Neurodiverse Human-Machine Interaction and Collaborative Problem-Solving in Social VR

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ABSTRACT

Social motor coordination is an important mechanism responsible for creating shared understanding but can be a challenge for Autistic individuals. Social virtual reality (VR) provides an opportunity to create a safe and inclusive environment for which interactions can be augmented to promote social interactivity. Due to the bi-directional nature of social interaction and adaptation, we created a framework to explore social motor coordination with a virtual artificial agent which can exhibit human-like behaviors. In this experiment, we assessed the interactive behaviors of participants completing a collaborative problem-solving task with the agent using multidimensional cross-recurrence quantification analysis (mdCRQA). Our results show that participants who discovered novel solutions to the task exhibited greater coupling to the artificial agent regardless of participant characteristics. Future work will explore how social VR environments can be augmented to promote social coordination.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Applied computing → Psychology**.

KEYWORDS

social VR, virtual agents, collaborative problem-solving, coordination, autism spectrum disorder (ASD)

ACM Reference Format:
Patrick Nalepka, Nathan Caruana, David M. Kaplan, Rachel W. Kallen, Elizabeth Pellicano, and Michael J. Richardson. 2022. Neurodiverse Human-Machine Interaction and Collaborative Problem-Solving in Social VR. In *Proceedings of the 10th International Conference on Human-Agent Interaction (HAI '22), December 5–8, 2022, Christchurch, New Zealand.* ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3527188.3563933

HAI '22, December 5–8, 2022, Christchurch, New Zealand

ACM ISBN 978-1-4503-9323-2/22/12…$15.00
https://doi.org/10.1145/3527188.3563933

1 INTRODUCTION

Research has demonstrated the natural tendency for co-acting individuals to coordinate their movements in social interactions [4]. This coordination occurs when it is the explicit goal of the experiment, but also emerges naturally when the group goal is unrelated [13]. Such interactions between co-acting members have shown to improve task performance more generally [14] and leads to feelings of pro-sociality [5]. However, Autistic people face challenges during social interaction [1, 3], which may stem from challenges in social motor coordination [2].

There is evidence demonstrating that assistive artificial systems can reduce the social challenges faced by Autistic individuals [11]. We present a framework to investigate social motor coordination within a neurodiverse sample when interacting in virtual reality. Due to the bi-directional nature of social interaction, our approach augments the social interaction by including an artificial agent which embodies a model of social motor behavior. Here, we present an experiment investigating the social motor coordination between a neurodiverse sample and the human-like virtual avatar (see Figure 1).

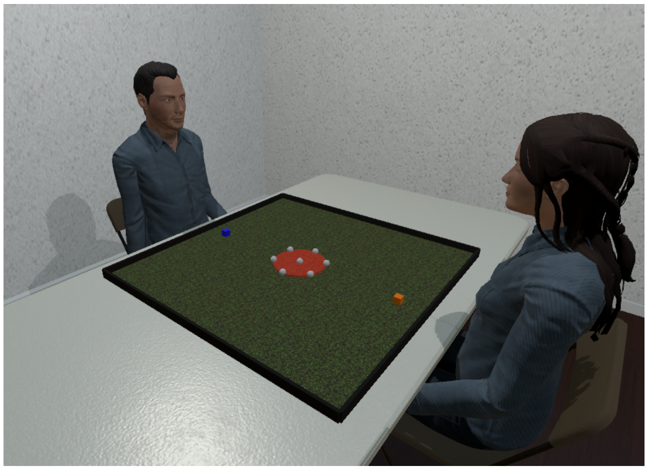

Figure 1: The social VR environment. One avatar was controlled by a human participant, while the other was driven by an artificial agent.

2 METHOD

2.1 Participants

Forty-two participants (M age = 14.7 years, ranging from 9 to 23 years of age; 27 male and 15 female) took part in the pilot experiment. Our sample comprised 22 autistic individuals and 20 non-autistic control participants. All autistic individuals had a formal diagnosis and met the criteria for an autism spectrum condition on the ADOS-2.

2.2 Materials and Task

The experiment was designed using the Unity game engine (ver. 2018.4.23f, Unity Technologies) (see Figure 1). Participants were seated at the long edge of a table measuring 2.2 (L) × 1.2 (W) × 0.81 (H) m and wore a virtual reality headset (Vive DevKit 2, HTC) with integrated eye-tracking (Tobii AB). Within the virtual environment, participants were embodied as a human-like avatar that was matched to the participant's gender. The avatars were created using Adobe Fuse CC (Beta Version 2014.3.14). The avatar's head movements were controlled by the VR headset, and the avatar's eyes were controlled by the gaze data detected by the headset's embedded eye tracker. Additionally, participants controlled the right index finger of the avatar, which was controlled via a Polhemus G4 tracking sensor (Polhemus Inc.) taped to the participants' right index finger. To emulate realistic movements of the non-controlled components of the avatar (e.g., the elbow and torso), the FinalIK (RootMotion Inc.) inverse kinematics calculator was used. Participants interacted with an artificial agent which controlled a human-like avatar which was gender-matched to the gender of a confederate who was involved in the experiment. The artificial agent controlled the hand position of the avatar along the transverse plane, and whose vertical component of the hand's position was fixed to the height of the virtual table. The human participant's hand position was similarly constrained.

The participant and artificial agent completed the human 'shepherding' task, previously used to study human-human [8] and human-machine interaction [9]. Shown in Figure 1, participants controlled "sheepdogs" which were represented as either a blue or orange cube and were tasked to corral and contain a set of evasive "sheep", modelled as spheres, to the center of a red circle. The sheep exhibited Brownian motion, but would flee away from the sheepdogs when threatened. The sheep's behavior was the same as outlined in [9]. All game pieces were contained within a 1×1 m field.

Previous work documented two strategies participants could use when completing the task [8, 9]. The first, *search and recover* (S&R), involved both participants independently corralling individual sheep towards the circle. The second, *coupled oscillatory containment* (COC), involved both participants making oscillatory movements around the entire herd to keep them contained. The COC strategy is non-obvious and is only discovered by a subset of participants completing the task. However, when discovered, resulted in near ceiling-levels of performance. The artificial agent implemented the same control architecture as detailed in [9] for completing the task, and was capable of adaptively switching between S&R and COC behavior.

2.3 Procedure

Participants were told to work alongside their partner to corral and contain the seven evasive sheep all within the red circle for at least 70% of a one-minute trial. Participants had a maximum of 45 minutes to meet this containment criteria on six occasions. This experiment manipulated the identity of the partner that participants interacted with during the experiment. Participants were either told that they would be completing the task with an artificial agent-controlled virtual avatar, or that they would complete the task alongside a human confederate (randomly assigned). In both cases, participants always interacted with the artificial agent whose behaviors were governed by the model detailed in [9]. In the condition where participants were told they would work with a human, a human confederate would be seated opposite of the participant and mimic the movements of the artificial agent to ensure the believably of the manipulation.

2.4 Measures and Design

This pilot study investigated the interpersonal coupling dynamics between participants and the artificial agent as they completed the task. Interpersonal coupling was assessed using multidimensional cross-recurrence quantification analysis (mdCRQA) [15]. MdCRQA can be interpreted as a multivariate cross-correlation analysis, which quantifies the frequency for which the states of two multivariate timeseries co-occur at various time lags.

The percentage of time-point comparisons where the timeseries co-occured is referred to as *REC%* and is interpreted as the amount of incidental coupling between interacting systems. Additionally, the maximum "run" of adjacent co-occurring time-points is referred to as *MaxL* (for maximum line length), and is a measure of the strength or stability of coupling between two interacting systems [12]. We used both REC% and MaxL to quantify the coupling between the participant and the artificial agent. The inputted timeseries were the 2-dimensional position values of participant and artificial agent movements during the trial.

The study implemented a between-subjects 2×2 design where neurotypical or Autistic participants were told their partner was controlled by either an artificial agent or human.

3 RESULTS AND DISCUSSION

Multi-level (mixed-effects) models were fitted where each trial was nested under each respective participant. The following fixed-effects were considered: *belief* (human or artificial agent), *participant* (neurotypical, Autistic), a *belief* × *participant* interaction, *success* (success, failure), *behavior type* (S&R, COC), and *discovery* (discoverers, non-discoverers). The following covariates were also included: *participant age* and *confederate identity* (male, female; as two confederates were involved in the study). The models were fit using restricted maximum likelihood so that the degrees of freedom (using the Kenward-Rogers method [6]) could be estimated for statistical testing.

For the amount of incidental coupling between the participants and the artificial agent (REC%), human-agent pairs exhibited less coupling during successful trials than non-successful trials, $t(387.9) = -2.58, p = .01$. Further, participants who discovered the novel solution to the shepherding task exhibited more instances of incidental coupling with the artificial agent than did non-discoverers, $t(26.2) = 2.91, p = .007$.

For coupling strength (MaxL), human-agent pairs exhibited less stable coupling during successful trials than unsuccessful trials, $t(93.1) = -8.21, p < .001$. Further, when pairs discovered and used the novel solution (i.e., COC behavior [8]), the stability of the coupling within the pair was also less, compared to when they exhibited the non-novel behavior, $t(370.7) = -3.87, p < .001$. No other effects were significant.

The results indicate that the belief manipulation, or characteristics of participants (i.e., whether they were neurotypical or Autistic), did not impact the quality of the interactions with the artificial agent. This may be due to the fact that the artificial agent was consistent in its behavior regardless of who the co-actor was, which may not be the case when interacting with other humans due to the adaptive nature of social interaction. Further, the results also demonstrate that social coupling may not necessarily predict task success [16], but may serve as a mechanism for which new and novel strategies are discovered [7] (as shown in the significant *discovery* effect on REC%). Indeed, previous work has shown that particular interactive behaviors may scaffold whether and when novel strategies are discovered in the shepherding task used here [10]. Once discovered, the benefits of the novel solution may be due to reducing the demands of coordination (as indicated by a decrease in the strength in the coupling [MaxL]).

Future work will explore how social VR can enhance interaction quality between humans (or humans with machines), as well as how such environments can be inclusive to all individuals.

ACKNOWLEDGMENTS

This research was supported by the ARC Centre of Excellence in Cognition and its Disorders (CCD) Legacy Support Scheme. PN and NC were supported by the Macquarie University Research Fellowship. EP and MJR were supported by the Australian Research Council Future Fellowships (FT190100077 and FT180100447, respectively).

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