A Bio-Inspired Artificial Agent to Complete a Herding Task with Novices

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Abstract

Models of robust human-human coordination can guide the design of adaptive and responsive human-robot systems. Here we test an artificial agent that embodies low-dimensional nonlinear dynamic equations derived from human behavior while completing a two-agent herding task, where the goal is to contain reactive spheres to the center of a target region. The model was able to complete the task alongside human novices in a virtual version of the experimental setup used in Nalepka and colleagues (submitted). Not only did the model lead participants to successful performance, but also 12 out of 18 participants reported that they believed their partner was a human participant in another room. The model was therefore able to capture the complex social behavior that defined robust task success in terms of lower dimensional dynamical equations that characterizes the emergent behavioral dynamics of embedded multiagent behavior.

Introduction

Joint human coordination is adaptive and robust – pairs of individuals can work together to complete tasks, such as carrying a couch, through a variety of different environments without much difficulty. Developing robotic systems that have these qualities will be useful for problems that need to be solved in a wide range of environments and contexts, with both human and robot partners. One possibility for creating such adaptive systems is provided by models of the low-dimensional behavioral dynamics (Warren, 2006) that emerge when human pairs complete tasks successfully. Because these models consist of a handful of ordinary differential equations, they can be used to drive the behavior of socially embedded artificial systems and exhibit a wide range of behavioral complexity in a relatively compact form.

Our approach (Richardson et al., 2015; in press) is based on research in cognitive science inspired by dynamical systems theory and complexity science. According to this research, the local actions and behaviors of relatively simple systems can give rise to complex coordinative behavior. Fairly well known examples of this research in non-human systems include the coordination of fish schools and bird flocks, where simple rules

at the local or individual level lead to complex coordinated movement (Couzin, Krause, Franks, & Levin, 2005; Hildenbrandt, Carere, & Hemelrijk, 2010; Reynolds, 1987). Applied to psychology, this has been used to explain path navigation and obstacle avoidance (Fajen & Warren, 2003; 2004; 2007), rhythmic movement coordination (e.g., Richardson et al., 2007; Schmidt & O'Brien, 1997; Schmidt & Turvey, 1994), and anticipation (Washburn et al., 2015). In the case of path navigation and obstacle avoidance, only a small set of nonlinear equations is required to accurately model and predict human movement towards a goal through a cluttered environment (Warren & Fajen, 2003; Warren, 2006). In this model the goal is treated as a point-attractor and obstacles, such as desks, chairs, or other people, are treated as repellors. Fajen and Warren's model has been implemented successfully as the basis for an artificial navigation system (Nemec & Lahajnar, 2009). Similar work has been done to extend this methodology to passing objects between partners in order to reach a goal location (Lucas et al., 2015). In the rhythmic coordination research, artificial agents have been developed to coordinate and produce new stable coordination patterns with partners (Kostrubiec, Dumas, Zanone, & Kelso, 2015; Zhang, Dumas, Kelso, & Tognoli, 2016). However, research is needed to extend this approach to understand and model the coordinative dynamics that emerge in more complex situations that require the control of a dynamically changing environment. In the remainder of the paper, we'll describe and test an artificial agent able to work with novices to contain a set of autonomous agents as an illustration of how these types of situations can be understood.

Behavioral Task

A two-player shepherding game was developed in Nalepka and colleagues (submitted) to understand emergent coordination dynamics in more complex and dynamically changing environments.[1] In the task, dyads stood on either side of a frosted glass tabletop (see Figure 3A) and controlled cube-shaped agents (sheepdogs) with wireless handheld motion sensors tracked using a Polhemus Liberty Latus motion tracking system. Participants interacted in a two-dimensional

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[1] The task was inspired by shepherding behavior in dogs, but is not set out to explain actual shepherding behavior (see Strömbom et al., 2014), but rather was referred to as such as a way to describe the task to participants.

environment projected onto the glass top (see Figure 1). The environment consisted a fenced grass area and three or seven balls (sheep). The goal of the dyad was to cooperate and discover a solution to contain all the sheep within the red target containment area for a certain length of time and for a certain amount of trials before time ran out (45 minutes). The sheep could move freely within the fenced playing field, but could not pass beyond the fenced region. If the sheep collided with the fence, the trial ended prematurely. If the sheep collided with one another they acted like solid objects and could not pass through one another. When left alone the sheep exhibited Brownian motion, but when a player's sheepdog was within 12 cm of a sheep, the sheep reacted to the players' proximity by moving in the direction opposite of the participant's position. Therefore, participants needed to learn how to push the sheep towards the center of the field without moving too close as to accidently cause the sheep to scatter away from the participant. Participants were not allowed to explicitly communicate with one another regarding their game play or strategy while engaged in the task.
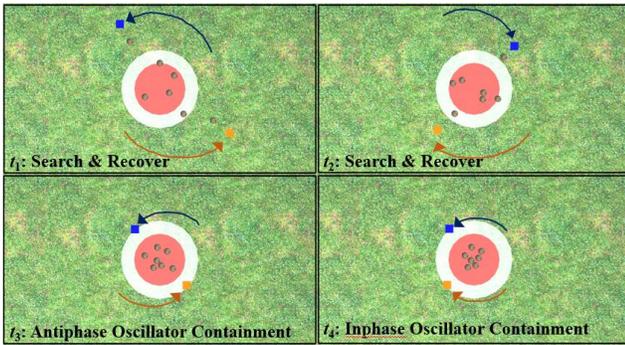

Figure 1: A prototypical time lapsed ($t_1...t_4$) depiction of game play, including an illustration of the search-and-recover (S&R) and coupled oscillatory contained (COC) behavioral modes exhibited by pairs. Arrows indicate movement direction.

Only 31 of 42 tested pairs were able to meet the success criteria, and all but two of them discovered the same coordinative strategy to corral the sheep. The dominant coordinative strategy consisted of two different modes of behavior. We will call these modes the *Search & Recover* (S&R) strategy, depicted in Figure 1t_{1-2} and the *Coupled Oscillator Containment* (COC) strategy, depicted in Figure 1t_{3-4} respectively. When employing the S&R mode of behavior, participants implicitly divided the task space in half, and each individual in the dyad pursued the sheep furthest from the center of the target region, placing their respective marker such that it propelled the farthest sheep on their respective sided towards the center. As the sheep clustered, an oscillatory movement of the sheepdogs began to emerge as the result of participants moving to similar regions in of the playing field to contain the sheep. After some time, a bifurcation occurred and participants begin to make regular antiphase (Figure 1t_3) or inphase (Figure 1t_4) oscillatory movements. This is the emergence of the COC strategy. Once this COC behavioral mode emerged, dyads would begin subsequent trials by moving directly into this behavioral mode. It was found that this

oscillatory behavior is consistent with the dynamics produced by coupled nonlinear oscillators, which have also been used to understand the dynamics of intra- and interpersonal rhythmic movement (e.g., Richardson et al., 2007; Schmidt et al., 1990; Schmidt & O'Brien, 1997; Schmidt & Turvey, 1994). These dynamics, as described by the Haken, Kelso and Bunz model (Haken et al., 1985; Schöner et al., 1986), indicates that two stable oscillatory modes are possible: inphase and antiphase behavior, with inphase behavior being more stable than antiphase. This relative stability is consistent with the experimental results and suggests that the dyads may be embodying similar dynamics when performing the COC behavior.

The Artificial Shepherd

Given the results in Nalepka and colleagues (submitted) we developed an expert artificial agent (EAA) based on a model, visually depicted in Figure 2, which characterizes the two behavioral modes present in past human data (chosen values will be presented in parentheses after each parameter). S&R involved participants selecting a sheep that is furthest from the red target region, and moving their sheepdog so that the targeted sheep is in a line between the player and the central region. This behavior can be modeled with two sets of equations below:

$$\ddot{r}_i + b_{ri}\dot{r}_i + \varepsilon_i\big(r_i - (\varphi_{sd,i(t)} + C_{md,i})\big) = 0 \qquad (1)$$

$$\ddot{\theta}_i + b_{\theta i}\dot{\theta}_i + \mu_i\big(\theta_i - \varphi_{s\theta,i(t)}D_{sd,i}\big) = 0 \qquad (2)$$

The model operates on a polar task axis where r_i is the radial distance of the player's sheepdog from the center of the field, with $\dot{r}$ and $\ddot{r}_i$ being its velocity and acceleration along that axis, respectively. Parameter θ_i is the angle, in radians, from the reference angle which is on the sagittal plane, with $\dot{\theta}_i$ and $\ddot{\theta}_i$ being the angle's velocity and acceleration terms. The subscript i indicates player identification. Parameters b_{ri} (5) and $b_{\theta i}$ (5) are the velocity damping terms, ε_i (20) and μ_i (15) scales the rate at which player i minimizes the difference between their current position to the target radial position, $\varphi_{sd,i(t)}$ and angle, $\varphi_{s\theta,i(t)}$ of the target sheep, $\varphi_{s(t)}$. The parameter $C_{md,i}$ (0.05) is a fixed value which indicates the minimal distance that the agent should stay away from the sheep. This parameter prevents the EAA from moving on top of the target sheep, as well as too close into the central containment region, preventing unreliable sheep repulsion behavior. The parameter $D_{sd,i}$ is a Heaviside parameter defined as,

$$D_{sdi} = \begin{cases} 0, & \varphi_{sd,i(t)} \le C_{sd,i} \\ 1, & \varphi_{sd,i(t)} > C_{sd,i} \end{cases} \qquad (3)$$

where $D_{sd,i}$ is zero when the farthest sheep is less than a fixed parameter $C_{sd,i}$, (0.08) indicating there is no furthest sheep to corral and so the EAA moves towards the reference angle axis. It should be noted that the model only pursues sheep that are on
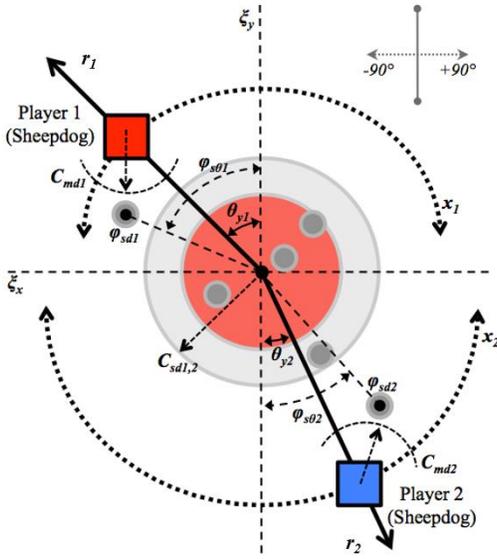
Figure 2: Illustration of the task space axes employed for the bi-agent herding model. Illustration of the task space employed for the sheep-herding model which captures player i's (where $i = 1$ or 2) sheepdog location at any time within the ξ_x and ξ_y planar game space in polar coordinates (r_i, θ_i), with r_i corresponding to the radial distance of player i from the center of the ξ_x and ξ_y planar game space and θ_i corresponding to player i's radial angle ($\pm 90°$) from the ξ_y game space axis on their side of the game field. x_i is the oscillatory perimeter path of each participant i's sheepdog with respect to half (π-radians) of the target containment region of success closest to the participant's side of the game space, such that each participant's perimeter path, x_i, is centered on the participants radial (r_i, θ_i) position within the (ξ_x, ξ_y) game space. Adapted from Nalepka and colleagues (submitted) with permission from the authors.

their half of the playing field, which is consistent with data found in Nalepka and colleagues (submitted).

When a certain level of proficiency is achieved, players transition from the S&R behavior to the COC mode of behavior whose global behavioral dynamics is consistent with the HKB model (Haken et al., 1985). To be consistent with the previous research modeling the dynamics of rhythmic human limb movements (Kay et al., 1987), and rhythmic interlimb and interpersonal coordination (see Haken et al., 1985; Kelso, 1995; Schmidt & Richardson, 2008), the COC mode of behavior was modeled using a set of coupled Rayleigh/van der Pol hybrid nonlinear oscillators of the form,

$$\ddot{x}_1 + \alpha_1 \dot{x}_1 + \beta_1 x_1^3 + \gamma_1 x_1^2 \dot{x}_1 + \omega_1^2 x_1$$
$$= (\dot{x}_1 - \dot{x}_2)(A + B(x_1 - x_2)^2)$$
$$(4)$$

$$\ddot{x}_2 + \alpha_2 \dot{x}_2 + \beta_2 x_2^3 + \gamma_2 x_2^2 \dot{x}_2 + \omega_2^2 x_2$$
$$= (\dot{x}_2 - \dot{x}_1)(A \mp B(x_2 - x_1)^2)$$

where $i = 1$ for player 1 and $i = 2$ for player 2, and the positive/negative (excitatory/inhibitory) damping parameter α_i scaled as a function of sheep distance using the linear equation,

$$\dot{\alpha}_i = \delta_i(C(\varphi_{sd,i(t)}^2) - D(C_{sd,i}) - \alpha_i) \qquad (5)$$

Parameter x_i indicates the player's position on the circular x task axis, centered on the player's (r_i, θ_i). The possible range of motion is roughly ($\theta_i \pm \frac{\pi}{2}$), with $\dot{x}_i$ and $\ddot{x}_i$ being its velocity and acceleration along x task axis. Note that x_i in Eq. 4 outputs a range of values roughly (-1,1) which is then multiplied by $\frac{\pi}{2}$ to convert the value into game space units after iteration. The parameter ω_i ($\frac{7}{4}\pi$) defines the stiffness or frequency of oscillator of player i's perimeter path movement, and the functions ($\beta_i x_i^3$) (1) and ($\gamma_i x_i^2 \dot{x}_i$) (5) corresponding to the Rayleigh and van der Pol escapements terms for each player's

x_i perimeter path movement, respectively. The coupling function to the right of the equals sign in each equation is the same as that previously derived by Kelso and colleagues (e.g., see Haken et al., 1985; Kelso, 1995), and defines both inphase (0°) and antiphase (180°) relative phase relationships as the stable coordination modes between the two oscillators (when $\alpha_i < 0$), with the relative strength of these two coordination modes defined by the parameters A and B (both -0.2). The system is bi-stable when $|4B| > |A|$, but mono-stable (inphase only) when $|4B| < |A|$.

The change between the two modes of behavior, S&R and COC, is the Hopf bifurcation in the variable x_i that occurs for each oscillator system. The bifurcation is driven by Eq. 5: when $\alpha_i > 0$, behavior along the x_i task axis corresponds to that of a nonlinear mass damped spring with a stable fixed point solution; when $\alpha_i < 0$, behavior along the x_i task axis corresponds to that of a nonlinear limit cycle oscillator, with an amplitude of movement approximately equal to

$$x_{i,AMP} = 2\sqrt{|\alpha_i|/\gamma_i} \qquad (6)$$

when $\alpha_i < 0$, $\beta_i > 0$ $\gamma_i > 0$ and $|\alpha_i| \ll \omega_i$ (see Kay et al., 1987 for more details). The value α_i in Eq.5 at any instance in time, (t), is a differential function of the distance, $\varphi_{sd,i(t)}$, of the furthest sheep on player i's side of the game space with respect to a maximum safe containment distance, $C_{sd,i}$, with parameter δ_i (25) which controls the rate at which $\dot{\alpha}_i$ reaches 0. Parameters C (9) and D (8) adjusts the weight given to $\varphi_{sd,i(t)}^2$ and $C_{sd,i}$ in determining $\dot{\alpha}_i$. If the distance, $\varphi_{sd,i(t)}$, of the sheep furthest from the center of the game space on player i's side of the game space is outside player i's maximum safe containment distance, $C_{sd,i}$, and $\alpha_i > 0$, then behavior along the x_i task axis corresponds to that of a nonlinear damped mass spring. Conversely, if the distance, $\varphi_{sd,i(t)}$, of the sheep furthest from the center of the game space on player i's side is inside player i's maximum safe containment distance, $C_{sd,i}$, and $\alpha_i < 0$, then behavior along the x_i task axis corresponds to that of a nonlinear limit cycle oscillator. Values near zero produce

minute scrubbing behavior by the agent which, anecdotally, is consistent with past human data.

After piloting, changes to how the target sheep, $\varphi_{s(t)}$, is determined were made from the model's original formulation in Nalepka and colleagues (submitted). The following Heaviside function,

$$\varphi_{s(t)} = \begin{cases} \min\limits_{j \in \Phi} \Phi_{dj}, & \alpha_i > \tau \\ \max\limits_{j \in \Phi} \Gamma_{dj}, & \alpha_i \leq \tau \end{cases} \quad (7)$$

determines which sheep the agent will pursue. Value Φ_{dj} represents the distance for a given sheep j, to the closest fence segment. Γ_{dj} represents the radial distance of sheep j from the center of the target region, and τ (0.5) represents a fixed parameter determining when the sheep selection strategy changes. Parameter τ is indirectly derived from a specific distance from the center of the field, but is more intuitively operationalized as being associated with a change in the mode of behavior, with $\min\limits_{j \in \Phi} \Phi_{dj}$ used when engaging in S&R behavior, and $\max\limits_{j \in \Phi} \Gamma_{dj}$ when utilizing COC behavior. Equation 7 was included because, due to the rectangular playing field, the EAA was placed in situations where it would pursue a sheep that, although further from the center, caused trials to fail as sheep closer to the center would hit the fence on the short end of the rectangle. This post-hoc method was included as to prevent the model from continuing letting their partner down. Additionally, the function that determines the target sheep was altered to select the position of the target sheep + 1% of its normalized velocity vector. This was done to prevent situations where the model would cause the target sheep to spiral around the target region due to the sheep maintaining its tangential velocity.

Current Study

The present research set out to test and validate the above model against a set of novice participants. For the current study, the coupling term in Eq. 4 was not included. This was done in order to determine if the COC behavior would emerge without the explicit coupling to the participant. The study had three aims: 1) to determine whether the EAA can perform the herding task with a human novice, 2) to determine whether novices learn to coordinate with the artificial agent to produce COC behavior consistent with data presented in Nalepka and colleagues (submitted) and 3) determine whether participants will remain in belief that they are performing the task alongside a human agent as a way to test the *humanness* of the model.

Method

Participants

Eighty participants took part in the study. Thirty pairs were formed in the novice control condition, and the remaining 20 completed the EAA condition. All participants received research credit as part of a class requirement for an undergraduate Psychology course.

Apparatus & Task

The task was designed using the Unity 3D game engine (version 5.2.0; Unity Technologies, San Francisco, California) and was presented to participants via Oculus Rift DK2 (VR) headsets (Oculus VR, Irvine, California). The presented virtual environment (Figure 3B) was modeled at 1:1 scale after the experimental room (Figure 3A). The task was presented in the VR headset to appear on a virtual tabletop modeled at 1:1 scale after the glass tabletop in the real environment which then acted as the solid physical surface for participants to move their motion sensors on. Participants used wireless Latus motion tracking sensors operating at 96 Hz (Polhemus Ltd, Vermont, USA) Participants moved the sensor along the glass tabletop and hand movements translated 1:1 to movements of the player's cube (sheepdog) in the virtual environment. Participants were given a body in the virtual world, modeled after a crash test dummy of height 1.8m whose motion was controlled using an inverse kinematic calculator (model and calculator supplied by Root Motion, Tartu, Estonia) based off the real movements of the participant's right hand (via a Latus motion sensor) and head (via the Oculus Rift). Regardless of height, each participant was calibrated to fit the body of the virtual model, giving each participant an equivalent image size of the playing area. The reason for virtual bodies was threefold: to best emulate the conditions in the original research by Nalepka and colleagues (submitted) where participants' arms were able to occlude the playing surface, to provide approximate information regarding the arm location of one's partner (to avoid hitting), and to further increase the believability that participants were interacting with a human in the EAA condition. Separate computers were used to power the headsets and data was transferred to the host computer via a LAN connection. The maximum display latency between the participants' real-time movements and the virtual (box) sheepdog was 33 ms. Game states were continuously recorded at 50 Hz, including the movements of the virtual sheep and the participant controlled sheepdogs.

Participants were able to move their sheepdogs anywhere in two dimensional space within the 1.17m by 0.62m fenced area of the grass task field. The goal of the game was to contain 3 or 7 wool covered stimulus balls (sheep) within the red circular target containment region measuring 19.2 cm in diameter for 70% of the last 45 seconds of a 60 second game trial (the first 15 seconds of each trial served as time for participants to initiate a behavioral coordination strategy and/or corral the sheep). All sheep needed to be inside this region for it to count towards the dyad's score. Participants received visual feedback regarding their performance at the end of completed trial (i.e., what percentage of time they managed to keep the sheep within the target area). A game trial ended prematurely (i.e., before 60 seconds), however, if one of the sheep managed to hit the perimeter fence or if all sheep escaped the 29 cm white circle that surrounded the red target region circle. At the start of a trial, the sheep were distributed within the red target containment region (Figure 3c-d), with the subsequent motion of the sheep governed by random Brownian motion dynamics. The sheep also dynamically reacted to the participant controlled sheepdogs as if threatened, being repelled away from

a participant's sheepdog when the sheepdog was within 12 cm of the sheep's game location. When threatened, the sheep would move directly away from the player at a speed proportional to the inversed of the squared distance between the sheep and the player. It is also important to note that sheep were programmed to be able to collide (as opposed to pass through) each other. Finally, pairs played the game for a maximum of 45 minutes, with the experiment ending either at the end of this experimental period or earlier if the pairs made it past the 70% success threshold eight times.
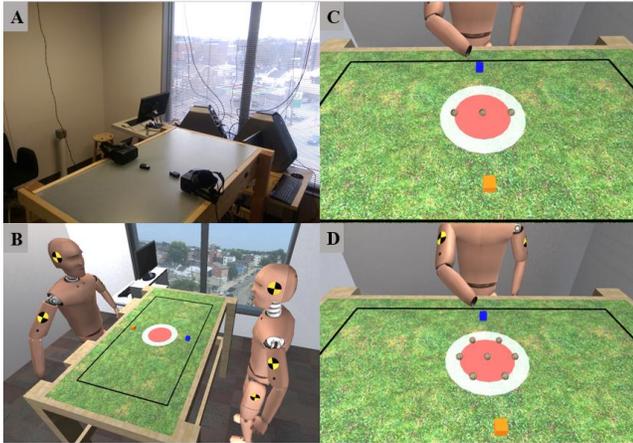

Figure 3: (A) Experimental Room, (B) Virtual replica of (A) presented to participants. (C-D) Depiction of the initial arrangement of the 3 and 7-sheep conditions, respectively from the perspective of the participant.

In the novice control condition, participants stood on either side of the table as depicted in Figure 3B. In the EAA condition, participants were told that their partner had come early and was set up to complete the task remotely in a room next door. In the EAA condition, the model controlled its respective sheepdog via the model presented above. To give additional realism, the EAA model body's head was programmed to linearly interpolate its gaze direction towards the target sheep position, $\varphi_{s(t)}$, with $\pm$ 2.5 cm movement noise. Additional noise was added to the model's radial ($\pm 1 \frac{m}{s^2}$ to Eq. 1) and oscillatory movement ($\pm \frac{\pi}{2} \frac{rad}{s^2}$ to Eq. 4). In both conditions, participants were not able to see their partner in between trials so as to avoid the display of task-irrelevant behavior that was not incorporated into the EAA.

Procedure

Prior to arrival participants were randomly assigned to either the three or seven sheep condition. Following informed consent, during which time participants were told that they would be required to play a virtual shepherding game, participants were either lead into the testing room and were randomly assigned to opposite sides of the tabletop display (the novice control condition), or told that their partner had come early and will perform the task in a different room (the EAA condition). Each participant was then handed a wireless Latus motion tracking sensor and informed that they would be using

these motions tracking sensors to control their respective cube (sheepdog) in order to corral a set of balls (sheep) into the red target region of the grass game field. Participants were instructed to hold the motion sensors with their right hand and control their sheepdogs by sliding the sensors on top of the tabletop display. This ensured that the location and movement of their corresponding sheepdog was aligned with the motion tracking sensors. Participants were then shown the game field and the rules of the game were described (i.e., rules for trial success and failure detailed above). Importantly, no instructions about how to best play the game or how to coordinate or corral the sheep within the game region were provided. Participants were simply told to complete the task to the best of their ability. Participants in the novice control condition were told that they were not allowed to talk or verbally strategize at any time during the experimental session (neither within nor between trails). An experimenter was present during the experimental session to enforce this no-talking rule. After the experiment, participants were debriefed on the purpose of the study and participants in the EAA condition were asked questions regarding their interaction with their partner. The first question asked participants if they noticed anything odd in the experiment, the second question asked if they had a feeling that their partner has completed this task before, and the third question asked if they thought at any point in the experiment they doubted that they were completing the task with a human.

Results

The first aim seeks to determine if the EAA can complete the herding task alongside novices. For all analyses, one pair in the novice control condition and two participants in the EAA condition were excluded from analyses due to program malfunction. The remaining participants who met the winning criteria, which was to keep the sheep contained in the red central region for 70% of the remaining 45 seconds of the trial eight times, were kept for analyses. Twenty-three of the remaining 29 pairs (79.3%) in the novice control condition met the winning condition, and all 18 participants in the EAA condition met the winning condition. This confirms that the developed EAA is able to perform the task alongside human novices.

To investigate differences in performance between groups, several summary statistics and performance variables were considered. A 2 (Condition: control, EAA) x 2 (Sheep: 3, 7) between-subjects ANOVA was conducted on the amount of time dyads took to complete the experiment. A significant condition x sheep interaction was found, $F(1,37) = 7.75$, $p = 0.008$, $\eta^2 = 0.17$. For the novice control condition, a significant main effect was found for the number of sheep, $F(1,20) = 21.18$, $p < 0.001$, $\eta^2 = 0.50$, such that less time was taken to complete the 3-sheep condition (15.66 minutes) than the 7-sheep condition (29.07 minutes) ($p < 0.001$; all post-hoc tests in this paper use Bonferroni corrections). No significant difference was found in the EAA condition (3-sheep: 16.53 minutes, 7-sheep: 18.86 minutes; $p = 0.37$). Next, a 2 (Condition: control, EAA) x 2 (Sheep: 3, 7) between-subjects

		Inphase	Antiphase	Both-Phase	No/Other-Phase
Novice Control	3-Sheep	82.14% (4.29%)	5.36% (2.53%)	7.14% (3.13%)	5.36% (2.85%)
	7-Sheep	66.67% (9.77%)	16.67% (8.07%)	8.33% (2.95%)	8.33% (2.95%)
Artificial Agent	3-Sheep	48.44% (12.15%)	26.56% (9.28%)	1.56% (1.56%)	23.44% (8.33%)
	7-Sheep	42.50% (11.21%)	21.25% (5.29%)	12.50% (5.59%)	23.75% (6.57%)

Table 1: Proportion of relative phase modes observed during COC behavior. Note: Both-Phase corresponds to trials in which pairs produced significant periods of both inphase and antiphase coordination. No/Other-Phase represents data remaining that were not categorized under the first three labels. Standard error in parentheses.

ANOVA was conducted to see if there were differences in the amount of time dyads were able to keep the sheep in the red target region on successful trials, measured as the percentage of time within the last 45 seconds of each trial. A significant main effect on condition was found, $F(1,36) = 7.78$, $p = 0.008$, $\eta^2 = 0.18$, such that pairs in the novice control condition had a lower score on average (83.14%) than those who completed the task alongside the artificial model (87.80%) ($p < 0.008$). Not only were participants in the EAA condition able to keep the sheep in the red target region for a longer percentage of time, but the amount of time taken to complete the experiment was consistent across sheep herd conditions.

Another measure to compare game performance across groups involved analyzing the movement of the sheep. In this measure, differentiating what makes a dyad *better* at containing the sheep is operationalized as a dyad's ability to minimize the spread of the sheep and to minimize their movement from the center of the red target region. These qualities were measured by taking the normalized average area of the convex hull that spans over the sheep (measure of spread/sheep), as well as taking the average root mean square (RMS) of the sheep's position from the center (measure of variability from center). Separate 2 (Condition: control, EAA) x 2 (Sheep: 3, 7) between-subjects ANOVAs were conducted on each of these dependent measures. First, significant differences between testing conditions, $F(1,37) = 32.00$, $p < 0.001$, $\eta^2 = 0.46$, and sheep herd size, $F(1,37) = 5.71$, $p = 0.02$ $\eta^2 = 0.13$, on the average sheep spread were found, such that sheep in the EAA condition were less dispersed (3.80 cm²/sheep) than in the control condition (5.52 cm²/sheep) ($p < 0.001$), and that sheep in the 7-sheep condition took up more area (5.02 cm²/sheep) than those in the 3-sheep condition (4.29 cm²/sheep) ($p < 0.01$).

Second, significant main effects were found for the root mean square (RMS) of the sheep's distance from the center of the red containment region across condition, $F(1,37) = 18.79$, $p < 0.001$, $\eta^2 = 0.34$, and sheep herd size, $F(1,37) = 41.76$, $p < 0.001$, $\eta^2 = 0.53$, such that the average sheep RMS was lower in the EAA condition (3.59 cm) than the control condition (4.18 cm)($p < 0.001$) and that sheep in the 7-sheep condition had a lower RMS (3.44 cm) than in the 3-sheep condition (4.33 cm)($p < 0.001$). These results indicate that participants in the EAA condition were better able to both minimize the spread of the sheep, as well as to keep the sheep closer to the center of the red containment region. Along with the results above, this is most likely due to the EAA producing relatively consistent expert behavior across all participants and trials. Consistent with findings from Nalepka and colleagues (submitted), it is more difficult to keep the sheep in the center of the containment

region, as indicated by the RMS results, in the 3, as opposed to the 7-sheep conditions. The reason for this is due to the sheep-sheep collisions that are possible. A higher probability of collisions are possible in the 7-sheep condition, causing the formation of sheep clusters, which behave as small moving masses which are easier to control than individual sheep.

The second aim was to determine whether participants in the EAA condition are able to discover the COC mode of behavior as a successful strategy to contain the sheep, as well as whether these participants would reproduce the dynamics of nonlinear coupled oscillators, whose behavior produces globally stable in/antiphase behavior as modeled by the HKB model (Haken et al., 1985). To test this, relative phase analyses were conducted on the last 45 seconds of each successful trial. Time-series of each pairs' instantaneous relative phase using the Hilbert transform on the radial angle of each player's sheepdog to a reference axis was calculated (see Pikovsky et al., 2001 for details about this transformation). A 4th order Butterworth band-pass filter excluding frequencies under 0.375 Hz and above 5 Hz was done to exclude oscillations that happen on a timescale irrelevant to the task. Distributions of the absolute relative phase angles that occurred across six 30° regions (i.e., 0°-30°, 30°-60°… 150°-180°) of relative phase between 0° and 180° was calculated for each trial. For these distributions, inphase and antiphase coordination is indicated by a concentration of relative phase angles near 0∘ and 180∘, respectively (Schmidt & O'Brien, 1997; Richardson et al., 2005). In order to determine if a pair's distribution of relative phases were significantly inphase or antiphase, 1000 random relative phase time-series of sample length (45 sec) and sample rate (50 Hz) were created to generate 1000 surrogate random relative phase distributions. The 950th largest value for each 30° relative phase region—17.933%— was then employed as the statistical threshold value and corresponded to a 0.05 significance level (Varlet & Richardson, 2015). In/antiphase coordination was deemed to have occurred for a given trial if the percentage of occurrence of relative phase angles for the 0-30°/150-180° relative phase region was greater than the 17.933% threshold. In addition, intermittent (both) inphase and antiphase were noted to have occurred for a given trial if both the 0-30° and 150-180° regions were greater than the 17.933% threshold level. Table 1 provides a summary of the proportion of trials averaged across pairs that were statistically classified as inphase, antiphase, intermittent in/antiphase (both-phase), or no stable/other stable-phase relationship.

Inspection of Table 1 reveals that over 75% of trials can be classified by dyads in both the novice control and EAA condition as performing in/antiphase rhythmic coordination in

order to complete the task. Additionally, the ratio between inphase and antiphase trials are consistent with previous research on visual rhythmic coordination (e.g., Schmidt at al., 1990; Schmidt & O'Brien, 1997; Richardson et al., 2007), such that inphase coordination occurs more often than antiphase coordination.

A reason for a larger proportion of trials classified as No/Other-Phase for dyads in the EAA condition can be due to the lack of the coupling term for the EAA used in the present experiment. Although the EAA was unable to adjust its frequency to establish a stable inphase/antiphase relationship with its partner, participants nevertheless fell into stable in/antiphase coordination for a majority of trials, giving evidence that even in conditions with unidirectional coupling, participants are able to adjust their movement to the EAA's movements, allowing stable inphase/antiphase coordination to still be possible in most instances. However, if the EAA's inability to adjust its frequency to that of its partner is a reason for the higher percentage of No/Other-Phase trials in the EAA condition, then it is expected that a larger average oscillatory frequency difference would be observed in the EAA condition overall, as opposed to the novice control condition. A participant's oscillatory frequency was determined by first computing a spectral analysis on the z-scores of each participant's radial angle data. To remind the reader, this data was filtered using a 4th order Butterworth band-pass filter excluding frequencies under 0.375 Hz and above 5 Hz in order to only include oscillatory frequencies that are relevant to the COC behavior. The frequency with the most power for each participant and the absolute difference between each participant's peak frequency was used for further analyses. The absolute peak frequency difference for each dyad was then submitted to a 2(Condition: control, EAA) x 2 (Sheep: 3, 7) between-subjects ANOVA. A significant main effect of condition was found, $F(1,37) = 6.02$, $p = 0.02$, $\eta^2 = 0.14$, such that participants in the EAA condition had a greater frequency difference at their respective fundamental frequency (0.14 Hz) than those in the control condition (0.07 Hz), confirming the possibility that the greater frequency difference is responsible for the higher percentage of No/Other-Phase trials in the EAA condition.

The final aim was to determine whether participants would remain in belief that their partner was a human for the entire duration of the experiment. Debriefing in the EAA condition indicated that 12 out of 18 participants (66.67%) believed that their partner was a human for the entire duration of the experiment. Participants were mixed in their views if their partner was as naïve to the study as they were, or if their partner was given additional information about the task (or were a confederate). Some noted that their partner exhibited some "quirky" behavior or found it odd that the partner was able to discover the oscillatory strategy so quickly. Three of the remaining six had passing thoughts that their partner may in fact be a computer, while the remaining three had strong convictions that their partner was a computer for the entire duration of the experiment. In order to determine whether the difference in peak oscillation frequency is associated with believability that one's partner was a computer, a Pearson's correlation was conducted on participants in the EAA condition. The participants who had no thoughts that their partner could be non-human were placed in the *Believed Human* bin (12 individuals), while those participants who either had doubts or were confident that their partner was a computer were placed in the *Thought Computer* bin (6 individuals). The correlation was significant, $r(16) = 0.60$, $p = 0.009$, such that those who thought their partner was a human were associated with having lower peak frequency differences with their EAA partner than those who weren't fully convinced their partner was human, suggesting stronger unidirectional coupling for those in the *Believed Human* bin. It is remains an open question as to what aspects of the EAA made participants question or reject that they were performing the task with a human partner.

Discussion

The research presented in this paper represents developing first pass at developing a minimal bio-inspired artificial model that can serve as a partner in a two-player herding task. The current model demonstrates its ability to complete the task alongside participants while also convincing 12 of the 18 participants to report believing that their partner was a human for the entire duration of the experiment. Future work involves adding a coupling term to the model in order to give it the ability to modulate its oscillatory frequency to match the frequency of its partner. This may further enhance the realism of the model. However, it is interesting to note that even without the model keeping track of the partner's state, the unidirectional coupling of the participants still led to inphase, antiphase or both-phase coordination with the partner for over 75% of trials, showing the human tendency to form these stable phase relationships in the context of relatively complex task constraints and a dynamically changing environment. A reviewer expressed concern that the behavior the EAA exhibited is too prescribed to the specific environment presented in this paper, and may not be appropriate for environments where sheep need to be contained in a triangular or other shape containment regions. Future work will have to test this possibility. Another avenue of interest is to further elucidate the perceptual variables human agents attune to as they complete this task. The current model was built to mimic the behavioral dynamics observed in human hand movement data, without considering the role perception plays in the task.

The EAA algorithm implemented in the herding task provides an example of how modeling human behavioral dynamics can guide the design of socially embedded artificial agents. Note, the proposed model does not aim for the most efficient or optimal model, but the one that best matches the relevant human behavioral dynamic. This model identifies the low dimensional dynamics that drive the coordination behavior required to accomplish the task with another agent and is designed to strike aa balance between providing an exact detailed description of every aspect of a specific human agent (i.e., white-box modeling) and a black box model that might be implemented in any number of ways.

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