

# First Step is to Group Them: Task-Dynamic Model Validation for Human Multiagent Herding in a Less Constrained Task

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## Abstract

Biological systems are capable of acting in a shared environment to produce emergent, self-organized behavior that is the result of the constraints imposed by local interactions—such as bird flocking or ant swarming behavior. These examples present minimal demands for a shared-intention between co-actors, whereas other instances necessitate the formation of a shared goal. In these goal-directed tasks, how much of the observed complexity can be explained by the constraints imposed by both the environment and adherence to the shared task goal? This paper begins to investigate this question by presenting results from a two-person cooperative “shepherding” task first developed in Nalepka et al. (2017) but with fewer constraints. Results provide further evidence that the emergent behavior is the result of the constraints imposed by the task. The included task-dynamic model suggests a general model that can be used to understand multiagent herding behavior in a variety of contexts.

**Keywords:** joint action, collective herding, task-dynamic modeling

## Introduction

Emergent collective behavior in animal systems can oftentimes be understood by agents whose behaviors are constrained by local information. In non-human systems, such as ant trails, the observed behavior to a food source can be attributable to local interactions between ants and the strength of a deposited pheromone trail (Deneubourg et al., 1989). For humans, the route chosen to go to class in the

winter can be attributable to the paths carved in the snow by previous students (Goldstone & Roberts, 2006). These examples don’t necessitate the formation of a shared-intention (Searle, 1990) as these agents are exploiting their environment to reach their own individual aims.

However, human actors can engage in complex goal-directed behavior such as playing in team sports where the actors are working towards a common shared goal – a joint-action. Work discerning the neurocognitive mechanisms that support the timing and prediction of actions have been proposed to explain how human systems successfully accomplish joint-action tasks (Vesper, et al., 2011). Indeed, suboptimal coordination not only leads to sub-optimal performance, but can have a negative impact on one’s self-esteem and one’s opinion of a co-actor (Lumsden, Miles, & Macrae, 2014). Similarly, suboptimal coordination during human-robot interaction (HRI) also leads to poorer performance and a depreciated user experience, with users often attributing poorer performance to a lack of predictability and reciprocal compensation on the part of the robot (Medina, Lorenz, & Hirche, 2015).

How much of the complexity observed in cooperative action can be attributed to the constraints imposed by the environment, as well as the task goal? An approach to understand the behavioral dynamics that shape and constrain natural human performance is to argue that humans organize themselves as “special-purpose devices” to satisfy the dynamics of a particular task (Saltzman & Kelso, 1987). For

example, in a reaching task, the body self-organizes so the hand becomes a damped mass-spring that moves towards, say, a mug (a fixed-point attractor). These low-dimensional models, in the case of reaching, can produce straight-line trajectories and deal with perturbations that may occur during the action.

To date, such task-dynamic models, expressed as ordinary differential equations, have been used to understand human path navigation and obstacle avoidance (Fajen & Warren, 2003; Warren, 2006) and tested in robotic systems, such as a skiing robot (Lahajnar, Koss & Nemeč, 2009). In the joint action literature, virtual agents have also been created to perform oscillatory movements with a human partner (Zhai, et al., 2014; Kostrubiec, et al., 2015) with the movement dynamics of the virtual agent defined by a coupled nonlinear oscillator that produces patterns of coordination consistent with the Haken-Kelso-Bunz (HKB) model of rhythmic coordination (Haken, Kelso, & Bunz, 1985); namely, stable, or intermittent in-phase ( $0^\circ$ ) and anti-phase ( $180^\circ$ ) modes of behavior. Perhaps most noteworthy is recent work by Zhai et al. (2014) and Kostrubiec et al. (2015), who demonstrated the ability for artificial agents incorporating nonlinear oscillatory models to coordinate with humans to reproduce the dynamics observed in human-human pairs, with the added benefit of enabling these nonhuman agents to *steer* humans to new coordinative modes that are unstable and difficult to master (like a  $90^\circ$  phase relationship).

Recently, Nalepka et al. (2017) created a virtual shepherding task (Figure 1) to explore and model goal-directed behavior in a multiagent task to understand how stable social behavior emerges in more complex tasks with changing environments. The task required pairs to coordinate their movements in such a way as to corral and contain reactive autonomous spheres (referred to as sheep) to the center of a game field by controlling their player cube (referred to as their sheepdog) with a handheld motion-tracking sensor. In the beginning, participants engaged in a behavior termed *search and recover* (S&R) which involved moving one's controller towards the farthest sheep so that the sheep would be repelled towards the containment region. Using this strategy, some pairs could meet the success criteria for the task (defined as keeping all sheep within the containment region for a certain proportion of time (see Figure 1). However, a subset of successful pairs transitioned to a new behavioral mode termed *coupled oscillatory containment* (COC) that was functionally superior to S&R. COC was defined by both participants performing oscillatory movements around the containment region to *wall-in* the sheep.

Interestingly, the COC behavioral mode exhibited similar dynamic stabilities as prototypical interpersonal or visual rhythmic coordination (Schmidt, Carello, & Turvey, 1990; see Schmidt & Richardson, 2008 for a review) described by the HKB model above, with pairs naturally exhibiting in-phase and anti-phase patterns of COC behavior. Therefore, the shepherding task supplies a functional consequence for coupled rhythmic behavior that can be used to study

interpersonal coordination more generally. Videos illustrating the shepherding task are found at <http://www.emadynamics.org/bi-agent-sheep-herding-game/>.

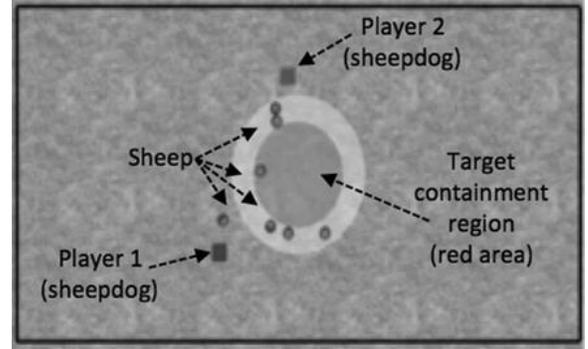


Figure 1: Depiction of task from Nalepka et al. (2017)

### The Shepherding Model

Nalepka et al. (2017) formulated a task-dynamic model of the human behavior observed in the shepherding task (also Richardson et al., 2016); they also successfully validated that this model, embodied in a virtual avatar, can complete the task successfully alongside a human partner (Nalepka et al., 2016). The model defines the task space in terms of a polar coordinate system (see Figure 2). The radial component (whose origin is the center of the containment region) of the system is defined using the following damped mass-spring equation,

$$\ddot{r}_i + b_{r_i} \dot{r}_i + \varepsilon_i (r_i - \xi_i (r_{ps(t),i} + \Delta r_{min,i}) - (1 - \xi_i) (r_{min,ps(t),i} + \Delta r_{min,i})) = 0, \quad (1)$$

where  $r_i$ ,  $\dot{r}_i$ , and  $\ddot{r}_i$  are the radial position, velocity and acceleration of player  $i$  ( $i = 1, 2$ );  $b_{r_i}$  is the radial damping term,  $r_{ps(t),i}$  is the radial coordinate of the player  $i$ 's radially farthest sheep on their side of the field,  $(r_{ps(t),i} + \Delta r_{min,i})$  is the preferred radial target position that the player approaches for this farthest sheep, and  $\varepsilon_i$  scales the strength of the centrally-directed radial force attracting player  $i$  to the targeted sheep. This force is gated by  $\xi_i$ , a Heaviside parameter:

$$\xi_i = \begin{cases} 0, & r_{ps(t),i} < r_{min,ps(t),i} \\ 1, & r_{ps(t),i} \geq r_{min,ps(t),i} \end{cases} \quad (2)$$

If the radial coordinate of at least one sheep is greater than or equal to  $r_{min,ps(t),i}$ , then the player will select the furthest sheep,  $r_{ps(t),i}$ , and move to  $(r_{ps(t),i} + \Delta r_{min,i})$ ; otherwise, when  $\xi_i = 0$ , the player will move towards  $(r_{min,ps(t),i} + \Delta r_{min,i})$ , their preferred distance from the center.

To be consistent with the previous research modeling the dynamics of rhythmic human interlimb and interpersonal coordination captured by the HKB model (Haken et al., 1985), the angular component of the players' movements (centered on the player's sagittal plane on their side of the

field) was modeled using the following modified set of coupled Rayleigh/van der Pol hybrid nonlinear oscillator equations,

$$\begin{aligned} \ddot{\theta}_i + b_{\theta i} \dot{\theta}_i + \beta_i \dot{\theta}_i^3 + \gamma_i \theta_i^2 \dot{\theta}_i + \omega_i^2 (\theta_i - \xi_i \theta_{ps(t),i}) \\ = (1 - \xi_i) (\dot{\theta}_i - \dot{\theta}_j) (A_i - B_i (\theta_i - \theta_j)^2), \end{aligned} \quad (3)$$

where  $\theta_i$ ,  $\dot{\theta}_i$  and  $\ddot{\theta}_i$  are the angular position, velocity, and acceleration of player  $i$ ;  $\omega_i$  is a player's natural angular oscillation frequency;  $b_{\theta i}$  is the angular linear damping term;  $\beta_i \dot{\theta}_i^3$  and  $\gamma_i \theta_i^2 \dot{\theta}_i$  are Rayleigh and Van der Pol escapement terms, respectively; and  $A_i$  and  $B_i$  are the parameters used in the HKB model to define the relative strength of in-phase and anti-phase coordination patterns. The parameter  $b_{\theta}$  is governed by the equation,

$$\dot{b}_{\theta i} + \delta_i \left( b_{\theta i} - \alpha_i \left( r_{ps(t),i} - (r_{min,ps(t),i} + \Delta r_{min,i}) \right) \right) = 0, \quad (4)$$

where negative values of  $b_{\theta i}$  produce oscillatory behavior, while positive values produce fixed-point behavior. Parameters  $\delta_i$  and  $\alpha_i$  govern the dynamics of  $b_{\theta i}$  across its range of allowable values.

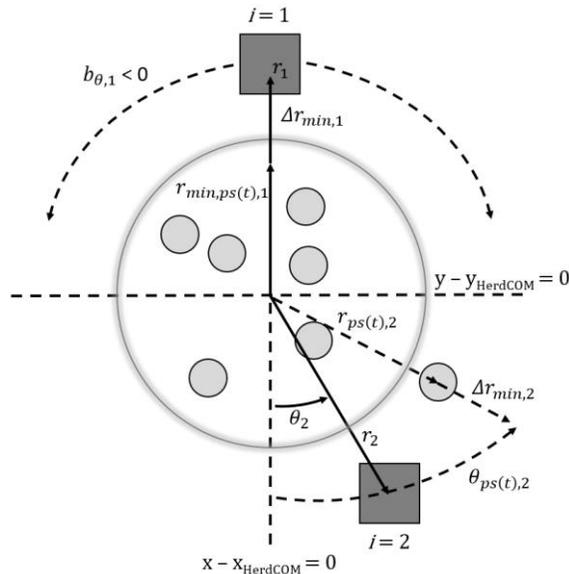


Figure 2: Depiction of model task space. Player  $i = 1$  is exhibiting oscillatory behavior, while player  $i = 2$  exhibits S&R behavior. The smaller circles illustrate the sheep that must be kept within the containment region (larger circle).

The interplayer system modeled by Eq. 1, 3 & 4 dictates the behavioral mode player  $i$  produces. If  $\xi_i = 1$ , the player is uncoupled from their partner  $j$  (via the right half of Eq. 3), and moves towards the angular component of the furthest sheep; otherwise, the player will center their angular component to  $0^\circ$  (here  $b_{\theta i}$  will move towards a negative value and begin to produce oscillatory behavior). Parameter  $\omega_i$  is the rate at which these angular destinations are reached. However, when  $\xi_i = 0$ , the player becomes coupled to the

angular component of their partner's movement. This coupling function reproduces both in-phase ( $0^\circ$ ) and anti-phase ( $180^\circ$ ) stable relative phase relationships, with the relative strength of these two coordination patterns defined by the parameters  $A_i$  and  $B_i$ .

## The Current Project

The behavioral modes observed in Nalepka et al. (2017) are very like the behavioral modes found in real sheepdog shepherding (Strömbom et al., 2014). However, it is unclear whether the oscillatory behavior seen in Nalepka et al. (2017) emerged from the local interactions of both players and the sheep, or if it was due to participants attuning to pre-defined environmental features of the task. Trajectories observed in Nalepka et al. (2017) tend to trace the outer white circle of the containment region (see Figure 1). In the original experiment, this white circle indicated a failure criteria that ended a trial if all sheep managed to escape. However, anecdotally, some participants asked if they could enter the containment region, opening the possibility that participants perceived certain visually-marked locations to be appropriate (like the white region) and others not (such as the red containment area). Thus, the oscillatory behavior observed may have been a consequence of this perceived task constraint and the circular goal region.

The present work removed these visual landmarks and edited the task to have fewer constraints to test the generality of the developed task-dynamic model. Criteria that would cause a trial to fail prematurely were removed, with participants simply instructed to corral the sheep together, without a target goal region in mind. To keep scoring criteria similar to the original work, a containment region (invisible to participants) moved in accordance with the center of the herd, consistent with Strömbom et al. (2014) who suggested that sheepdogs corral sheep that are furthest from the center of the rest of the herd.

We tested a new set of naive participants to determine whether S&R and, more importantly, COC behavior would still emerge. We also compared the participant performance to the performance of a slightly modified version of the virtual shepherding model presented above. In short, the model was modified so that the center of the task dynamic space that defined the (0,0) point of the radial distance and polar task axes was dynamically tied to the herd's center of mass (COM), as opposed to being fixed in the center of game field (0,0). At any time  $t$ , the herd's COM was calculated as the average sheep position in Cartesian coordinates and was subtracted from each game object's (x,y) positions.

## Method

### Participants

Thirty-eight participants ( $M$  age = 18.82, 17-22), recruited as 19 pairs completed the experiment. All participants were undergraduates from the University of Cincinnati and received course credit for participation. For model simulations, 10 artificial pairs were created with the

following parameter values:  $b_r = 10.9987$ ,  $\varepsilon = 98.70672$ ,  $r_{min,ps(t)} = .062$  m,  $\Delta r_{min} = .061539$ ,  $\delta = 23.08993$ ,  $\alpha = 80.59288$ ,  $\beta = .161641$ ,  $\gamma = 7.22282$ ,  $\omega = 7.85$ ,  $A = -.2$ , and  $B = .2$ . The model was designed to perform COC behavior if all sheep on the player's side of the field was within  $r_{min,ps(t)}$ , as described above. Up to  $\pm 1 \frac{rad}{s^2}$  and  $\pm 1 \frac{cm}{s^2}$  noise was randomly added to both  $\ddot{\theta}_{p_i}$  and  $\ddot{i}_{p_i}$  at a rate of 50 Hz.

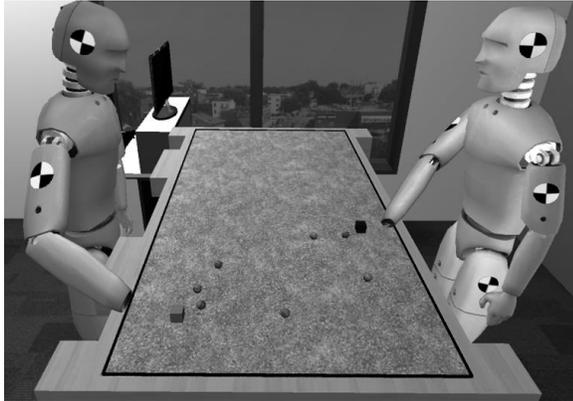


Figure 3: Virtual experimental room with example initial sheep arrangement.

### Apparatus and Task

The task was designed using the Unity 3D game engine (version 5.2.1; Unity Technologies, San Francisco, California) and was presented to participants via Oculus Rift DK2 (VR) headsets (Oculus VR, Irvine, California). The virtual environment (Figure 3) was modeled at 1:1 scale after the experimental room. The task was presented in the VR headset to appear on a virtual tabletop modeled at 1:1 scale to the glass tabletop in the real environment, which acted as the solid physical surface on which participants could move their motion sensors. 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 1.8 m whose motion was controlled using an inverse kinematic calculator (model and calculator supplied by Root Motion, Tartu, Estonia) based on the real movements of the participant's right hand (via the Latus motion sensor) and head (via the Oculus Rift).

Participants could move their sheepdogs anywhere in two-dimensional space within the 1.5 by 0.8 m fenced area of the grass task field. The goal of the task was to jointly find a solution to corral seven wool-covered stimulus spheres (sheep) towards one another so that they turned to a red color. The sheep were programmed to turn red when all sheep were within 10.8 cm of the herd's COM. Note, if the fence was 10.8 cm from the herd center, the sheep did not turn red. This was done intentionally to keep participants from adopting a strategy which involved keeping the sheep cornered. On each trial, sheep appeared randomly within a .50 by .80 m boxed

area, randomly centered either on the center of the game field, or  $\pm .50$  m to either side. Forces from a random direction were applied to each sheep at a sample rate of 50 Hz, resulting in Brownian motion dynamics. If a sheep collided with the fence, a repulsive force was applied to move the sheep back towards the center. 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 inverse of the squared distance between the sheep and the player. If the sheep were red for at least 70% of the last 45 seconds of a two-minute trial, the pair received a point. The experiment ended when the participants scored eight points, or after 45 minutes, whichever came first.

### Procedure

Following informed consent, participants stood on either side of the experimental table where they put on their respective virtual headsets and were given a motion sensor to hold in their right hand. Following calibration, participants were informed about the task goal and the conditions for success and failure. Participants were not told how near the sheep needed to be to turn red. Instead, they were instructed that if the sheep were not red, then they either needed to be closer together, or that the herd was too close to the fence. Participants were told that once the experiment began, they were not allowed to speak with one another until after debriefing. The experimenter remained in the room to enforce the no-talking rule and to answer any questions.

### Results

A preliminary review of participant behavior revealed that all pairs exhibited S&R behavior and, more importantly, that several pairs discovered and exhibited the same type of COC strategy observed by Nalepka, et al. (2017). Here we present the COC classification criterion utilized, and the performance differences observed between COC trials (from the COC-classified pairs) and S&R trials (from S&R-classified pairs). The focus of the analysis presented here was to confirm that (a) COC is a robust emergent mode of behavior and (b) that COC behavior was superior to S&R behavior. The results from the model simulations followed the same analyses and were employed to determine whether the task-dynamic model could effectively capture the dynamics observed in this less constrained task context. Classification and analyses were conducted on the last 45 seconds of each two-minute trial. This was set because participants were told that performance was measured during this time and that the first 75 seconds was to be used as time to corral the sheep and initiate resultant containment strategy. Because success was defined as keeping the sheep within 10.8 cm of their COM, all data were converted to polar coordinates with the center located at the herd COM. For the purposes of this paper, only successful trials were analyzed.

As defined by Nalepka et al. (2017), a trial was classified as COC if the peak angular oscillatory component was between 0.5 Hz and 2 Hz. More specifically, the classification criterion was as follows,

$$\varphi_{i,k} = \frac{\omega_{freq,i,k} - .5}{|\omega_{freq,i,k} - .5|} \omega_{power,i,k}, \quad (5)$$

where  $\omega_{freq,i,k}$  is the peak angular oscillatory component for player  $i$ , of pair  $k$  and  $\omega_{power,i,k}$  is its associated power. The average for both players,  $\bar{\varphi}_k$ , is taken and if the resultant average is positive, the trial is classified as predominately COC. Conversely, negative values resulted in a trial being classified as an S&R trial. For analyses, the angular component of each dog was detrended and z-score normalized and submitted to MATLAB's *pwelch* function using a 50% overlap window of 512 samples.

Thirteen of the 19 pairs met the success criteria for the task. One of the remaining six pairs had five of the eight successful trials completed and were included in the analysis, while the remaining five did not have a single successful trial. Successful S&R trials had an average classification value  $\bar{\varphi}_k = -0.47$  and successful COC trials had a value  $\bar{\varphi}_k = 0.23$  for human pairs, while it was  $\bar{\varphi}_k = .22$  for the artificial pairs, which only exhibited successful COC trials. In total, nine pairs exhibited predominately S&R behavior to complete the task (with two pairs exhibiting one and three trials classified as COC), while the remaining five pairs completed the task with at least four trials classified as COC ( $M_{\#trials} = 5.8$  classified as COC). The artificial pairs completed the experiment in less time ( $M = 16.8$  min,  $SD = 1.03$ ) than both S&R ( $M = 29.75$  min,  $SD = 8.03$ ) and COC ( $M = 26.00$  min,  $SD = 6.32$ ) human pairs,  $F(2,20) = 12.75$ ,  $p = .001$ ,  $\eta^2 = .56$ .

The following four variables were examined to characterize performance differences between behavior modes: (1) *containment time*—the number of seconds the sheep were within 10.8 cm of the herd center while also 10.8 cm away from the nearest fence; (2) *average sheep radial distance*—the average distance from the herd center; (2) *herd travel*—the total distance travelled by the herd center; (4) and *herd area*—the area of the convex hull formed by the set of sheep positions. Only S&R trials were considered for S&R pairs and COC trials for both COC pairs and artificial pairs.

Performance differences were found for all variables: *containment time*,  $F(2,21) = 68.18$ ,  $p < .001$ ,  $\eta^2 = .87$ , *average sheep radial distance*,  $F(2,21) = 142.74$ ,  $p < .001$ ,  $\eta^2 = .93$ , *herd travel*,  $F(2,21) = 140.46$ ,  $p < .001$ ,  $\eta^2 = .93$ , and *herd area*  $F(2,21) = 11.61$ ,  $p < .001$ ,  $\eta^2 = .53$ . Figure 4 provides a summary of the findings. Performance by COC pairs on COC trials were found to be superior to performance by S&R pairs in all cases: *containment time* (COC  $M = 44.1$  s,  $SD = 1.01$ ; S&R  $M = 39.91$  s,  $SD = 1.42$  [ $p < .001$ ]), *average sheep radial distance* (COC  $M = 2.73$  cm,  $SD = .41$ ; S&R  $M = 3.99$  cm,  $SD = .20$  [ $p < .001$ ]), *herd travel* (COC  $M = 62.74$  cm,  $SD = 10.91$ ; S&R  $M = 106.90$  cm,  $SD = 19.16$  [ $p < .001$ ]) and *herd area* (COC  $M = 23.87$  cm<sup>2</sup>,  $SD = 13.80$ ; S&R  $M = 55.66$  cm<sup>2</sup>,  $SD = 29.32$  [ $p = .02$ ]). Compared to COC human pairs, the

artificial pairs contained the sheep closer to the herd COM ( $M = 2.32$  cm,  $SD = .04$ , [ $p < .01$ ]) and had less herd travel ( $M = 8.92$  cm,  $SD = .44$ , [ $p < .001$ ]).

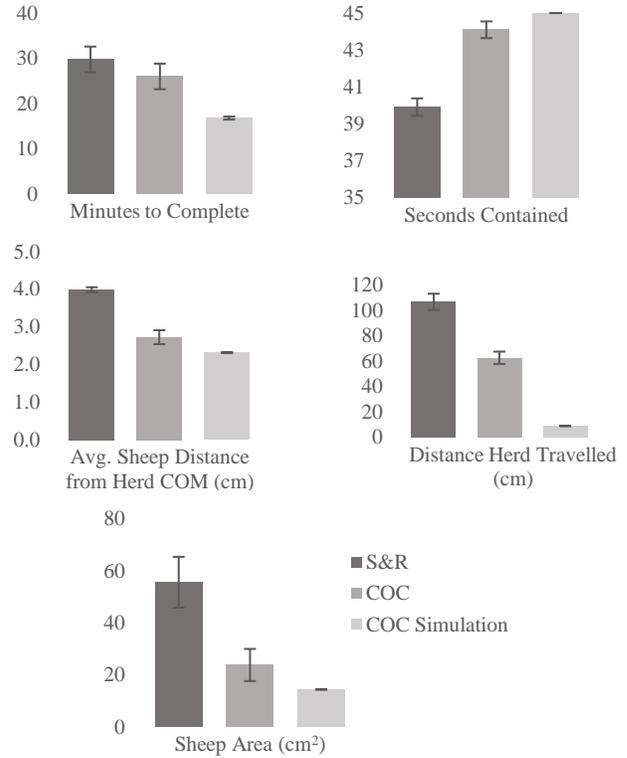


Figure 4: Result Summary Plots.

## Conclusion

Consistent with findings by Nalepka et al. (2016; 2017), the results provide further support that COC behavior is not a consequence of players tracing a visually salient boundary to contain the sheep, but rather emerges naturally from interactions between players within the shepherding task environment. Further, the task-dynamic model developed by Nalepka et al. (2017) can be minimally modified to function in this less constrained herding task space, by tracking the center of the herd. It is important to note that seven pairs completed the experiment without exhibiting any COC behavior. This may be due to the relaxed scoring criteria that allowed for stable S&R behavior. Increasing task difficulty, like increasing the time needed to contain the sheep, is predicted to cause more pairs to transition to COC behavior, as it was associated with better task performance.

An approach to understand multiagent coordination is to treat human systems as self-organized “special-purpose devices” whose dynamics adhere to the constraints dictated by the task and environment (Saltzman & Kelso, 1987; Richardson et al., 2016). Task-dynamic models that embody these constraints can be embedded in robot systems to produce human-like behavior. Because the presented model embodies the constraints inherent to herding autonomous agents, the model can be extended to include systems that can

work alongside humans in other herding-like tasks such as fire evacuation and environmental hazard containment. Similarly, these systems can potentially be used to *steer* novices to discover more optimal modes of behavior – in the shepherding task, but possibly in rehabilitation or educational contexts in the future.

Finally, the shepherding model is symmetrical, but many examples exist where distinct but complementary actions are needed to reach a collective goal – for example a basketball player performing a “pick” while their teammate breaks free to take a shot. Work has been done to incorporate the recent shepherding model by Strömbom et al. (2014) to two virtual sheepdogs, who each are responsible for either *collecting* or *driving* the herd (Watanabe and Fujioka, 2017). However, the sheepdogs’ roles were rigidly defined and led to greater sheep dispersion compared to single dog performance who could adaptively switch between both modes. Models that allow multiple agents to switch between multiple behavioral modes without interference are still needed to develop systems that can work fluidly alongside humans of various skillsets.

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