PAPAc: A Pick and Place Agent Based on Human Behavioral Dynamics

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ABSTRACT
Humans often engage in tasks that require or are made more efficient by coordinating with other humans. The coordination involved in these tasks can be understood in terms of the behavioral and affordance dynamics of socially embedded agents engaged in joint action activities. Behavioral dynamics provide mathematical (differential equation) models of human behavior and interaction and affordance dynamics identify and model the ways that an agent's action capabilities evolve over time. Taken together, models of human joint-action based on these approaches may provide a basis for developing robust, natural, and easy to engage artificial agents. In this paper we introduce behavioral and affordance dynamics models of human joint action in a pick-and-place task. Based on these models we provide a proof of concept pick-and-place artificial agent and implement the agent in a 3D virtual environment to interact with human co-actors.

Author Keywords
Human-Agent Interaction; Pick-and-place; Behavioral Dynamics; Affordances; Human-centered Algorithms; Joint Action

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INTRODUCTION
Coordination with others, such as loading a dishwasher with a partner, typically results in more efficient, quicker, and more successful task completion. Notably, when humans work together, coordination usually does not require lots of advanced planning, nor is considerable, if any, effort expended explicitly communicating intent or expectations during task coordination. Indeed, to the extent that intent, expectations, and planning play a significant role in successful coordination, they are often nearly transparent to the coordinating individuals. Coordination with others often just works. This type of effortless, spontaneous and natural coordination is a goal for successful human-agent interaction. One way to approach this goal is to take design cues from cognitive science research on human joint action and coordination. In recent decades, attempts to understand successful human coordination in cognitive science have largely focused on identifying neural and representational mechanisms that underlie the development of shared intentional states and social action observation [1]–[4]. However, equally important is identifying the dynamical processes that constrain and shape the emergence of successful human joint action coordination within a task context. Following this research, the behavioral order that characterizes successful coordination is often self-organized and synergetic, emerging naturally from the task-relevant physical, biomechanical, and informational couplings and constraints that exist between co-actors and within a joint action task space [5]–[9]. The resulting conception of human joint action coordination is that it is best characterized as a complex dynamical system that can be understood and modeled using low-dimensional task or behavioral dynamics principles [7], [8], [10], [11]. Insights from this research have not been concretely applied within the domain of artificial agent design, and in particular within the context of human-artificial agent interaction.

Motivated by this later research paradigm, the current study had two objectives: a) develop a pick-and-place agent (henceforth PAPAc, 'c' for its implementation in a continuous pick-and-place task) based on the behavioral and affordance dynamics of human pick-and-place behaviors; and b) provide an initial demonstration of PAPAc's ability to accomplish a continuous joint action pick-and-place task with a human co-actor in a shared 3D virtual space. In this paper we briefly review the research and theory relevant to a complex dynamical systems understanding of human-human joint action behavior. In particular, we focus on the behavioral

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dynamics approach to understanding and modeling human-human joint action coordination. We will then introduce a novel pick-and-place algorithm, PAPAc, which can be implemented in a variety of non-human agent systems which interact in real time with human agents in a joint action pick-and-place task. We will demonstrate with a proof of concept study that this approach yields an agent that successfully interacts with a human-partner in a real-time 3D virtual task environment as well as discussion of potential limitations and challenges to the proposed approach. Our overarching aim is to introduce an approach to developing HRI and HCI algorithms based on a behavioral and affordance dynamics understanding of human joint action. The proposed approach offers several advantages to high-level social and cognitive approaches to human joint action, including not needing to perceive, model or understand the intentions of other actors to produce robust interactions. This is because, for at least some aspects of human joint action, coordination is an emergent feature of the task features, action capabilities, and interaction of the co-acting agents [7], [12].

BEHAVIORAL DYNAMICS OF HUMAN COORDINATION

Behavioral Dynamics

Behavioral dynamics are the complex patterns of movement behaviors that emerge in the course of a system's interactions with its environment within a given task context. Typically, these dynamics are understood to be self-organized, resulting from the reciprocal interaction of an agent and their environment under some set of constraints, often specified in terms of a task or set of goals [11]. The behavioral dynamics approach to understanding human behavior was first introduced to understand and model the movement patterns of individuals performing solo-actions [11], [13]. However, it is equally applicable to joint action and multi-agent activities [7], [14]–[16]. The behavioral dynamics approach to human behavior builds on a complex systems approach to human behavior and emphasizes self-organization and contextual emergence and, in turn, provides a mathematical model of human and multi-agent behavior as emerging from lawful interactions among physical and informational processes, biomechanical couplings, and contextual constraints [17]–[20]. This later feature of the behavioral dynamics approach, i.e. the production of mathematical models of contextualized human behaviors, provides a relatively straight forward conduit for translating human joint action research to applications in human-agent interaction contexts.

A behavioral dynamics model defines both the minimum task degrees of freedom and the task dynamic topology required to characterize the relevant behavioral capacities of a behaving system [11], [19], [21]. A key requirement for effectively modeling the behavioral dynamics of actions or movements within a task is to define a functional, yet low-dimensional description of the task space. A foundational example of such behavioral dynamics modeling is provided by the work of Fajen and Warren [11], [13], [22], [23], in which the authors successfully modeled the self-organized behavioral dynamics of human locomotory navigation and route selection. Of particular relevance for the current study, is that extensions of this model have been demonstrated to characterize human hand movements in object moving and placing task [7], [16], [18], [24], [25]. In this context an agent's end effector (i.e. hand) was defined abstractly as a directional vector within a Euclidian (*x, y*) planar task environment. The hand's heading direction, φ, and the angle of the target goal location, θ_g, were defined with respect to one of the planar task axes (i.e., an exocentric reference frame was employed). The terminal objective of the agent was then defined as simply turning towards a target goal location by changing their heading direction or turning rate, $\dot{\varphi}$, until $\varphi - \theta_g = 0$. The topology of this terminal objective was captured using an adapted mass-spring system

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

where $\dot{\varphi}$, and $\ddot{\varphi}$, correspond to the velocity and acceleration of the agent's heading angle, φ, and b and k are damping and stiffness terms, such that $-b_g\dot{\varphi}$ acts as a friction force on the turning rate, and the function $-k_g\left(\varphi - \theta_g\right)$ operates to minimize the difference between the agent's current heading angle, φ, and the angle, θ_g, driving the agent towards the goal. The rate of change in the agent's heading angle is modulated by $f(d_g)$, which modifies the rate of change in heading angle as a function of the distance, d_g, to the goal—typically this is set such that the closer the goal the more rapid deviations of φ away from θ_g are minimized. In addition to the attractive force of the task goal, Warren and Fajen [13] introduced a repulsive function that accommodates obstacles within a task space. Accordingly, obstacle avoidance behavior is produced when

$$+\sum_{i}^{N} k_o(\varphi - \theta_{oi})e^{-|\varphi - \theta_{oi}|}f(d_{oi}) \qquad (2)$$

is added to (1) , where for each obstacle, o_i, $+k_o\left(\varphi - \theta_{o_i}\right)$ operates push the agent's heading direction, φ, away from the heading angle, θ_{o_i}, that leads towards the obstacle as a function of distance, $f(d_{o_i})$. As above, k_o acts as a stiffness term moderating the effects of each obstacle on the agent's heading direction. Here, the addition of the exponential function, $e^{-|\varphi-\theta_{o_i}|}$, ensures that the angular acceleration away from an obstacle quickly rises near the obstacle and results in a positive (right) truing rate when heading to the right of $\theta_{o_i}$and a negative (left) truing rate when heading to the left of θ_{o_i}.

Although (1) characterizes a relatively simple system, it successfully predicts the movement patterns of human agents across numerous experimental procedures and environmental tasks. In the context of pick-and-place tasks, this model has successfully characterized the behaviors of human agents in a variety of setups, including joint action contexts in which multiple participants must coordinate with one another [7], [16], [24], [26]. With the addition of (2), the model has provided strong evidence that relatively complex human navigation behaviors can emerge without a priori planning as a self-organized result of interacting environmental attractors and repellers (see [11], [23] for reviews).

Similar navigation equations can be extended to a range of complex multi-agent locomotion or pedestrian tasks [14], [15] as well as a wide range of joint action and multi-agent movement coordination tasks [7], [16], [18], [24]. In the context of robotics it has been shown that this approach to individual path navigation results in a system that is capable of avoiding local minima within a navigation space [27] as well as is capable of successfully avoiding an arbitrary number of obstacles [27], [29]. However, this approach has yet to be applied in the context of real-time joint action where at least one agent is a non-human artificial system. Notably, however, one of the salient components of joint action coordination is that each agent makes decisions regarding goals and sub-task goals in ways that may be assumed to require an understanding of each co-actors intents. A behavioral dynamics model on its own does not address the emergence of decision making or task switching in a joint action context. These dynamics are understood and modeled in terms of the agents' action capabilities when embedded in a task context, i.e. their affordance dynamics.

Affordance dynamics

Affordances are agent-environment action potentials that capture the complementary relations between an agent and an environment [30]–[35]. For example, a surface of a given height affords climbing (or not) in relation to an individual's body height and leg length [36] or when sitting, an object is reachable (or not) based on the distance of the object relative to the arm-torso extension capabilities of the reaching agent. Affordances are not limited to an agent's bodily capacities and dimensions, an affordance may also be defined in as agent-tool(s) or agent-other(s) synergies, where the agent's opportunities for action are enhanced, constrained, or otherwise changed when using a tool or the abilities of others. Regarding the former, if an object is out of reach to a tool-less agent, the agent's reach capacities may be extended with a tool thereby expanding or changing the affordances available to the agent to those available to an agent-tool system [37]–[39]. Likewise, when agents work together, the affordances available to the multi-agent system are different than those available to a single agent [6], [40], [41]. The embodiment of a tool or cooperative co-action increases or extends the agent's available degrees-of-freedom thereby changing how an affordance can be actualized or changing the number of available affordances.

With regard to understanding the dynamics of human and multi-agent coordination, affordance research provides more than just a vague theoretical guideline for understanding human action in a given environment. Affordances may be formalized in terms of action or body-scaled ratios that capture the relations between the action relevant features of an agent or multi-agent system, A, and the environmental features, E, which can predict critical shifts in perception or actualization of affordances [36], [40], [42]–[44]. For example, individuals exhibit abrupt transitions between one-hand and two-hand grasping or between one-person and two person grasping at a critical object-size/hand-size or object-size/arm-span ratio [45]–[48]. Accordingly, when E is an action relevant environmental property and A is an action relevant agent property, E/A may represent a generic control parameter that characterizes afforded agent-environment states. Moreover, the E/A ratio defines the stability of a given afforded state as determined by the current state of an agent-environment system.

It is important to recognize that an E/A ratio is not static in that the E/A ratio that characterizes different action capabilities may change depending upon the specific dynamics of the system. This can be seen in a previous study using a simple joint action pick-and-place task. In this task, a participant had to pick up an object and move it to a specified target location [16]. The participant could either take the object to the target alone or pass it to a co-actor who was closer to the farthest target locations. Participants were observed switching between passing and not passing modes of behavior at an E/A ratio defined by

$$\frac{d_g}{R_A} \tag{3}$$

where, d_g is the distance of the participant's hand to the target location and R_A is a measure of the participant's maximal preferred reach. However, participants switched between action modes at different E/A ratios depending on whether target locations were moving away from them or moving towards them, i.e. exhibited hysteresis. In order to model these dynamics the pass decision was characterized by

$$\dot{x} = -\alpha + x - x^3 \tag{4}$$

where x represents the state variable for action section (i.e., affordance mode) of the previous action selection process and $\dot{x}$ is the action selection state variable for the current trial. α corresponds to the re-normalized E/A ratio (eq. 3) calculated as

$$\alpha = \left(\sigma - \frac{d_g}{R_A}\right)\delta \tag{5}$$

with σ and δ as constant scaling factors. The resulting system exhibits a saddle-node bifurcation as α is scaled up or down past a critical value $\pm\alpha_c$ (approximately 0.35). Moreover, the system exhibits a region of bi-stability between $\pm\alpha_c$ corresponding to the observed hysteretic behavior. As such, for $\alpha < -\alpha_c$ and $\alpha > +\alpha_c$ the system has a single stable fixed point at $-x_{st}$ and $+x_{st}$, respectively. However, for $-\alpha_c < \alpha < +\alpha_c$, the system has two stable fixed points at, $-x_{st}$ and $+x_{st}$, respectively, as well as an unstable fixed point between the two. As a result, assuming no noise in the system, when α is scaled from $\alpha < -\alpha_c$ to $\alpha > +\alpha_c$, it will remain in the state characterized by $-x_{st}$ until $\alpha > +\alpha_c$. Note that for with a small amount of noise, the system state may change for some value $0 < \alpha < +\alpha_c$. Though a number of researchers have identified and acknowledged the importance of affordance dynamics, the significance of affordance dynamics to understanding affordances is not widely acknowledged outside of psychological studies [49]–[52].

While an understanding of affordances as dynamics has not percolated into robotics research, affordances, understood simply as states defined in agent-environment terms, are known and applied in robotics research (see [53] for a survey). Often affordances in robotics are used as means to solving classification or categorization problems, where the affordances provide action-oriented representations of perceived environmental surfaces to trigger actions or behaviors [54]–[57]. In that context, affordances act as intermediate representations of objects defined in terms of what the robot can do or not do with the object. This streamlines a robot's perceptual information processing, though the affordance is treated in a way that still requires further processing. If an object affords grasping, i.e. is graspable, this fact can be stored and used in planning the robots actions. An alternative application of affordances is as action mode switches that are realized in a given agent-environment context. Understood this way, the affordance dynamics are implemented in the robot as a kind of switch that directly activates or deactivates action relevant percepts or goals. This approach has been implemented in a variety of contexts [58]–[61]. However, in these cases the focus is entirely on the affordances of the robotic agent. In the context of human-robot and human-agent interaction, the affordances that are actualized are both those of the human and the artificial agent's. Moreover, when the task is a familiar one, as is picking up and passing objects, one can reasonably expect that both the affordances and affordance dynamics that a human co-actor will find most comfortable or predictable will be those that are most like every day experiences. To this end, the design of a human interacting artificial agent's affordance dynamics should not only take into consideration the agent's own capabilities, but also the expectations and abilities of the human co-actor. In the current study, we developed an artificial agent based on the behavioral and affordance dynamics of human co-actors engaged in a pick-and-place task in order to demonstrate the feasibility of these dynamics as the basis for a robotic or artificial agent co-actor in a similar task.

PICK-AND-PLACE AGENT FOR CONTINUOUS TASKS (PAPAC)

Previous studies have identified both the behavioral and affordance dynamics of human-human joint action in two variations of a virtual joint action pick-and-place tasks, [16], [24], [26]. In both tasks, two participants stood at a table wearing virtual reality headsets while their head and right hand movements were tracked and represented in a 3D virtual environment with an isomorphic virtual table. Participants were instructed to move disc objects that appeared on one side of the virtual table to target locations indicated on the other. In one version of the task, henceforth the simple version, only one participant picked up the object while the co-actor kept their hand in one location. The participant picking up the object could take the object to the target location on their own or pass the object to the co-actor. Participants completed 600 pick-and-place cycles, 200 with target and pickup locations randomized and 400 where targets and pickups appeared in an orderly manner. The aim of this study was to identify and model the movement and decision dynamics of the person picking up objects with a minimally interactive co-actor. The basic elements of the model that characterizes the behaviors of the participant that picks up the object have already been introduced in (1), (4), and (5), where (1) characterizes the

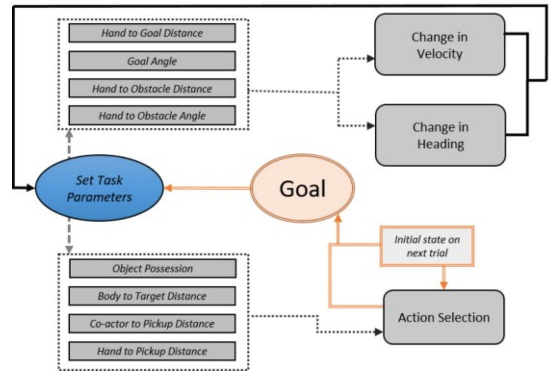

Figure1. The structure of PAPAc. Movement dynamics are calculated in the upper loop and affordance dynamics are calculated in the lower loop. As PAPAc moves through the task environment and switches action modes, task parameters are adjusted.

movement trajectories of an agent's hand and (4) and (5) characterize the decision dynamics of an individual agent's decision to pass or work alone in the task context. In the second version of the task, henceforth the continuous version, both participants could pick up the object and then decide to either take it to the target on their own or pass it to their co-actor. The aim of this study was to identify how increased interaction between co-actors affected their behavior and affordance dynamics. The behavioral model developed in the continuous version of the task served as the basis for PAPAc. In developing the core mathematical model, features of individual behavior and the task space relevant to the parameterization of the model were also identified. Of particular interest in these studies were (A) the affordance dynamics that characterized an actor's choice to pick up an object and the choice to move an object alone or to pass it to a co-actor, (B) the location that a participant would choose to release an object when passing it to a co-actor, and (C) the trajectory dynamics of the participant's hand movements when moving towards, with, or passing an object.

With regard to the affordance dynamics that characterized a participant's choice to move an object alone or to pass it to a co-actor, results revealed that the participant's decision to pass or not-pass an object was a function of the distance from the agents hand while resting to the target. These dynamics are captured by (4) and (5). When both participants were allowed to pick up the object, the decision to pick up the object or let the co-actor pick it up was a function of the difference between distances of each individual's current hand location to the pickup object. The dynamics of the pick decision are similar to those of the pass decision and will be introduced in the description of PAPAc below. Regarding pass locations, participants were consistent with regard to the location that they chose to release/pass the objects to the co-actor during passing events. Moreover, the specific location chosen did not appear to be dependent on the pickup location of the objects, nor the end target location. Rather, in the simple version of the task participants either picked a location relatively close to the co-actor's hand or relatively closer to the drop-off target locations and simply continued to release/pass objects in that same general location throughout the study. In the continuous version, nearly all participants passed in a location close to their co-actor's resting hand location (roughly just in front of each participant's right shoulder). Finally, participants exhibited a consistent pattern of somewhat curved movement trajectories across pickup, pass, and target movements, with movement curative resulting from participants employing a stable set of non-straight-line initial movement angles that co-varied with pickup location, likely tied to the turning radius of hand motions and a lack of long term trajectory planning. Participants also exhibited non-stationary velocity profiles, with peak velocity occurring within the first ½ of a corresponding for each sub-goal movement. These velocity dynamics are reproduced in PAPAc with the addition of a velocity dynamics component.

Movement Dynamics

The structure of PAPAc is illustrated in fig. 1 The movement component of PAPAc characterizes the trajectory dynamics of an end effector engaged in a continuous pick-and-place task. PAPAc's movements were controlled by a task specific parameterization of the Fajen and Warran model similar to (1) and (2),

$$\ddot{\varphi} = -b_g\dot{\varphi} - k_g\left(\varphi - \theta_g\right)\left(e^{-c_1 d_g} + c_2\right) + k_{o_j}\left(\varphi - \theta_{o_j}\right)e^{-c_3\left|\varphi-\theta_{o_j}\right|}e^{c_4 d_{o_j}} \tag{6}$$

where $\dot{\varphi}$, and $\ddot{\varphi}$, 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 $-b_g\dot{\varphi}$ acts as a friction force on turning rate, and the function $-k_g(\varphi - \theta_g)$ operates to minimize the difference between the current heading angle, φ, and the angle θ_g, of the corresponding sub-task goal/target location (i.e., the pickup location for pickup movements, the pass location for passing movements, and the target location for target movements, and a resting location when inactive). The distance of PAPAc to the current goal location is defined by d_g. The presence of the factor $\left(e^{-c_1 d_g} + c_2\right)$ 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 [13]. Note that the parameters θ_g and d_g change continuously as the position of PAPAc moves through the task space. The addend $k_{o_j}\left(\varphi - \theta_{o_j}\right)$ induces obstacle avoidance behaviors by acting as a repulsive force on PAPAc's heading direction, pushing the heading direction away from any nearby obstacles, o_j, defined in the task space. In the current task paradigm only the co-actor's hand is included as an obstacle. The factor $e^{-c_3\left|\varphi-\theta_{o_j}\right|}e^{c_4 d_{o_j}}$ causes the repulsive effects of the obstacle avoidance component to decay exponentially as PAPAc moves away from any obstacles, where c_3 scales the strength of the repulsive force on the heading direction and c_4 scales the distance from the obstacle, d_{o_j}, at which the repulsive force is no longer effective.

Typically, human hand movements in directed reaching tasks, i.e. tasks where the hand to a specified location, the movements exhibit a non-constant velocity [62], [63]. This velocity dynamic was observed and modeled in the previous human-human pick-and-place studies [16], [26]. In PAPAc, velocity is controlled by means of the additional 2nd order differential equation,

$$\ddot{v} = -b_v\dot{v} - k_v\left(v - C_v\left(1 - e^{-d_g}\right)\right), \tag{7}$$

where b_v and k_v act as damping and stiffness terms on the rate of change of PAPAc's velocity, v, which increases and decreases as a function of the current goal distance, d_g. When the PAPAc is far away from the target location $\left(1 - e^{-d_g}\right) \approx 1$ and v increases. As the distance to the goal location decreases, however, $\left(1 - e^{-d_g}\right)$ approaches zero and v decreases accordingly. C_v 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.

Action Selection Dynamics

The second component of PAPAc drives the action selection dynamics of the agent. In the current implementation there are two task-defined choices driven by this component. First, one of the co-actors 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 switching between action modes, i.e. pick up/rest object and alone/pass action modes respectively. In the context of the current task the action mode selection dynamics for PAPAc are be driven by

$$\dot{x} = -\alpha_k + x - x^3 \tag{8}$$

where x represents the state variable for action section (i.e., affordance mode) of the previous action selection process and $\dot{x}$ is the action selection state variable for the current trial. α_k corresponds to the specific sub-task action mode and agent-normalized E/A ratio, k, where the decision to pick up is defined for PAPAc by

$$\alpha_s = \left(\sigma_s - \frac{d_{g_s}}{R_s}\right)\delta_s - \left(\sigma_{s_c} - \frac{d_{g_{s_c}}}{R_{s_c}}\right)\delta_{s_c} \tag{9}$$

In this parameter equation, the value of α_s is determined by the difference in the normalized E/A ratio of PAPAc and the normalized E/A ratio of the co-actor, where d_{g_s} is the distance from current location of PAPAc to the pickup object's location and $d_{g_{s_c}}$ is the distance from current location of the co-actor to the pickup object's location normalized by the PAPAc's reach capabilities, R_s, and the co-actor's reach capabilities, R_{s_c}, respectively. Note, in the current instantiation of PAPAc in a virtual agent, R_s is specified in terms of human reach capabilities in the task in order to make interaction with PAPAc more natural and easily predicted with minimal learning on the part of the co-actor. $\sigma_s, \delta_s, \sigma_{s_c}$, and δ_{s_c} act as constant scaling factors. Accordingly, PAPAc will move to pick up the object if its current normalized reach to the object is closer than the normalized reach of the co-actor. This equation is based on observations of human co-actors (n = 10 pairs) engaged in a joint action pick-and-place task. The C4.5 decision tree algorithm was applied using a 10 fold cross validation to a data set of 2998 pick decisions in order to create a decision tree with a minimum node size of 50 instances. When the only attributes used to build the tree were the current location of each actor's hand to the pickup location the resulting decision tree was able to correctly predict 87% of the pick decisions. Notably, the design of the pick decision component means that if there is no co-actor and the pickup object is in reach, PAPAc will always reach for the object. Likewise, if the resting position of PAPAc is in a slightly closer to the object pick up than the co-actor, then PAPAc will return to resting and automatically head to pick up if the other agent does not move.

The decision to pass the object to the co-actor or complete the task alone occurs only after PAPAc has picked up the object. Once the object has been picked up, the PAPAc determines if it should pass according to the solution to (4) and E/A ratio defined by,

$$\alpha_p = \left(\sigma_p - \frac{d_{g_p}}{R_p}\right)\delta_p \qquad (10)$$

where d_{g_p} is the distance of PAPAc's resting location to the target location, and R_p is a measure of PAPAc's reach capabilities, again defined in terms of normal human capabilities in this case. In this equation, σ_p and δ_p are constant scaling factors. This results in PAPAc almost always passing when the target is farthest from PAPAc and nearest the co-actor and often passing to the second farthest target fitting observation in human co-actors (n = 10 pairs). This was determined using the C4.5 decision tree algorithm, which was 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 current location of one of actor's hand to the pickup location the resulting decision tree was able to correctly predict 79% of the pickup decisions.

Task space perception and Task Environment Variability

In its current form PAPAc assumes access to information specifying goal locations in the task space, the location of itself and its co-actor in global task space coordinates, and the action capabilities of itself and its co-actor. Providing this information to PAPAc via agent localized sensors is nontrivial, but is not the central aim of the current project. Notably, the information required for PAPAc to complete the task is not defined in modality specific terms. Moreover, extracting this information from the task environment does not require representation of high level or abstract features of the joint action task space, e.g. PAPAc does not depend on information regarding the mental states of the human co-actor. This is an advantage of using behavioral and affordance dynamics of human action as inspiration for artificial agent design. The intelligence exhibited by the agent, including joint action decisions, emerges from readily available information in the task environment. This provides a useful tool for designing robots and artificial agents that interact with human co-actors by taking advantage of the fact that at least some intelligent social behaviors can emerge from low level information and relatively simple agent and environment interactions.

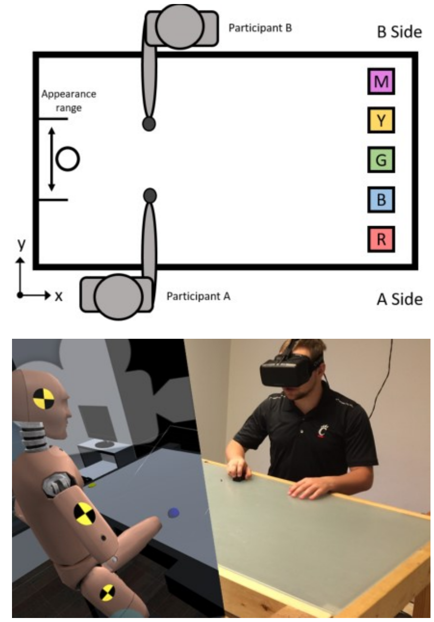

Figure 2. Implementation setup and testing environment. A diagram of the task space layout is presented at the top. In 2 person setup, participants stood across from one another at a table wearing virtual reality headsets. Only one person was present when PAPAc was implemented. The table was represented in the virtual environment and when a participant controlled an avatar's movements they viewed the table from the perspective of the avatar being controlled.

IMPLEMENTATION AND RESULTS

As an initial proof of concept we implemented PAPAc in a 3D virtual environment where it could interact with human co-actors in a shared space. An illustration of the task setup is provided in Figure 2. The use of a virtual environment allowed us to validate the agent in the same environment that human-human data was collected. It also allowed for a safe test space while maintaining relatively high-speed movements in a shared space. The virtual environment was presented to a human co-actor in a head mounted display (Oculus DK2) and the human co-actor's right hand movements were tracked with a wireless Polhemus Latus (Polhemus Ltd, Vermont, USA) motion tracker. Both agents were represented as identical virtual avatars modeled after a crash test dummy. The human agent's hand-held wireless Polhemus Latus motion-sensors controlled the movements of their avatar's right hand movements. PAPAc drove the movements of the other avatar's right hand. An inverse kinematics controller (model and controller supplied by Root Motion, Tartu, Estonia) driven by these movements controlled the right arm and body movements of the virtual avatars. 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.

PARTICIPANTS

PAPAc was tested with 6 University of Cincinnati students (aged 22 to 31) recruited to participate in a joint action pick- and-place task with PAPAc in the virtual reality space. The aim was to provide a proof-of-concept demonstrating that PAPAc can successfully engage in the joint action pick-and-place task in 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.

Participants

6 University of Cincinnati students (aged 22 to 31) were recruited to participate in this experiment. 5 male and 1 female participated in the study.

Proof-of-Concept

Participants stood at a 1.65m x 0.836m 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 with a table that was isomorphic in size to the table in the laboratory room. The avatars were placed on opposite sides of the table such that their right shoulders were aligned, i.e. one avatar was centered on the table and the other stood to the left of center. The task required participants to work with PAPAc 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. The target location for a given trial was indicated by the color of the disc. For example, if the trial target was the middle target position (green), then the disc would be green. A trial involved successfully moving a single 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 two practice blocks (1 block of 12 trials with only one target location and 1 of 20 trials with randomized target locations) and 2 experimental blocks of 150 trials, 30 trials for each target location. Target locations were randomized in these blocks. After the first experimental block the participant's perspective was switched to the other side of the table, i.e. the participant began on side A and after the first experimental block side B and the participant on side B moved to side A. This allowed for direct comparison of PAPAc-human data with the results of a human-human interaction study [26]. Experimental blocks lasted between 10 and 15 minutes.

The participants were instructed that when the disc appeared either they or the other agent could pick it up and attempt to move it to the target location. A pickup occurred when either avatar's hand came in contact with the disc. When picked up, the disc moved with the avatar's hand until it reached the target or the disc was passed to the co-actor. The participants were informed that if the reach to the target was either too far or uncomfortable, they could pass it to the other co-actor. A pass involved picking up the disc and then releasing it somewhere on the table by lifting their hand from the table. PAPAc initiated passes at a fixed distance from trial pass location by adding a small change in location along the z-axis extending perpendicular from the table's surface. To complete a pass, the other co-actor would pick up the disc and move it to the target. A trial was completed when the disc reached the correct target. Importantly, participants knew that their co-actor was a computer program but were not given any instructions regarding how to interact with PAPAc beyond how to initialize a pass and that they would be completing the task together.

The sub-task goal locations used by PAPAc to calculate movement trajectories and decisions were defined by the disc location upon appearance, the specified target location, a pass location and a resting location. The pass location was defined based on a k-means cluster analysis of human-human pass locations in a similar joint action task [26]. When human pairs completed this task their pass locations were highly predictable, typically occurring near the resting hand position of their co-actor. 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). In the current task when PAPAc was on side A, passes locations were clustered around (0.33m, 0.53m) and when PAPAc was on side B passes were clustered around (0.33m, 0.14m) both adjusted slightly to accommodate variation introduced by the lifting movements used to release the object. In each case, pass locations were randomly varied from trial to trial using a random log normal distribution [16], [64]. The agent resting location was defined in relation to the virtual avatar's shoulder position. The resting location was initially located 0.15m from the edge of the table along the y-axis extending from the avatar. This location was randomized on each trial within a 0.4m x 0.2m rectangular region centered on the resting position defined for each side of the table.

RESULTS

All participants were able to successfully complete all of the trials with PAPAc. PAPAc picked up the disc an average of 47% (n = 6, SD = 6%) of the trials and passed an average 14% (n = 6, SD = 2%) of the times that it picked up the disc first. This is in line with results from human-human pairs, which averaged 46% (n=10, SD = 23%) of pickups and 14% (n=10, SD = 17%) passes when they picked up the disc first. An independent samples t-test found no significant difference between the average percentages of pick-and-place decisions for each group. Participants quickly engaged the task, took turns with PAPAc, and passed to PAPAc in a manner qualitatively similar to human-human pairs. The average human-human trial completion time was 2.91 seconds (n = 10, SD = 0.83) and the average human-PAPAc trial completion time was 2.95 seconds (n=6, SD = 0.20).

Trajectories produces by PAPAc (illustrated by fig. 3 bottom) did not interfere with the human co-actor's movements or trajectories. The structure of interactions evolved a similar pattern over time, however the variability in the decision making component of PAPAc obscures the extent to which patterns of movement interactions were quantitatively similar to or different from human-human pairs. As can be seen in figure 3, PAPAc exhibits a pronounced turn when picking up the disc and upon task completion. This turning behavior can be eliminated by resetting PAPAc's heading direction following completion of these sub-task goals. Based on initial testing, the trajectories resulting from resetting heading direction at each sub-task goal change results in heat maps that more closely resemble human-human trajectory heat maps (see Figure 3). However, mid-trajectory changes, as when PAPAc switches from returning to resting position to moving to pick up the object become unnaturally abrupt. In the current instantiation of PAPAc, the decision was made to not reset heading direction in order to keep all trajectory movements smooth. While selective heading resets, e.g. only reset when just completed a pick up or target trajectory, it remains unclear what drives human participants to sometimes shift trajectories smoothly and other times to shift abruptly. Notably in previous studies, initial goal trajectories systematically do not match straight line goal trajectories [16].

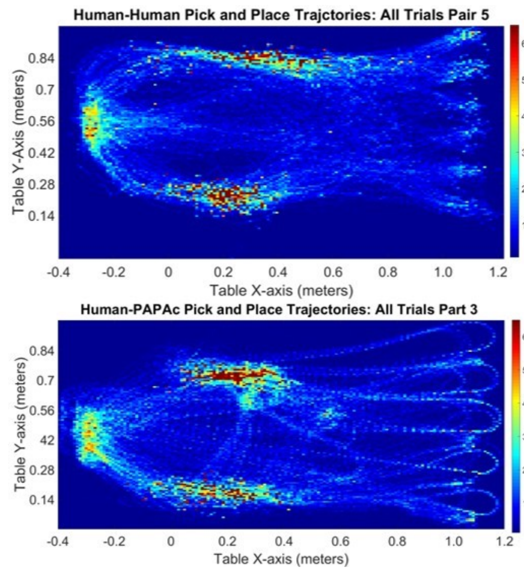

Figure 3. Heat maps representing movements of a sample human-human pair and a sample PAPAc-human pair. Colors lower on the colorbar next to each heat map indicate fewer trajectories passed through an area and colors higher on the color bar indicate more trajectories passed through the area.

DISCUSSION

While the aim of the current implementation of PAPAc is relatively modest, there are many possibilities for HRI research. PAPAc can interact with a human co-actor in a shared task, making decisions and adapting to the co-actor's decisions, without needing to sense or interpret the high-level cognitive states or intentions of the its co-actor. This is facilitated in the current context by the fact that the task instructions significantly constrain the behavior of the human participant to a particular task activity. However, PAPAc is designed such that minor adjustments could make it capable of switching between working alone and working with a co-actor. In the current instantiation PAPAc will already pick up an object regardless of whether or not a co-actor is present. This is because, without a co-actor near the pickup location, PAPAc will always move to pick up the disc if it is within its reach capabilities. However, the passing action selection component assumes another actor is available to receive passes. This could be remedied by modifying the pass component with a dynamic reach capability parameter. A minimal form of this parameter would switch between maximum reach capability and a human comfort reach capability depending on the presence of an active co-actor. This modification would allow PAPAc to work alone in its task when no co-actor is present and automatically switch to working with another co-actor when one is present. Notably, at any point the addition of abilities to interpret co-actor communications or intentions could augment the basic action and mode switching dynamics of PAPAc.

Hardware implementation of PAPAc will need to include a robust collision avoidance system. While the current obstacle avoidance component can work for stationary and slow moving obstacles the fact that PAPAc's velocity is not affected by obstacles means that it will not adapt its velocity in the presence of obstacles. When the obstacle is moving, or actively attempting to collide with a PAPAc controlled device would more often than not fail to avoid the obstacle. However, the addition of an obstacle avoidance component to the PAPAc's velocity function similar to the one added to the heading function may serve to provide robust obstacle avoidance. Note that because PAPAc's primary navigation function drives the current heading direction of PAPAc, it will not get trapped in local minima unless the local minima is actively attempting to trap it [27]. Indeed, even when trapped, PAPAc's heading direction will continue to shift, attempting to find a path around its nearest obstacle and towards its goal. Further research in VR will determine the extent to which a modified form of PAPAc can avoid moving, and even aggressive obstacles (agents).

CONCLUSION

PAPAc is a relatively simple joint action pick-and-place algorithm designed for a relatively simple pick-and-place task. As a proof of concept implemented in a 3D environment and interacting with real human co-actors, it demonstrates the application of behavioral and affordance dynamics models of human behavior and joint action to the design of artificial systems. Notably, PAPAc interacted with multiple untrained human co-actors in a way that appeared natural and involved no significant learning curve. While only one element in the design of human-agent interaction systems, components like PAPAc, built on models from behavioral and affordance dynamics may provide a key to developing low dimensional agent systems that can interact (or not) with human co-actors in a robust and emergent manner.

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