Three's a Crowd: Human Perception of Social Distance with Robot Swarms

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***Abstract*—Robot swarms could prove useful in human robot coordinated tasks such as supervised monitoring or surveying of an area. However, managing social interactions is often difficult with a single robot agent, much less a swarm. To this end we seek to further understand human perception of social metrics, specifically comfortable social distance, when interacting with a swarm rather than a single robot agent. We theorize that a swarm's presence will be perceived differently than that of an individual robot and that human collaborators will feel less comfortable at a given distance from a robot if it is part of a swarm than if it is alone. In this study, participants walked in a tasked (set waypoint) and non-tasked (walking freely) manner while being followed by either a single agent or a swarm of three. We have analyzed our theory by using participant responses targeted towards their perception of the swarm and their comfort level while completing the task.**

I. System

The system consists of Sphero SPRK robots tracked by a Vicon overhead motion tracking system. The Spheros are small differential drive robots controlled via a bluetooth connection to a ROS enabled computer. Spheros are tracked using a custom removable chassis with unique reflective patterns. The overhead infrared Vicon system is able to use the light reflected off of these markers to identify the patterns and provide the location of the robots. Connection to the Sphero robots via bluetooth using ROS is possible using an open source Python package developed by Melonee Wise. This package was modified to allow for connections to multiple robots.

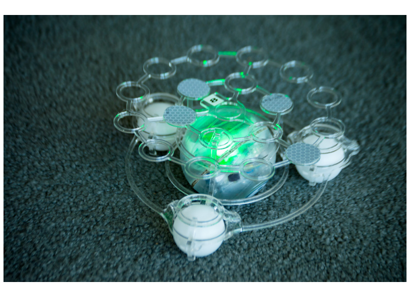

Fig. 1. Sphero with Tracking Chassis

The location of participants was also determined using the overhead Vicon system. Participants were outfitted with shoe covers with a unique reflective pattern on the surface. Spheros followed the subject using a velocity matching algorithm in conjunction with a social force model. The velocity matching algorithm allows the robots to move along with the subject by trying to match the direction and speed of the user while maintaining a specified distance [1] [2]. The social force model provides collision mitigation through the use of attractive/repulsive fields and distance maintenance between the robots and the user as well as repulsive fields between the robots that make up the swarm. [3].

II. Method

A. Participants

Eleven students (8 male and 3 female) between the ages of 18 and 25 from Cornell University volunteered for this study without compensation. Students were familiar with the idea of robots but had no previous extensive interaction with robots or any interaction with this particular system. The study was run within-subject; all participants completed all 4 of the tasks in a random order to avoid ordering effects.

B. Measures and Procedures

Participants were asked to move from their starting location to a marked goal location while being followed by an individual robot and a swarm of three robots then to move freely around the field while being followed by an individual robot and a swarm of three robots.

Fig. 2. Participant Walking with Single and Several Spheros

Participants were then asked to complete a survey based on the Godspeed Questionnaire [4]. The survey aimed to capture their response, comfort level, and perception while interacting with the different robot configurations.

C. Algorithms

The control script for each robot takes into account 3 parameters at each time step and assigns them a set weight, obtained through manual tuning. These 3 parameters are the velocity of the human, the attractive or repulsive social force with the human, and the repulsive social force with the other robots on the field. The robots use the velocity of the human to match its general direction and speed. The attractive force of the human is to aid in following when robots lag behind. The repulsive forces of the human and other robots are used to mitigate collisions. The resultant velocity of the robot is the sum of the social force vectors acting on it, $\vec{F_i}$, and the vector matching the velocity of the user, $\vec{V_{match}}$. This process is depicted below in figure 3.

$$\vec{V_{res}} = \vec{F_i} + \vec{V_{match}} \tag{1}$$

Ideally, the velocity vector of the human would be directly mapped to the robot's velocity vector. However, Sphero robots do not take control inputs in standard units, therefore the human's velocity, $\vec{V_H}$, magnitude must be scaled by β_1 to fit the Sphero reference frame.

$$\vec{V_{match}} = \beta_1 \vec{V_H} \tag{2}$$

The social forces acting on the robot can be described as the sum of the force due to human proximity and all the forces due to proximity of all other robots.

$$\vec{F_i} = \vec{F_{iH}} + \sum_{j=1}^{N} \vec{F_{ij}} \tag{3}$$

The force of the human on each robot is defined piecewise. If the robot is some allowable distance from the human defined at it's lower bound by d_{th1} and at it's upper bound by d_{th2} then no attractive or repulsive force is applied. If the robot is closer than this bound to the human a repulsive force is applied in the direction of the vector connecting the centroid of the two and whose magnitude is the product of the weighting factor β_2 and the squared difference of the distances. If the robot is farther than this bound from the human then an attractive force is applied along the vector connecting the two centroids with a magnitude of the product of the scaling factor β_3 and the squared difference of the distance and maximum distance threshold. By using two separate scaling factors for attraction and repulsion we can tune the response of being too close and too far separately.

$$\vec{F_{iH}} = \begin{cases} -\beta_2(d - d_{th1})^2 \hat{d} & d < d_{th1} \\ 0 & d_{th1} < d < d_{th2} \\ \beta_3(d - d_{th2})^2 \hat{d} & d > d_{th2} \end{cases} \tag{4}$$

Forces between robots act as repulsive forces and since each robot is an agent, the force of one robot acting on another is applied to the other robot in the opposite direction. If robots are far enough away no force is applied but if they are close enough a repulsive force acting along the vector connecting the two centroids is applied with a magnitude equal to the product of the scaling factor β_4 and the difference squared between the current and ideal distance.

$$\vec{F_{ij}} = -\vec{F_{ji}} = \begin{cases} -\beta_4(d - d_{al})^2 \hat{d} & d < d_{al} \\ 0 & d > d_{al} \end{cases} \tag{5}$$

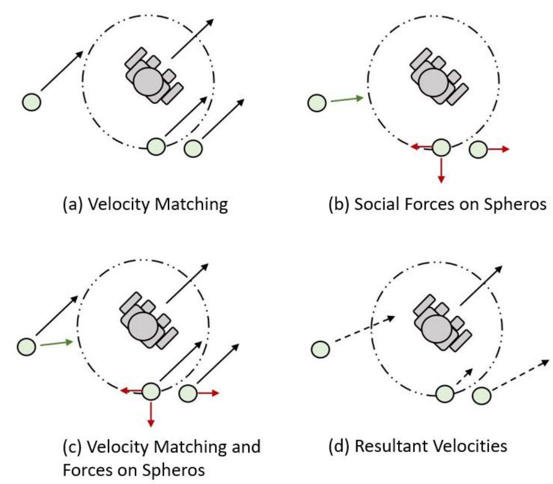

Fig. 3. Velocity Matching and Social Forces on Spheros

D. Evaluation

After each of the four trials, participants were asked to rate their experience with the robot(s) on a scale of 1 to 5 for the following characteristics that were selected for this purpose from the Godspeed Questionnaire:

- Natural
- Alive
- Responsive
- Pleasant
- Intelligent
- Relaxed

These descriptors were chosen to capture how similar the experience was to a daily side-by-side walking action, which is traditionally very organic and low-stress.

III. Results

The proposed social forces and velocity matching algorithm successfully produced the target following behavior most of the time. However, neither collision avoidance with other robots or social distance maintenance was assured at all times.

A number of participants used similar language to describe their experience, mainly comparing it to interacting with pets. Especially in the one robot case, participants often felt like they were walking a dog. This remark also arose in the three robot case but participants often found this situation more hostile. The experimental set-up was meant to simulate human-like behavior so the similarity to a pet environment was not intended but, based on the small size of the robots and the close nature of their following patterns, is understandable.
The mean responses (on a scale of 1 to 5) of each category for each case are shown in table I below.

	One/Fixed	One/Free	Three/Fixed	Three/Free
Natural	4.18	4.09	2.81	3.54
Alive	3.27	3.72	3.63	4.00
Responsive	3.54	3.54	3.54	4.09
Pleasant	4.09	4.36	3.63	3.90
Intelligent	3.36	3.45	3.36	3.54
Relaxed	3.18	3.27	2.90	2.54

TABLE I
SURVEY RESULTS

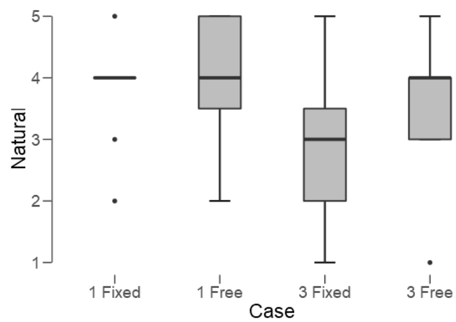

Fig. 4. Survey Results for Natural

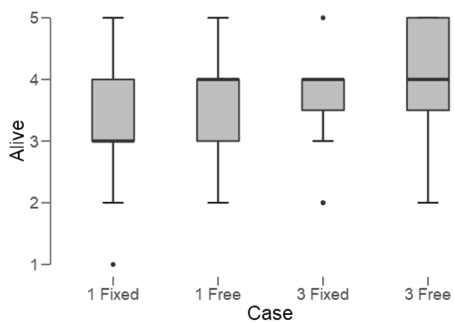

Fig. 5. Survey Results for Alive

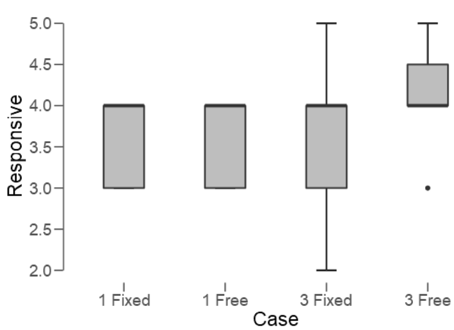

Fig. 6. Survey Results for Responsive

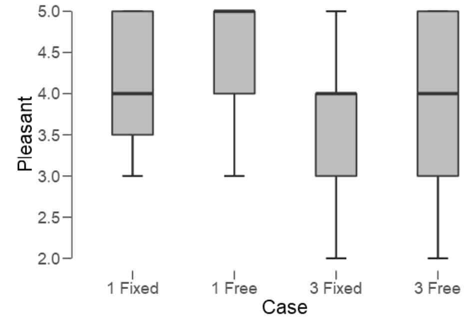

Fig. 7. Survey Results for Alive

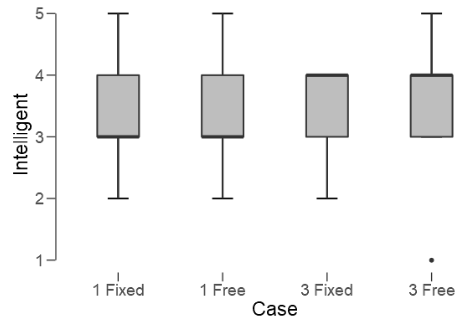

Fig. 8. Survey Results for Intelligent

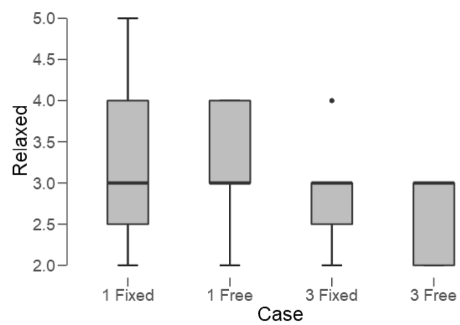

Fig. 9. Survey Results for Relaxed

We used a repeated measures ANOVA test and post hoc multiple comparisons with Bonferroni correction to gauge the effects of each case on each measured survey response [5]. We found that number of robots had a significant effect on the Natural rating of the robot $F(1.89,18.93)=7.99$, $p = 0.003$, $\eta^2 = 0.44$. Our post hoc test showed that the 1 fixed case ($M = 3.818$, $SD = 0.751$) led to a higher score than the 3 fixed case ($M = 2.818$, $SD = 1.168$) at $p = 0.010$ and the 1 free case ($M = 4.091$, $SD = 1.044$) led to a higher score than the 3 fixed case at $p = 0.047$. We also found that number of robots had a significant effect on the Alive rating of the robot $F(3,30) = 3.39$, $p = 0.031$, $\eta^2 = 0.25$ but our post hoc test revealed no statistical significance in which case lead to a higher score. For the Intelligent, Responsive, Pleasant, and Relaxed ratings our ANOVA tests found no statistically significant differences between the means.

IV. Conclusions

Because much of the data obtained was inconclusive, with only 2 of the 6 descriptors yielding a statistically significant p-value indicating a correlation with experiment outcome, it is believed that the chosen measures for the experiment were flawed and did not serve as an accurate representation of the participants' experiences. Of the descriptors, Natural and Alive were significantly improved for the single robot case as compared to the multi-robot case. This suggests that the participants did feel less comfortable when being followed by more robots and that the social distance that was being maintained was expected of an individual, but not of a group.

Participants often expressed excitement during the experiment and, as mentioned, compared it to interacting with pets but this engagement was not holistically captured in their responses. Moving forward, it would be interesting to run another similar experiment with refinements to both the following algorithms and the method of data collection.

Although the social forces model combined with velocity matching produced an acceptable following behavior, improvements could be made to better guarantee a social distance without collisions. Barrier certificates and quadratic solvers could achieve this target behavior more robustly [6]. Collisions could also be avoided using collision-free operational polygons as in past experiments with small robots modeling flocking behavior [7].

To improve data collection, we would likely substitute a mix of quantitative measures and a more in-depth questionnaire for the one-word ranking system used in this trial. For the tasked runs, measures such as time to completion, eye level, and number of times the participant stopped to check on the robot could help indicate comfort level. Likewise, lengthier questions more directed to the specific experiment could help capture their experience better. In our current set-up, participants likely interpreted the descriptor words differently or did not know how to associate them with their experience therefore causing inaccurate or skewed data.

By implementing these changes in the physical implementation of the system and in our methods of data collection, we hope to more accurately capture the experience created by our following algorithms and draw more complete conclusions.

V. Acknowledgements

We'd like to thank Professor Hoffman for his guidance in exploring this topic and Professor Kress-Gazit for the use of her lab resources to conduct our experiment as well as Autonomous Systems Lab graduate student Ji Chen with whom we collaborated in order to autonomously control the Spheros.

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