the left end of the table.

1.2 Pick-and-Place Behavior

The pick-and place algorithm consists of two components: movement, and action selection (e.g. pass or don't pass). The movement component controls the robot end-effector's heading direction, φ, and angle to a task goal location, θ_g, relative to an axis of the planar task space. The system topology is captured by an adapted mass-spring system

$$\ddot{\varphi} = -b_g\dot{\varphi} - k_g(\varphi - \theta_g)f(d_g), \qquad (1)$$

where $\dot{\varphi}$, and $\ddot{\varphi}$, correspond to the velocity and acceleration of the end effector's heading angle and b and k are damping and stiffness terms. The function $f(d_g)$ modifies the rate of change in heading angle as a function of the distance to the current goal, d_g.

Action selection in each task phase is described as

ACM ISBN 978-1-4503-5615-2/18/03.
DOI: https://doi.org/10.1145/3173386.3177022

$$\dot{x}_k = -\alpha_k + x_k - x_k^3, \qquad (2)$$

where $\dot{x}_k$ is the action selection state variable for the specific task phase k, and x_k is the previous action selection state for that task phase. For each task phase, α_k is the difference between each co-actor's normalized task phase relevant action (i.e., reach) capabilities [4]. The general structure of α_k is

$$\alpha_k = \left(\sigma_{k_r} - \frac{d_{g_{k_r}}}{R_{k_r}}\right)\delta_{k_r} - \left(\sigma_{k_c} - \frac{d_{g_{k_c}}}{R_{k_c}}\right)\delta_{k_c}, \qquad (3)$$

where k indicates the task-phase, r and c denote the robot or co-actor respectively. The distances of each actor's end effector to the task phase goal are $d_{g_{k_r}}$ and $d_{g_{k_c}}$ and R_{k_r} and R_{k_c} are the maximum reach capacity of each agent, respectively. Scaling parameters σ_{k_r}, σ_{k_c} δ_{k_r}, and δ_{k_c} scale the normalized affordance ratios to the task space. In the first phase $d_{g_{1_r}}$ and $d_{g_{1_c}}$ are measured from each actor's current end-effector position to the object to be picked up. During the second task phase, $d_{g_{2_r}}$ is measured from a neutral rest position to the object to be picked up and $\left(\sigma_{k_c} - \frac{d_{g_{k_c}}}{R_{k_c}}\right)\delta_{k_c} = 0$.

2 METHODS

After a brief set of practice trials, participants completed two 10-min trials with a Kinova Mico[2] 6DOF arm. Trials consisted of an average of 81 (SD = 10) pick-and-place cycles.

The position of the robot's end effector on a 2D (x, y) Cartesian plane parallel to the task surface was driven by the online integration of Eq. 3 using Euler's method in a loop cycling at 10hz. At each loop, the end effector's current (x, y) position was used to calculate distance and angle to a current task goal (i.e. pick up object, target, pass, or neutral location). Task switching was driven by the sign of the approximated solution to Eq. 2 based on the task phase relevant α_k.

2.1 Participants

Thirteen University of Cincinnati students (18-21 years) were recruited to participate in the experiment (7 female). Participants received credit as part of a class requirement for an undergraduate Psychology course, with the procedures and methodology employed reviewed and approved by the University of Cincinnati Institutional Review Board.

2.2 Results

The robot was able to finish all task trials with participants. On average, participants initiated a pick-up for 50% (SD = 7.1%) of the trials in the first block and 53% (SD = 6.1%) of the time in the second block. When taking the difference between the percentage of pickups by each individual in an HRI pair, the average was 3.4% (SD = 12.2%) while for HHI pairs in previous experiments it was 7.6% (SD = 47.3%) [6]. An independent samples t-test demonstrated no difference in the pick-up division of labor between the HHI and HRI contexts ($t(21) = -0.314$, $p = .757$).

Table 1: Exit Questions

Exit Questions	Yes
Did you find the robot helpful in the task?	100.0%
Did the robot ever get in your way?	0.0%
Would you prefer to work alone?	69.2%
Did you like the behavior of the robot?	84.6%

Regarding pass decisions, participants chose to pass an average of 39% (MD = 39%, SD = 11%) of the trials in which they picked up the object. The robot passed 48% (MD = 49% SD = 7%) of the trials that it picked up the object. A Wilcoxon Signed Rank Test indicated that the average pass decisions of participants were significantly higher in the HRI than HHI contexts ($U = 57$, $z = -2.690$, $p < 0.01$) with HHI participants passing an average of 24% (MD = 28%, SD = 11%, n = 20) of the time [6]. This difference merits further investigation.

In follow-up interviews conducted immediately after the experiment, all participants reported that the robot was helpful in completing the task and was never in their way (see Table 1).

3 Conclusion

The current study provided an illustration of the implementation of a behavioral dynamics model of interpersonal interaction in an HRI context. When combined with other HRI tools and methods the approach can facilitate development of HRI systems which can be deployed in more complex task contexts. We believe that this approach provides a valuable and new tool for the development of HRI systems which can produce adaptive, robust, legible, and natural human interaction behaviors.

ACKNOWLEDGMENTS

This research was funded by The National Science Foundation (1513801) and National Institute of Health (R01GM105045).

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