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Title

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Permalink

Journal

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Publication Date

2017

Peer reviewed

Behavioral Dynamics and Action Selection in a Joint Action Pick-and-Place Task

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Abstract

Many common tasks require or are made more efficient by coordinating with others. In this paper we investigate the coordination dynamics of a joint action pick-and-place task in order to identify the behavioral dynamics that underlie the emergence of human coordination. More precisely, we introduce a task dynamics approach for modeling multi-agent interaction in a continuous pick-and-place task where two agents must decide to work together or alone to move an object from one location to another. Our aims in the current paper are to identify and model (1) the relevant affordance dynamics that underlie the selection of the different action modes required by the task and (2) the trajectory dynamics of each actor's hand movements when moving to grasp, relocate, or pass the object. We demonstrate that the emergence of successful coordination can be characterized in terms of behavioral dynamics models which may have applications for artificial agent design.

Keywords: Behavioral Dynamics, Affordances, Multi-agent Coordination, Dynamical Modeling, Joint action, Pick-and-place, Dynamical Systems Theory, Decisions

Introduction

Often, everyday tasks can be accomplished more quickly and efficiently when individuals work together and coordinate their actions to accomplish task goals. However, increasing the number of individuals engaged in a task constructively increases the complexity of the task by expanding the degrees of freedom and interactions that define the task action space. Computational approaches to dealing with the increased complexity of joint action tasks largely focus on reducing complexity by identifying representational or neural structures that support successful joint action (Graf, Schütz-Bosbach, & Prinz, 2009; Rizzolatti & Craighero, 2004; Sebanz & Knoblich, 2009). Equally important, however, is understanding what aspects of successful multiagent coordination naturally emerge from the physical and informational dynamics of a given task context (Richardson & Kallen, 2016; Richardson, Marsh, & Schmidt, 2010; Richardson et al., 2015). The aim of the current project was to identify these task dynamics for a simple joint action pick-and-place task. Of particular interest, was the degree to which the complex patterns of interpersonal movement coordination and action (affordance) selection that emerge could be

captured by extending a low dimensional behavioral dynamics (Warren, 2006) model of individual environmental route navigation (Fajen & Warren 2003) and pick-and-place behavior (Lamb et al., under review, Washburn, et al. 2015). Because the pick-and-place behaviors exhibited by the proposed low dimensional model emerge from the physical and informational dynamics of a given task context, the proposed model may be developed as a simple artificial agent system that can interact with human co-actors. An artificial agent system based on the model would be able to interact with human co-actors in the task without access to a co-actor's cognitive states, i.e. without a theory of mind.

Methods

Participants

20 University of Cincinnati students (aged 18 to 28 years) were recruited to participate in the experiment. Participants received credit as a part of a class requirement for an undergraduate Psychology course. All participants provided written consent prior to completing the study, with the procedures and methodology employed reviewed and approved by the University of Cincinnati Institutional Review Board.

Materials and Apparatus

An illustration of the experimental task setup is provided in Figure 1. Participants stood at a 1.65m x 0.89m x 0.995m table in a laboratory room and completed a joint action pick-and-place task in a virtual environment. The virtual environment consisted of a room similar to the laboratory room and a table that was isomorphic in size and location to the table in the laboratory room. The virtual environment was displayed to each participant using Oculus Rift DK2 virtual reality headset (Oculus VR, Irvine, California). The physical table acted as a solid surface limiting the participants' movements within the virtual environment and creating a surface on which the participants could move a hand-held wireless Polhemus Latus motion-sensor (Polhemus Ltd, Vermont, USA) that tracked their right hand movements within the virtual environment at 96 Hz. The participants'

head movements were also tracked using Oculus Rift DK2 head tracking system.

The virtual environment, task objects, and task controllers were designed using the Unity 3D game engine (version 5.2.0; Unity Technologies, San Francisco, California) and Sketchup 2015 (Tremble Navigation Technologies, Sunnyvale, California). The maximum display latency between the participants' real-world movements and their movements in the virtual environment was 33ms. The experimental task states were continuously recorded at 70 Hz.

As indicated in Figure 1, Participant locations were identified in terms of the "A" side or the "B" side of the table, where the body of the participant on the A side of the table (participant A) is nearer to the center of the appearance range than the body of the participant on the B side (participant B). Participant A was positioned on the A side of the table, standing half way between the middle of the table and the pickup location. Participant B was positioned such that their right shoulder was directly across the table from the right shoulder of participant A (see Figure 1).

Within the virtual environment, the participants were represented as identical virtual avatars modeled after a crash

Figure 1: Illustration of experimental setup. At the beginning of each trial a virtual disc would appear on the left side of the table within the appearance range. Disc color indicated target location for that trial. The targets squares (M = magenta, Y= yellow, G = green, B = Blue, R = red) were always visible on the right side of the table.

test dummy with a height of 1.8m. Both the participants' right hands were represented by a semi-transparent blue sphere at the end of the dummy's right wrist in order to simplify interaction with the task environment. An inverse kinematics

controller (model and controller supplied by Root Motion, Tartu, Estonia) driven by the Polhemus motion sensor movements and the head movements of the participants controlled the right arm and body movements of the participants' virtual avatar, respectively. The resulting arm and body movements were not identical to the real world arm and body movements of the participants, but were close enough to render any differences between the real and virtual body postures of the participants unnoticeable or not functionally relevant.
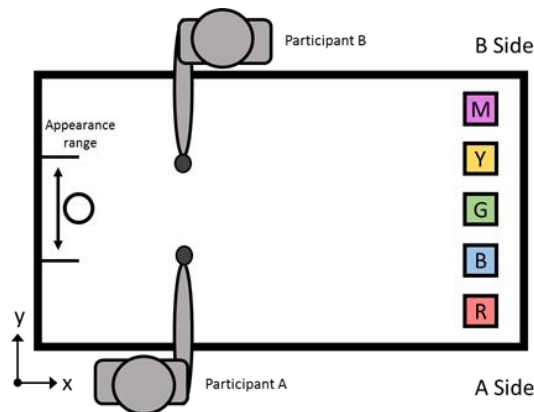
Experimental Task

The experimental task required participants to work together to move virtual disc objects (henceforth disc) that appeared on one end of a virtual tabletop to one of five evenly spaced target locations on the other end of the table (see Figure 1). The target location for a given trial was indicated by the color of the disc. A trial involved successfully moving a disc to the correct target location. Target colors and locations did not change during the task. However, discs appeared in random locations along the y table axis within the middle third of the table (appearance range). Participants completed 2 blocks of 150 trials, 30 trials for each target color. Target colors were randomly presented.

The participants were instructed to pick up the disc when it appeared and attempt to move it to the target location. Either participant could pick up the disc, but they were instructed not talk or gesture to one another during the task. A pickup occurred when a participant's sphere came in contact with the disc. When picked up, the disc moved with the participant's sphere until it reached the target or the participant passed the disc. The participants were informed that if the target was either too far away or uncomfortable to reach, they could pass it to the other participant. A pass involved picking up the disc and then releasing it somewhere on the table by lifting their hand from the table. To complete a pass, the other participant would pick up the disc and move it to the target. A trial was completed when the disc reached the correct target.

Procedure

Participants were told that the experiment was investigating the dynamics of joint action pick-and-place behavior and that they would be completing a simple pick-and-place task with one another. The participants were then embedded within the virtual environment using the HMD and viewing height and sensor calibration was performed. Task instructions were then provided to the participants and after participants indicated that they understood the task procedure and goal, they were given an opportunity to complete 2 practice blocks. The first practice block consisted of 12 trials where the disc always appeared in the center of the appearance region and indicated the middle (green) target. Each participant took 6 turns picking up the disc and either passed it or took it to the target. The second practice block involved 20 trials, 4 trials for each target location. In this practice block, the pickup location was randomly assigned within the appearance range on each trial.

As mentioned above, experimental trials were broken up into 2 blocks of 150 trials. After the first experimental block participants switched sides of the table, i.e. the participant on side A moved to side B and the participant on side B moved to side A. Participants switched HMDs and moved to the other side of the lab room table to effect this switch. Experimental blocks lasted between 10 and 15 minutes.

Results

In order to model the emergence of successful joint action during the current pick-and-place task, the analysis was directed towards answering two general questions. First, what task variables determined the participants' decision to pickup and/or or pass. In other words, what were the affordance (action opportunity; Gibson, 1979) based action selection dynamics that characterized pickup and pass behavior? Second, what were the trajectory dynamics of the participant's hand movements when moving to grasp, relocate, or pass the disc within a two-dimensional task space. Below we consider each of these questions in turn.

Decisions

For the pick-and-place task investigated here there were two affordance based action selection decisions that we examined. First, participants had to decide whether or not to pick up the disc when it appeared. In order to understand the basis for this decision we applied the C4.5 decision tree algorithm (Quinlan, 1993) using a 10 fold cross validation to participant pick decisions ($n = 2998$) in order to create a decision tree with a minimum node size of 50 instances. This analysis revealed that the only attributes used to build the tree were the current location of each actor's hand to the disc, with the resulting decision tree able to correctly predict 87% of the pick decisions. Attributes that were considered for each participant included: hand's current distance to the disc, hand's current distance to target, disc location, and target location. These attributes were not considered relevant to modeling the decision behavior if it was not included in the decision tree produced by the C4.5 method or if its exclusion resulted in a change in predictive success of < 3%.

The C4.5 decision tree algorithm was also applied using a 10 fold cross validation to a data set of 2998 passing decisions in order to create a decision tree with a minimum node size of 50 instances. When the only attribute used to build the tree was the distance of the resting location of one of actor's hand to the disc the resulting decision tree was able to correctly predict 79% of the pickup decisions. Resting hand location for each side was defined as a position 0.15m from the edge of the table directly in front of the participant's right shoulder. The same set of attributes considered for the pickup decision were considered for the pass decision, with the addition of the previous pass decision. None of these other attributes

significantly increased pass prediction beyond that predicted by actor resting location alone.
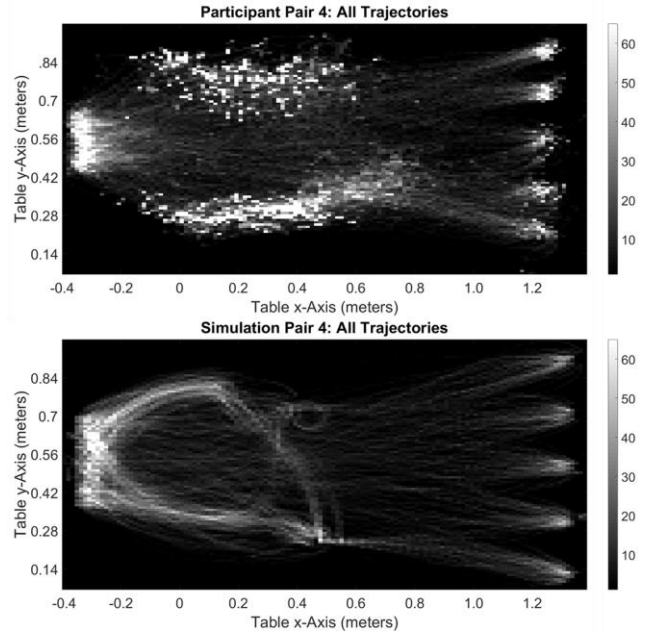
Figure 2: Heat-maps of example participant (top) and model simulation (bottom) trajectories during the experimental task.

Movements

An example of the complete set of participant pair trajectories are illustrated in figure 2 (top) as a heat map. This heat map plot was created by dividing the table into 125x108 grid and for each trial, the number of times a participant's location was recorded in a given grid cell was tallied to create a histogram of trajectory locations in table coordinates. A greyscale value was assigned to each cell from a scale of 64 shades. All participants exhibited a qualitatively similar sideways "spaghetti monster" heat-map, with concentrations of trajectories (brighter areas), corresponding to discs (far left side of heat-map plot), pass/rest locations (top and bottom left of center on the heat-map plot), and target locations (5 distinct points across the right of the heat map plot). Because of the number of subtask trajectories, trajectory heat maps provide a relatively straightforward tool for comparing qualitative similarities between both human participants and between human data and simulation data.[1]

Participant trajectories tended to curve slightly away from straight-line trajectories. This may be due to the fact that after completing a subtask goal participants employed a simple strategy of heading in the general direction of the next subtask goal instead of taking an initial heading defined by the straight-line angle from their current location to the goal location.

Participant subtask movements exhibited a bell shaped velocity profile with the peak velocity occurring around half

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[1] For each side of the table, subtask trajectories examined include: rest-to-pickup, pickup-to-target, pickup-to-pass, rest-to-receive, receive-to-target, pass-to-rest, and target-to-pickup.

way through the trajectory. Across all subtask trajectories, the average peak velocity was 1.231m/s (Mdn = 1.252m/s, Q1 = 0.924m/s, Q3 = 1.373m/s) and the peak velocity occurred on average around 57% (SD = 15%) of any given subtask trajectory. For the 14 subtask trajectories examined, average peak velocity for each subtask trajectory was significantly correlated, $r(14) = 0.89$, $p<0.001$, with the average straight-line distance of each subtask trajectory. Shorter trajectories had lower average peak velocities than longer trajectories.

In order to identify where participant's passed the disc on pass trials, cluster analysis was conducted, using the K-means cluster analysis algorithm, which finds cluster centers that minimize the sum of squared error (SSE) for a given number of clusters, k. We analyzed the release/pass locations to determine whether these locations typically clustered around 1, 2, or 3 cluster centroids. The optimal number of clusters was defined as the value of k such that the difference of the SSE for a reference distribution, determined by Monte Carlo sampling of a reference distribution, was greatest compared to the other values of k. For each pair, separate evaluations were run for each side of the table. For side A, when a participant on side A passed at least once during the experiment ($n = 8$ pairs), the optimal number of clusters was 1 for all passes on this side of the table. Likewise, when a participant on side B passed at least once during the experiment ($n = 9$ pairs), the optimal number of clusters was 1 for most pairs ($n = 7$). When a participant on side A passed during the experiment ($n = 8$), the passes clustered around an average (x, y) table location of (0.24m, 0.62m). When a participant on B side of the table passed ($n = 9$), the passes clustered around an average (x, y) table location of (0.33m, 0.18m).

Model

The current study had two overall aims. The first aim was to identify the behavioral dynamics that underlie a continuous joint action pick-and-place task, in which two participants had to move objects from one tabletop location to another either alone or by passing the object to another co-actor. Our second aim was to develop a behavioral dynamics model that can characterize the joint action behaviors and choices (pickup or not; pass or not) of the participants engaged in during the joint action pick-and-place task. With respect to this aim we developed a model of both the participant's movement in the task space and their decisions to both pick up the object when it appears on a given trial and to pass the object.

Movement Dynamics

In order to model the dynamics of each participant's, henceforth agent, hand movements throughout the task, a task specific parameterization of the Fajen and Warran model of human locomotory navigation was employed (Fajen & Warren, 2003, 2004, 2007; Warren & Fajen, 2008). This model has also been extended to model single actor pick and place behavior (Lamb et al., under review). In the current context, the model characterizes a heading direction or

angle, φ_i, of an agent's hand or end-effector (where each agent is indexed by i) during each task trial was defined by

$$\ddot{\varphi}_i = -b_{g_i}\dot{\varphi}_i - k_{g_i}(\varphi_i - \theta_{g_i})(e^{-c_1 d_{g_i}} + c_2), \quad (1)$$

where $\dot{\varphi}_i$, and $\ddot{\varphi}_i$, correspond to the velocity and acceleration of the agent's end-effector heading angle, respectively, and b and k are damping and spring/stiffness terms, such that $-b_{g_i}\dot{\varphi}_{A_i}$ acts as a friction force on turning rate, and the function $-k_{g_i}(\varphi_i - \theta_{g_i})$ operates to minimize the difference between the current heading angle, φ_i, and the angle θ_{g_i}, of the corresponding subtask goal/target location (i.e., the pickup location for pickup movements, the release/pass location for passing movements, and the target/drop-off location for target movements). The distance of the agent i's end effector to the current goal location is defined by d_{g_i}. The presence of the factor $(e^{-c_1 d_{g_i}} + c_2)$ in the second addend of the right-hand side introduces an exponentially decaying function characterized by a constant offset parameter c_2 and an exponential decay rate, which is a function of the constant parameter c_1 and the Euclidean distance, d_g, between an agent's current hand location and the current goal location. The parameter c_2 ensures that the rate of change in heading direction never goes to zero (Fajen & Warren, 2003). Note that the parameters θ_{g_i} and d_{g_i} change continuously as the position of the agent's hand/end-effector moves through the task space.

Finally, in order for to capture the non-constant velocity profile observed in participants, v_i is introduced to characterize the movement velocity of the agent's end-effector (hand). v_i is defined by means of the additional 2nd order differential equation

$$\ddot{v}_i = -b_{v_i}\dot{v}_i - k_{v_i}(v_i - C_{v_i}(1 - e^{-d_{g_i}})), \quad (2)$$

where b_{v_i} and k_{v_i} act as damping and stiffness terms on the rate of change of v_i, which increases and decreases as a function of the target (goal) distance, d_{g_i}. When the agent's end-effector or hand is far away from the target location $(1 - e^{-d_{g_i}}) \approx 1$ and v_A increases. As the distance to the goal location decreases, however, $(1 - e^{-d_{g_i}})$ approaches zero and v_i decreases accordingly. C_{v_i} is a constant parameter that specifies the maximum velocity in m/s, such that the same equation can be used for a wide range of different movement distances, with differential peak velocities resulting for shorter and longer distances (see Lamb et al., under review for more details on this velocity function).

Action Selection Dynamics

In the experimental task there are two task defined choices. First, one of the agents must choose to pick up the task object while the other agent chooses to stay out of the way. Second, once an object is picked up, the agent with the object must decide to either take the object to the goal location or pass it to their co-actor. In both cases, the decision can be

characterized as a selection between action modes or affordances, i.e. pick up the object or wait and take the object to goal or pass. Moreover, previous research using a non-random pick-and-place task paradigm suggests that recent action modes may affect the current action mode selection (Lamb et al., Under Review). As a result, in the current context the action mode selection dynamics may be captured by

$$\dot{x}_i = -\alpha_{j_i} + x_i - x_i^3 \qquad (4)$$

where x_i represents the state variable for action section (i.e., affordance mode) of the previous action selection process and $\dot{x}_i$ is the action selection state variable for the current trial. α_{j_i} corresponds to the specific subtask action mode and agent-normalized E/A ratio where the decision to pick up an object can be defined for Agent 1 by

$$\alpha_{s_1} = \left(\sigma_{s_1} - \frac{d_{g_{s_1}}}{R_1}\right)\delta_{s_1} - \left(\sigma_{s_2} - \frac{d_{g_{s_2}}}{R_2}\right)\delta_{s_2} \qquad (5)$$

and for Agent 2 by

$$\alpha_{s_2} = \left(\sigma_{s_2} - \frac{d_{g_{s_2}}}{R_2}\right)\delta_{s_2} - \left(\sigma_{s_1} - \frac{d_{g_{s_1}}}{R_1}\right)\delta_{s_1} \qquad (6)$$

where $d_{g_{s_i}}$ is the distance from current location of the ith agent's end effector to the disc's location. Similarly, the decision to pass was defined by

$$\alpha_{p_i} = \left(\sigma_{p_i} - \frac{d_{g_{p_i}}}{R_i}\right)\delta_{p_i} \qquad (7)$$

$d_{g_{p_i}}$ is the distance of the agent's resting end-effector (hand) location to the target location, and R_i is a measure of the agent's maximal preferred reach. In both equations equation, σ_{j_i} and δ_{j_i} are constant scaling factors. In Eq. 5, 6, and 7, d is a subtask action mode parameter that identifies the state of the subtask action relevant environmental property.

Model Simulation

To determine whether systems defined by the movement trajectory dynamics (Eq. 1 and 2) and the action selection dynamics (Eq. 4, 5, 6, and 7) of the current model could complete the task independently complete the current pick-and-place task, a MATLAB (2016a) simulation was conducted. A flow diagram illustrating the structure of the simulation is provided in Figure 3. The simulated environment consisted of a 1.5m x 0.89m rectangular space matching the experimental table's dimensions. The simulation target and disc locations were initialized in the same manner as in the experimental task. 10 different simulation sequences were conducted, with each simulation sequence consisting of 400 trials. Each simulation sequence

was initialized with the same pickup/target order used for a participant pair. The passing location centers corresponded to the observed passing location centers for each participant pair. Cluster centers corresponding to each participant pair were used to initialize the simulation sequence based on that pair's appearance/target order. Experimentally observed within pair variability in pass locations was likely due to the many complex interactions from which this passing behavior emerges (Holden, 2002; 2005; Stephen & Mirman, 2010). However, in our simulations this variability is produced by a sequence of random values generated from a lognormal distribution that were added to the passing location centers in order to produce a pass location distribution that was similar to the experimentally observed data.

For each action selection the pickup and passing solutions to parameter equations, action selection dynamics, Eq. 4, were integrated for 1500 steps using the MATLAB ODE45 function with the end state of the integration used to drive the pickup and pass decisions (and return to rest position). The output state of the action selection equation was stored as an input for integration of the action selection equation in the next trial ($x = 0$ for the first trial in a sequence). Heading angles were initialized in the cardinal direction of the next subtask goal, e.g. pick up to target trajectories initialized with a heading angle of 0° heading directly to the right side of the table. Random noise was added to the initial angle from a uniform distribution with min/max values of ± 17°. The movement dynamics, Eq. 1 and 2, were integrated for each subtask movement using the Euler integration (.01 time step), with integration terminated when the model location was within 4 cm of the target location. Random noise was added to the model heading direction, φ_i, at each time step of the integration using a uniform distribution with min/max values of to ± 1.14°.
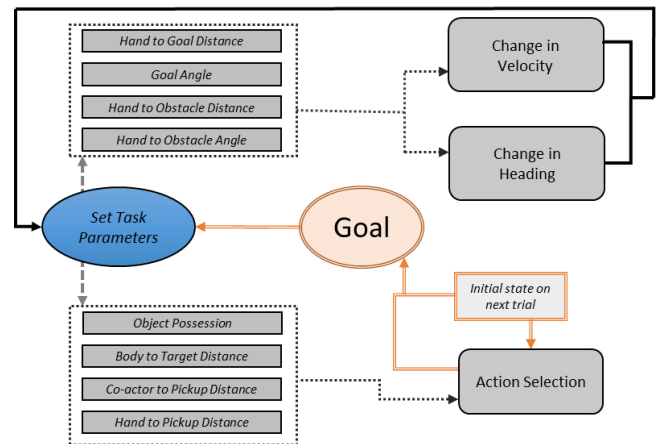
Figure 3: Structure of simulation. Eq. 1 and 2 are implemented in the upper loop and Eq. 4 through 7 are implemented in the lower goal selection loop.

An example simulation run is illustrated by the bottom heat-map in Figure 2. For all simulation runs, the simulation agents successfully completed the pick-and-place task within the task constraints. All simulation agent trajectories

remained within the task space and subtask trajectories were within the same regions as those produced by human participants. Simulation agent trajectories exhibited less variability as can be seen in figure 2, though the importance of this variability for a human co-actor engaged in the task is something that will require further research. To the extent that it is relevant, this variability may be replicated in an artificial agent implementation of the model by the addition of noise terms, through coupling to the human agent, and possibly by noise introduced by the agent's hardware instantiation (e.g. motor variability in a robotic system).

The simulation agents were also able to spontaneously select between picking up the object or not and between passing the object or completing the task alone in a manner similar to the real participants. For pickup trajectories it is notable that pickup decisions may be made and changed as co-actors move or do not move throughout the task space. If both simulation co-actors are roughly the same distance the pickup location at the beginning of a trial, noise and velocity profile variations still results in just one agent picking up the object. If a simulation agent picked up an object, that agent always passed for the farthest target and often did for the second farthest, with the decision to pass for this target fluctuating due to previous pass decisions and noise in the system, matching experimentally observed participant behaviors.

Conclusions

The current model is useful for providing insight into how complex movement and decision dynamics might emerge from a system given relatively simple information structures. Notably, the model does not assume the need to understand or predict co-actor intentions or beliefs. This makes the model an ideal candidate for implementation in an artificial agent system that can interact in real-time with human co-actors but does not have access to sophisticated sensory or computational systems for interpreting high level cognitive states. We are currently in the process of implementing a version of this model in virtual and robotic systems to test with human co-actors in order to validate the capabilities of behavioral dynamics models applied in this way.

Acknowledgments

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