Coordination Dynamics in Multi-human Multi-robot Teams

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***Abstract*—As robots enter human environments, they will be expected to collaborate and coordinate their actions with people. In order for robots to become more fluent at this, particularly in groups, robots must be able to recognize, understand, and anticipate coordinated human activities. However, how robots engage in this process can influence the dynamics of the team, particularly in multi-human, multi-robot situations. In this paper, we investigate how the presence of robots affects group coordination when both the anticipation algorithms they employ and their number (single robot or multi-robot) vary. Our results suggest that group coordination is significantly affected when a robot joins a human-only group, and is further affected when a second robot joins the group and employs a different anticipation algorithm from the other robot. These findings suggest that heterogeneous behavior of robots in a multi-human group can play a major role in how group coordination dynamics stabilize (or fail to), and may have implications for how we design future human-robot teams.**

***Index Terms*—Social Human-Robot Interaction; Cognitive Human-Robot Interaction; Gesture, Posture and Facial Expressions**

I. Introduction

HUMANS interact in groups in many situations in their daily life. In group situations, activities performed by a group member continually influences the activity of other group members [1]. These influences can lead to intentional or unintentional coordination of the movements of the humans in a group. An intentional coordination of movements may be observed in cooperative group tasks, such as when people dance together; whereas unintentional coordination may occur in non-cooperative tasks, like people walking in a group [2], [3]. Humans are skilled at coordinating their movements in group situations.

Along with technological advancements, robots are now becoming our partners in many activities, from dexterous factory jobs to assisted living. While working alongside humans, a robot might encounter people performing various social actions, and engaging in group activities, such as exercise, or performing synchronous movements in therapy [4]–[7]. Thus, robots need the ability to interpret, anticipate, and adapt to human actions to synthesize fluent interaction with humans accordingly.

Fig. 1. In the study, three participants danced together across three conditions, A) humans alone, B) humans with one robot, and C) humans with two robots. In B) and C), there were two variations, where different anticipation algorithms were executed on the robot.

There are many studies in the literature focused on improving a robot's motion through the interpretation of human actions and activities [8]–[11]. These include a wide range of behaviors, from gross motor motion (e.g., lifting stuff, walking together) to dexterous manipulation tasks (e.g., stacking objects). All of these experiments show successful results in recognizing human activities, either when the humans performed as individuals or with the collaboration of another human.

Recent work in robotics has focused on developing methods which can predict human activity to make interaction more fluent [12], [13]. For example, Hawkins et al. [14] developed a probabilistic model to determine an appropriate action for an assistive robot to take when providing parts during an assembly task. Hoffman et al. [15] proposed an adaptive action selection mechanism for a robot to make anticipatory decisions based on the confidence of their validity and relative risks. Their model was validated through an experiment, and the results suggested an improvement in joint task efficiency compared to a purely reactive model.

Many approaches have been taken to model inter-human joint action in groups, which has also been extended to human-robot synchronous group coordination [16]–[24]. For example, Mörtl et al. proposed a step-wise approach to model the inter-human movement synchronization in a goal directed action task [25]. Iqbal and Riek [26] proposed an event based method to measure coordination in human groups, which was later extended to human-robot groups [27], [28].

Lorenz et al. [29] investigated movement coordination in a human-human and human-robot team. The study involved both a human-human and human-robot dyad tapping on two positions on a table at certain times. The authors explored whether goal-directed, but unintentional coordination of movement occurred during these interac-

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tions. Their results suggested that humans synchronized their movements with the movements of the robots.

While this prior work aims to enable robots to act appropriately in a group, recent work has shown that this may not be enough. Richardson et al. [30] found that people show a higher degree of coordination of their actions when they were visually coupled while interacting in a group. The results of their study also suggested that solely verbal interaction was an insufficient medium for unintentional coordination to occur during an interaction. Moreover, verbal interaction did not enhance the unintentional coordination that emerged during visual interaction. Similarly, Coey et al. [2] investigated the relationship between the stability intrapersonal coordination and the emergence of the spontaneous interpersonal coordination.

During human-robot group scenarios, the effect of visual and auditory feedback from robots has not been well explored beyond a human-robot dyad. However, groups are a common domain in which humans and robots will likely interact in the future, and how human and robot group members influence one another may prove important. Therefore, it is important to look deeply into human-robot group dynamics, with an eye toward how robots affect human group members' behaviors when they encounter intelligent robots working alongside them.

During the course of our research, we designed several methods to enable robots to autonomously engage with human teams, by leveraging concepts from non-linear dynamics and neuroscience (see [26], [28], [31]). However, we are interested in exploring what happens when multiple robots interact with multiple people simultaneously, and how they affects teaming behaviors. Furthermore, what happens to the team when those robots are running the same or different motion anticipation algorithms?

To address these research questions, we have designed a human-robot teaming scenario, where one or two autonomous mobile robots observe a group of human dancers, and then successfully and contingently coordinates their movements to join the team. The robots employed two methods to coordinate their movements with the human group, one which takes team dynamics into account and one which does not.

Previously, we compared the two anticipation algorithms presented here on several dimensions, such as how appropriate the timing of events were by the robot. We found that when the robot took group dynamics into account, it performed more appropriately with the rest of the group. In this work, we want to explore how both the human and whole group dynamics changed within multi-robot scenarios.

II. Anticipation Methods

As the testbed for this experiment, we designed a synchronous dance scenario where a heterogenous team of people and robots could coordinate their motion in real-time. In concert with an experienced dancer, we choreographed an iterative dance routine to the song *Smooth Criminal* by Michael Jackson, which is in 4/4 time. There are four *iterations* in a dance session, and is performed cyclically in a counter-clockwise manner. The group performs this dance facing each of the cardinal directions (North, West, South, and East) during an iteration. Each iteration includes the dancers taking the following steps in order: move forward and backward twice, clap, and a counter-clockwise 90-degree turn [28].

We employed two event anticipation methods for the robots to move within a human-robot group: SIA (synchronization-index based anticipation) and ECA (event cluster based anticipation) [28]. (See Fig 2).

A. Synchronization Index Based Anticipation (SIA)

The SIA method depends on the internal dynamics of the group. The main idea behind this method is that for a given iteration, the participant who moves the most synchronously with the other dancers is good for the robots to follow, so that they are coordinated with the rest of the team. To generate future actions for the robot using SIA, we measured the most synchronous person of the group at the beginning of each iteration [28].

We can express task-level events associated with two dancers with time series x_n and y_n respectively, where each time series has N samples and $n = 1 \ldots N$. Suppose m_x and m_y are the number of events occurring in time series x and y respectively. The events of both series are denoted by $e_x(i) \in E$ and $e_y(j) \in E$, where, $i = 1 \ldots m_x$, $j = 1 \ldots m_y$, and E is the set of all events. The event times on both time series are t_i^x and t_j^y ($i = 1 \ldots m_x$, $j = 1 \ldots m_y$) respectively [26].

In the case of synchronous dance, the dancers should perform the movements roughly at the same time, or within a time lag $\pm\tau$ [26], [28]. Now, suppose $c^\tau(x|y)$ denotes the number of times a single type of event $e \in E$ appear in time series x shortly after it appears in time series y. Here, $c^\tau(x|y) = \sum_i^{m_x} \sum_j^{m_y} J_{ij}^\tau$, where, $J_{ij}^\tau = 1$, if $0 < t_i^x - t_j^y < \tau$, = 0.5, if $t_i^x = t_j^y$, or = 0, otherwise.

Now, $Q_\tau(e)$ represents the synchronization of events in two time series, where we are only considering a single type of event e in both time series [26]. From $c^\tau(x|y)$ and $c^\tau(y|x)$, we can calculate $Q_\tau(e)$ as, $Q_\tau(e) = (c^\tau(x|y) + c^\tau(y|x))/(\sqrt{m_x m_y})$.

Now, suppose, there are n types of events $\{e_1, e_2, \ldots, e_n\} \in E(n)$, where $E(n)$ is the set of all types of events, and $m_x(e_i)$ be the number of events of type e_i occurring in the time series x [26], [28]. So, the overall synchronization of for multiple types of events in time series x and y of that pair is:

$$\forall e_i \in E(n) : Q_\tau^{xy} = \frac{\sum [Q_\tau(e_i) \times [m_x(e_i) + m_y(e_i)]]}{\sum [m_x(e_i) + m_y(e_i)]} \tag{1}$$

After measuring the pairwise synchronization index, we built a directed weighted graph from these indices, called a *group topology graph (GTG)*, where each time series is represented by a vertex [26], [28]. We measured the individual synchronization index of series s_i as:

$$I_\tau(s_i) = \frac{\sum_{j=1,\ldots,H,\ j \neq i} Q_\tau^{s_i s_j} \times f(s_i, s_j)}{\sum_{j=1,\ldots,H,\ j \neq i} f(s_i, s_j)} \tag{2}$$

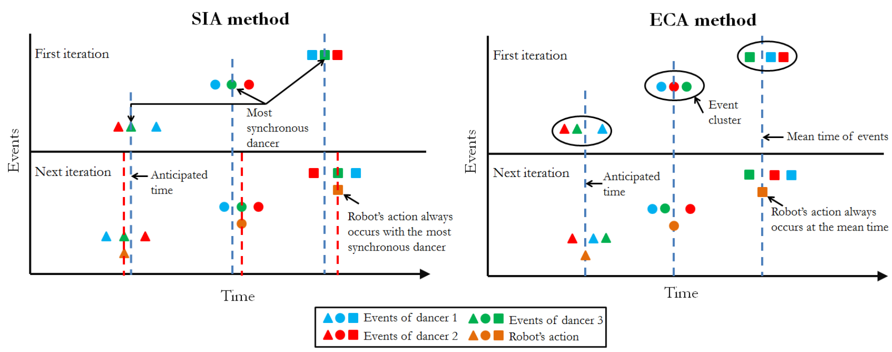

Fig. 2. Two anticipation methods. (L) Synchronization Index Based Anticipation (SIA), (R) Event Cluster Based Anticipation (ECA) method [28].

Here, $f(s_i, s_j) = 1$, iff $edge(s_i, s_j) \in GTG$, or = 0, otherwise.

A high individual synchronization index of a dancer indicates close synchronization with the other group members. Thus, the person with the highest individual synchronization index during an iteration is considered the most synchronous person of the group [28].

B. Event Cluster-Based Anticipation Method (ECA)

ECA was designed to serve as a comprable algorithm which does not take group dynamics into account, is theoretically simple, and is easy to implement. The core idea of ECA is that it takes the average timing of events during one iteration to predict the timing of those same events for the next iteration [28].

For example, given a single event e, ECA calculates the timing of the event performed by three human participants, i.e., $t(dancer_1(itr_i), e)$, $t(dancer_2(itr_i), e)$, $t(dancer_3(itr_i), e)$. Here, t represents the timing of an event, and itr_i represents the iteration i. Then, for each cluster of similar events occurred within a time threshold ϵ, ECA calculates the average time of all events and used that time as the event timing for the next iteration. These events and the times were the predicted events and timing for the next iteration of the dance for the robot. Thus, $t(robot(itr_{(i+1)}), e) = (t(dancer_1(itr_i), e) + t(dancer_2(itr_i), e) + t(dancer_3(itr_i), e))/3$ [28].

C. Comparison Between the Methods

In our previous work, we thoroughly evaluated the performance and the accuracy of these anticipation methods in the context of a human-robot dancing. We performed a set of experiments where a robot employed one of these algorithms, and danced synchronously with three people [28]. The goal of that study was to develop these methods and to investigate their differences in multiple dimensions.

The results of that study indicated that the human-robot group danced more synchronously when the SIA was, in contrast to ECA. We also calculated the timing appropriateness measure during that study. The results also suggested that SIA allowed the robot to move more coherently and appropriate in time, when compared to ECA. (for a detailed analysis, please check [28]).

After a thorough evaluation of these anticipation methods, we found these two methods are suitable for human-robot teaming scenarios. We also found these methods are appropriate to investigate our research questions in this work, as the methods are different enough in the way how they interact with a group. Thus, we are employing these methods on the robots during this study. However, the study design and the research questions of this paper are different from our previous investigation.

III. Data Acquisition

In the setup, four clients with Microsoft Kinect v.2 sensors captured team motion, and detected dance events in real-time. A server managed the clients and maintained a consistent time across them and the robots [28].

Each client extracted five high-level events from each participant's movements during the dance: *start moving forward*, *stop moving forward*, *start moving backward*, *stop moving backward*, and *clap*. (The detection process is described in [28]). After receiving client events, the server used the anticipation methods described in Section II to generate appropriate movement commands for the robot. These commands included: *move forward*, *move backward*, *stop*, and *turn*.

The server translated the clap commands into rotation commands for the robot, since the robot cannot clap. Each iteration ended with a synchronous clap by the participants. The last participant clap time was taken as the end time of the current iteration, and the starting time of the next iteration [28].

IV. Experiments

To explore the effects of visual and auditory feedback from the robots during an intentional coordination task, we physically incorporated robot(s) in the group in such a way that participants were able to hear the robot's motors at all times, and view a robot during some iterations (See Fig 1). This scenario provided the opportunity to investigate the effect of robot motion (including auditory, and visual feedback) on the group's coordination.

We also provided an external rhythmic signal to participants to help them to maintain a consistent, synchronized tempo during the dance. Participants were instructed to maintain awareness of the other participants' and robots' movements, and to dance synchronously as a group.

We recruited a total of seven groups for our main study, with three people per group. Data of one group were excluded due to the robot losing connectivity with the server, so here we report the results from six groups (18 participants in total). 11 participants were women, 7 were men. Their average age was 24.7 years (s.d. = 4.5 years), and the majority were undergraduate and graduate students. Participants were recruited by word-of-mouth. Upon scheduling a time slot, participants were randomly assigned to join a group with two others. Each participant was compensated with a $10 gift card.

After giving informed consent, participants viewed an instructional video of the choreographed dance and the experimenters explained the different movements. The participants then had time to practice the dance movements as a group as many times as they wanted. During the practice session, the robot did not dance with them. Following the practice session, the group participated in six dance sessions, in four phases.

1) *Phase 0*: Only the humans participated in the dance.
2) *Phase 1*: One robot joined the group. The dancers participated in two dance sessions, where the robot moved using either ECA then SIA, or SIA then ECA. The order was counterbalanced to avoid bias within this phase.
3) *Phase 2*: Two robots joined the dance with the humans. The dancers also participated in two dance sessions, with either SIA or ECA methods controlling the robot's movements. The order was counterbalanced to avoid bias within this phase.
4) *Phase 3*: Two robots moved with the humans. However, movements of one robot were generated using ECA, and movements of the other robot were generated using SIA. The anticipation methods for the robots were counterbalanced to avoid bias.

We controlled for several factors relating to how participants altered their behaviors relative to the robots' motion in several ways. First, we provided an external rhythmic signal to the human participants to help them maintain a consistent tempo. Second, we deliberately choreographed an easy dance (walking, turning, and clapping), and gave substantial practice time before the experiment began. This enabled participants to develop their muscle memory, so that they would not be easily distracted during the experiment. Third, because we had six counterbalanced conditions (i.e., random ordering per phase for each participant group), any effects relating to the robots being distracting will be greatly lessened.

During all sessions, the clients recorded depth, infrared, and skeletal data of the participants, and the server logged all event and timing data. A single camera mounted on a tripod recorded standard RGB video of the experiment for manual analysis purposes only. How the server handled multiple robots is different than our previous implementation in [28]. In this implementation, the server generated both prediction timings for the robots, but sending only the prediction timings depending on the anticipation algorithms that the robot was using in the cases of *Phase 3*.

Following each session, participants completed a short questionnaire asking them to rate in a discrete visual scale describing how well-synchronized the group was during that dance session.

We used two Turtlebot v.2 robots in our experiments. Those are approximately 2 feet tall, and run the Robot Operating System (ROS) (Hydro) on Ubuntu (v 12.04).

V. Analysis and Results

To address the first two research questions, we need to measure how well coordinated the human participants' movements are when we consider them separate from the group, without the robots. In order to address the research questions three and four, we need to measure how well coordinated the whole group are including both the humans and the robots. Here, we describe the method to measure the degree of synchronization among the group.

During the experiments, the humans and the robots physically moved very close in proximity. Therefore, we assumed that each group members influenced all other group members, as well as everyone was influenced by all other group members. Thus, each member was considered connected with all other members in the GTG [28].

However, when SIA method was used, the robot only followed the most synchronous person of the previous iteration. Thus, we only took the pairwise synchronization index between the robot and that person into account while building the GTG and calculating the individual synchronization index of the robot for that iteration [28].

From the GTG, we measured the *connectivity value* (CV) and the overall group synchronization index (G_τ), both by including and by excluding the robot [28].

$$CV(s_i) = \frac{\sum_{j=1,\ldots,H,\, j\neq i} f(s_i, s_j)}{H-1} \tag{3}$$

$$G_\tau = \frac{\sum_{i=1,\ldots,H} I_\tau(s_i) \times CV(s_i)}{H} \tag{4}$$

The value of τ allowed us to detect two synchronous events when the events happened within τ in two time series. From the pilot studies, we found that even when the humans performed their actions synchronously, the lag between their actions ranged from 0.25-0.6 sec. So, to be conservative, we selected τ as 0.25 sec. The events of the robots were detected from the timestamped odometric data from the robots [28].

To address our research questions, we measured both the group synchronization index only considering the human participants (GSI(H)) across all experimental sessions, as well as the group synchronization index of the whole group (GSI(G)). First, we analyze the effect on the group synchronization index only considering the human participants for different experimental scenarios. Then, we analyze the effect on the whole group synchronization index for different experimental scenarios.

1) Effect on the GSI(H) values: We conducted an one-way repeated-measures ANOVA with the Bonferroni correction on the human group synchronization index (GSI(H)) values of all six experimental sessions, consisting of one session of *Phase 0*, two sessions of *Phase 1*, two sessions of *Phase 2*, and one session of *Phase 3*.

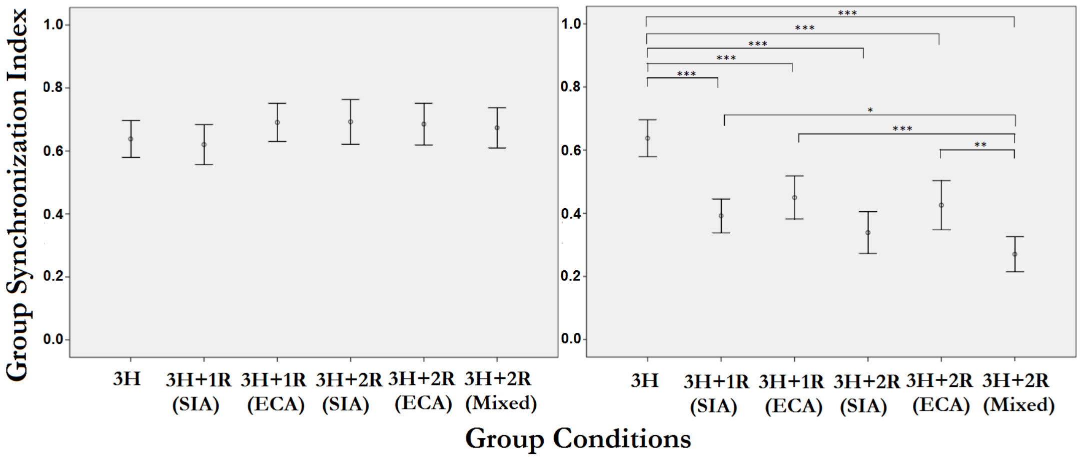

Fig. 3. The group synchronization index (GSI) values for different group conditions along x-axis, where 3H means 3 humans, 1R means 1 robot, 2R means 2 robots, SIA means synchronization index based anticipation, and ECA means event cluster based anticipation. The graphs on the left shows the GSI values of the human group, and the right shows the GSI values of the whole group. The significant difference in GSI values between groups are shown in * (* = $p < 0.05$, ** = $p < 0.01$, and *** = $p < 0.001$)

Mauchly's test indicated that the assumption of sphericity had been met, $\chi^2(14) = 9.38, p > 0.05$. One-way repeated-measures ANOVA with the Bonferroni correction indicated that the human group synchronization indices were not significantly different across all experimental conditions, $F(5, 115) = 1.37, p > 0.05, \omega^2 = 0.03$. These results suggest that the human group synchronization index was not affected by adding one or more robot as a performer to the group, irrespective of the anticipation algorithms. Fig 3 shows errors bars of GSI(H) values across all experimental conditions.

2) Effect on the GSI(G) values: We conducted an one-way repeated-measures ANOVA with the Bonferroni correction on the whole group synchronization index (GSI(G)) values of all six experimental sessions, consisting of one session of *Phase 0*, two sessions of *Phase 1*, two sessions of *Phase 2*, and one session of *Phase 3*.

Mauchly's test indicated that the assumption of sphericity had been met, $\chi^2(14) = 18.56, p > 0.05$. One-way repeated-measures ANOVA with the Bonferroni correction indicated that the group synchronization indices (GSI(G)) across the experimental conditions were significantly different, $F(5, 115) = 22.59, p < 0.05, \omega^2 = 0.21$.

These results also suggest that the GSI(G) values of the $Session1$ were significantly different than all other experimental conditions (for all conditions $p < 0.001$). This indicates that there is a change in the degree of group synchronization when one or more robots joined the group, independent of the anticipation algorithms.

The results also indicate that the GSI(G) values of the $sessions$ of $Phase1$ were not significantly different than the $sessions$ of $Phase2$ (for all conditions $p > 0.05$). It suggests that there is no significant effect on the GSI values when we add an additional robot to a three human and one robot group of the same robot behavior, regardless of the robot anticipation algorithms.

However, the results also indicate that the GSI(G) values of the $sessions$ of $Phase1$ were significantly different than the $session$ of $Phase3$ ($p < 0.05$ for SIA method of $Phase1$ and $Phase3$, and $p < 0.001$ for ECA method of $Phase1$ and $Phase3$). This suggests that there is a significant effect on the GSI values when we add an additional robot with different behavior to the group, regardless of the robot anticipation algorithms.

Our results also indicate that the GSI(G) values of the $session$ of $Phase2$ when the SIA algorithm was used were not significantly different than the $session$ of $Phase3$ ($p > 0.05$). However, the GSI(G) values of the $session$ of $Phase2$ when the ECA algorithm was used were significantly different than the GSI values of the $session$ of $Phase3$ ($p < 0.01$). This suggests that there is no significant effect on the GSI values when the both robots were performing SIA and when the robots performed a mixed behavior. On the other hand, there is a significant effect on the GSI values when the both of the robots were performing ECA and when the robots performed a mixed behavior. Fig 3 shows the errors bars of GSI(G) values across all experimental conditions.

VI. Discussion

To our knowledge, intentional coordination tasks have not been explored in the context of multi-human, multi-robot group interaction scenarios. Our study explored how robots might change this dynamic in intentional group coordination. Our results indicate that heteronegenous behavior of robots in a multi-human multi-robot group have a significant impact on the overall group coordination. This is an important finding, because this indicates that the way the robots move in a multi-human multi-robot group may directly impact the dynamics of the whole group, which raises an important concern about how we must design robots to perform along with humans in coordination to achieve common goals.

Our statistical analysis indicates that the addition of a second robot with heterogeneous behavior (*Phase 3*) significantly reduces the group coordination over a single robot condition (*Phase 1*). Similarly, the analysis suggests that an addition of a robot to the human-only group also significantly reduces the group coordination over the human-only group (*Phase 1* vs. *Phase 0*). This is an important finding, because the addition of a robot with same behavior does not change the group coordination significantly (*Phase 1* vs *Phase 2*, for both algorithms). These results might suggest that an addition of a robot with heterogeneous behavior to a group significantly reduces the overall group coordination, and might be an important indicator of human-robot group dynamics.

Overall, these results indicate that the group coordination is significantly affected when a robot joins a human-only group, and is further affected when a second robot joins the group and employs a different anticipation algorithm from the other robot. However, these effects were not found to be significant when the two robots employed the same anticipation algorithm.

Although participants were overall more synchronous by themselves than with the entire human-robot team, this does not imply that the team was grossly asynchronous, and the robot did not have influence on the human movements. For example, suppose that a robot moved sooner than the participants due to physical factors, such as sensor noise or actuator issues. When this happens, it may still influence the human team members to start moving earlier as well. However, the humans do not have this issue and are able to maintain consistent, real-time temporal adaptation among themselves (c.f. [32]), although the whole human group was deviated from the original rhythm. This is something we plan to explore in depth in our future work.

We can also extend our method to work beyond synchronous activities, such as timed but varied collaborative tasks. For example, a human-robot team working in an industrial setting has specific sequences of activities to perform over time, some of which might be independent, and might not happen synchronously. However, the events must happen contingently; so we can extend our methods to these scenarios.

This research may be helpful for others in the robotics community in exploring novel concepts that affect group dynamics beyond dyad groups. As a whole, humans have complex social structures, and it is necessary for robots to understand these underlying concepts if they are to become widely accepted. This work also has implications not only for human-robot interaction, but also for multi-robot systems research, such as robot swarms.

Building on this foundation, we want to explore the effect of including multiple types of robots with different expertise levels in a human-robot group to perform both intentional and unintentional coordinated movements. We are also interested to explore how different robot morphologies (like humanoids) might affect group synchrony.

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