Motivating Physical Activity via Competitive Human-Robot Interaction

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Abstract: This project aims to motivate research in competitive human-robot interaction by creating a robot competitor that can challenge human users in certain scenarios such as physical exercise and games. With this goal in mind, we introduce the Fencing Game, a human-robot competition used to evaluate both the capabilities of the robot competitor and user experience. We develop the robot competitor through iterative multi-agent reinforcement learning, and show that it can perform well against human competitors. Our user study additionally found that our system was able to continuously create challenging and enjoyable interactions for humans and the majority of human subjects considered the system to be entertaining and useful for improving the quality of their exercise.

Keywords: Competitive-HRI, Reinforcement Learning

1 Introduction

Competition is ubiquitous in the natural world [1, 2] and in human society [3, 4, 5]. Despite its universality, *competitive interaction* has rarely been investigated in the field of Human Robot Interaction, which has mainly focused on *cooperative interactions* such as collaborative manipulation, mobility assistance, feeding, and so on [6, 7, 8, 9, 10]. In some ways it is not surprising that competitive interaction has been overlooked: of course everyone wants a robot that can assist them; who would want a robot that thwarts their intentions? Yet, we also accept that human-human competition can be healthy and productive, for example in structured contexts such as sports. In this paper we explore the idea that human-robot competition can provide similar benefits.

We believe that physical exercise settings such as athletic practice, fitness training, and physical therapy are scenarios in which competitive HRI can benefit users. Physical exercise is essential to our physical and mental health. In addition, the quality of some physical rehabilitation is closely related to patients' commitment to exercising regularly. However, the major cause of poor adherence to physical exercise is due to a lack of motivation [11, 12, 13]. It has been shown that enjoyment, competition, and challenges are important motivational factors for the practice of physical exercise [14, 12]. In this project, our goal is to create a robot that can provide these motivations to human users via adversarial behaviors. The main contributions of this paper are listed below:

Motivating Competitive-HRI Research. We discuss how competitive interaction can influence people in a positive manner and the technical difficulties competitive-HRI tasks represent. This discussion motivates our proposed Fencing Game, a competitive physically interactive game, as an evaluation environment for competitive-HRI algorithms and user study.

System Designed and Implementation. A highly generalizable robotic system is created to support our competitive-HRI research. A multi-agent reinforcement learning(RL) method is used to train a robot to play competitive games with multiple gameplay styles.

User Study. We performed a user study to gain basic understandings of competitive-HRI and draw useful insights for future research. We found that more than 80% of subjects found competitive interaction with our robot to be entertaining and desirable. Our system was able to provide challenging gameplay experiences that significantly increase human players' heart rates. Furthermore,

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we observed that human subjects who constantly explore different strategies tend to achieve higher rewards in the long run.

Figure 1: Competitive fencing games between a PR2 robot and human subjects. The detailed game rules are described in Sec. 2. Please refer to this link for anonymous example gameplay videos.

2 Competitive Interaction

In this section, we discuss the significance of competitive interaction and justify why we believe that it deserves increased attention in the HRI community. We will first discuss how competition can influence people in a positive manner from a psychological perspective. Afterward, we will discuss the technical challenges in competitive-HRI tasks and propose the use of the Fencing Game as the main task that this project will focus on.

Positive Influences of Competitive Interaction. Competition between players provides motivation and can foster improvement in performance at a given task. Plass et al. [15] compared competitive versus cooperative interactions in an educational mathematics video game. The results revealed that, compared to working individually, the subjects performed significantly better when working competitively than cooperatively. In particular, competitive players demonstrated higher effectiveness in problem solving compared to non-competitive players. This study also observed that subjects experienced a higher level of enjoyment via an increased tendency to engage in the game [16]. Furthermore, they also displayed higher situational interest, *i.e.* the subject paid more attention and had more interaction during the game [17]. Viru et al. [18] showed that competitive exercises can improve athletic performance in a treadmill running test. Subjects' average running duration was increased by 4.2%. During cycling and planking exercise, Feltz et al. [4] were able to inspire higher performance from subjects by placing them in competition with a manipulated virtual partner.

Inspired by these studies, we envision that a personal robot can become a competitive partner that provides enjoyment, increases motivation, and inspires improvement in activities such as physical exercise. For this reason, we initiate our competitive-HRI research by focusing on creating a physical exercise companion.

Technical Challenges. Creating an actual robot that can compete with a human physically is challenging. The robot needs to constantly reason about the human's intent via their actions, and strategically control its high degree-of-freedom body to counteract the opponent's adversarial behavior and maximize its own return. Therefore, a big part of our competitive-HRI research focuses on solving these technical challenges to create a robotic system with real-time decision making capability and body agility that is comparable to that of humans.

The Fencing Game. Based on the expected technical challenges, we designed a two-player zero-sum physically interactive game. The Fencing Game is an attack and defense game where the human player is the antagonist with the goal of maximizing their game score. The robot is the protagonist who aims to minimize the antagonist's score. Fig. 1 shows three images of human subjects playing the game, and the algorithm in Appendix A.1 summarizes the scoring mechanism for this game. The orange spherical area located between the two players denotes the target area of the game. The antagonist on the right earns 1 point for every 0.01 seconds that their bat is placed within the target area without contacting the opponent's bat. The antagonist will lose 10 points if the antagonist's bat is placed within the target area and makes contact with the protagonist's bat simultaneously. Moreover, the antagonist will get 10 points of reward if the protagonist's bat is placed within the target area, waiting for the antagonist to attack, for more than 2 seconds. Each game will last for 20 seconds. The observation space for both agents includes the Cartesian pose and velocity of the two

bats, as well as the game time in seconds. For the sake of simplicity, both agents in this project are non-mobile. Yet, mobility can be easily integrated into future iterations of this game.

3 Related Work

Reinforcement Learning in Competitive Games. Competitive games have been used as benchmarks to evaluate the ability of algorithms to train an agent to make rational and strategic decisions [19, 20, 21]. Multi-agent reinforcement learning methods allow agents to learn emergent and complex behavior by interacting with each other and co-evolving together [22, 23, 24, 25, 26, 27]. Many recent efforts have used multi-agent RL methods to learn continuous control polices that can achieve high complexity tasks. Bansal et al. [28] created control policies for simulated humanoid and quadrupedal robots to play competitive games such as soccer, and wrestling. Lowe et al. [29] has extended DDPG [30] to multi-agent settings by employing a centralized action-value function.

Human-Robot Competition. There are a few studies focusing on human-robot interaction in competitive games. For instance, Kshirsagar et al. [31] studied the affect of "co-worker" robots on human performance when they are performing in the same environment and competing for a monetary prize. This study showed that humans were slightly discouraged when competing against a high performing robot. On the other hand, humans exhibited a positive attitude towards the low performing robot. Mutlu et al. [32] showed that male subjects were more engaged in competitive video games when they played with an ASIMO robot. However, the majority of the subjects preferred cooperative games when they played with this robot. Short et al. [33] analysed the "rock-paper-scissors" game and found that human subjects were more socially and mentally engaged when the robot cheated during the game.

Robots in Physical Training. In the context of using robots to assist humans in physical exercises, a robot developed by Fasola and Mataric [34] was able to provide real-time coaching and encouragement for a seated arm exercise. Süssenbach et al. [35] developed a motivational robot for indoor cycling exercise that employed a set of communication techniques in response to the subject's physical condition. The results showed that the robot sufficiently increased the users' workout efficiency and intensity. Sato et al. [36] created a system capable of imitating the motion and strategy of top volleyball blockers for assisting vollyball training.

These works are typically limited to a few competitive scenarios that require simple and repetitive motions. In this work, we leverage reinforcement learning to create a robotic system that can potentially play various physically competitive games against human players.

4 System Design

Humans are highly efficient at recognizing patterns and learning skills from just a small number of examples [37]. Existing research also shows that human subjects can adapt to robots and improve their performance in just a few trials in physical HRI tasks [38, 39]. However, games against a robot competitor are less challenging if a human player can easily predict its behavior and quickly find an optimal counter-strategy. We hypothesized that human players can quickly learn to improve their performance against a given robot policy, but a change in the robot's gameplay style could interrupt this learning effect and keep the games challenging. A gameplay style is characterized by patterns in the agent's end-effector motion trajectories. For example, one antagonist may prefer using more stabbing movements, while another antagonist may prefer slashing movements. Therefore, there are two primary objectives that govern the generation of robot control policies. First, a policy should allow the robot to play the Fencing Game sufficiently well, such that the games are intense and engaging to the human users. Second, we propose to obtain three policies with unique gameplay styles for our user study. A multi-agent reinforcement method created the robot control policies that are used in the user study. We designed and implemented the physical system based on a PR2 general-purpose robot. The implementation of our physical system is detailed in Appendix A.2.

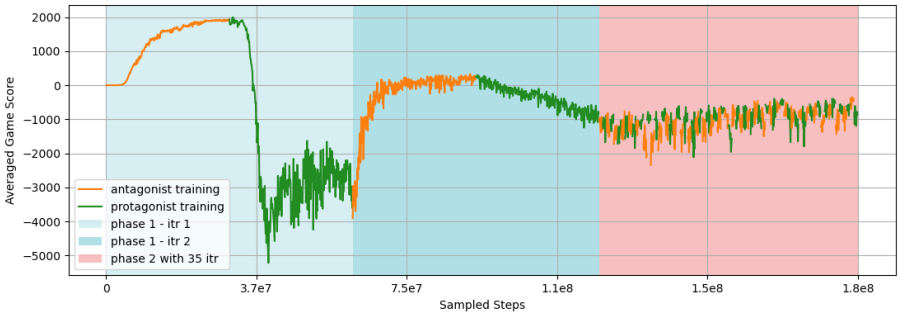

Figure 2: The antagonist's average game score during one complete round of phase one and two training. The two iterations of phase one training enabled two agents to interact according to the game rules. The phase two training performed 35 small updates resulting in random characteristics for both agents.

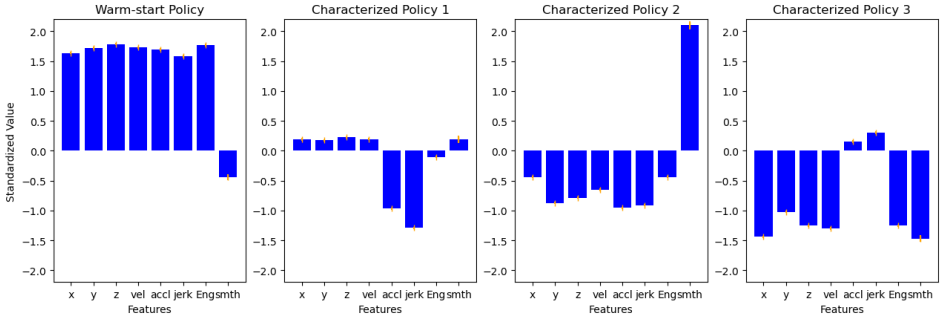

Figure 3: Visualization of quantified gameplay style of the four policies used in the user study. Error bars indicate the standard deviation of the feature values among the population.

4.1 Learning to Compete

To generate robot control policies that comply with the two aforementioned requirements, we formulate the Fencing Game as a multi-agent Markov game problem [40]. Both the antagonist agent and the protagonist agent are represented by a PR2 robot model in a Mujoco simulation environment. Both agents are trained in a co-evolving manner by playing games against each other. We break down the multi-agent proximal policy optimization method proposed by Bansal et al. [28] into two separate training processes, which reduces the computational power consumption needed to obtain multiple pairs of agents with acceptable performance. As a result, we were able to complete all sampling and training processes on a desktop computer (cpu: $1 \times i7$, gpu: $1 \times GTX970$). Our version of multi-agent PPO, the two-phase iterative training algorithm, is presented in Algo. 1.

Learning to Move and Play. The first phase of the training can be seen as a pre-training process, which aims to allow both agents to quickly learn the motor skills required for joint control and the rules of the game. The agents are rewarded by both the weighted sum of a continuous reward and the game score at each timestep. The continuous reward encourages the agents' exploration in the task space. The policy of the antagonist μ with parameters θ_i^μ will first be trained by collecting trajectories that result from playing against the protagonist with its most recent policy. This process continues until timeout or μ has converged. The protagonist's policy ν with parameter θ_i^ν will then be trained against the antagonist with its most recent policy. We were able to acquire robot policies that play the Fencing Game sufficiently well by only running this training sequence twice ($N_{iter} = 2$). The pair of resulting policies from phase one will be called the warm-start policies.

Creating Characterized Policies. It has been shown that by using different random seeds to guide policy optimization toward different local optima, an agent can learn different behaviors and approaches to complete the same task [41, 26]. The highly variable nature of multi-agent systems enhances this random effect. The agents in multi-agent systems are more likely to learn drastically

different strategies and emergent behaviors when they continuously learn by competing with each other [42, 28, 43, 44]. The second phase of training generates a policy with random characteristics by exploiting this fact. Both agents are initialized with their warm-start policies from phase one and trained in the same iterative scheme shown in Algo. 1. The agents are solely rewarded by the game scores. When training each of the agents, instead of having an agent face against the opponent's latest policy, one of the previous versions of the opponent's policy in the history will be randomly selected in phase two. We created a policy library that contains six pairs of randomly characterized policies that resulted from six different rounds of phase two training. Fig. 2 demonstrates the change of game scores during the two-phase training process.

4.2 Selecting Agents With Distinct Gameplay Styles

In order to identify the most distinctive protagonist policies in the library described in the last subsection, each agents' gameplay style needs to be quantified and compared. We first generate trajectories for all protagonist policies in a tournament [45], where each agent plays 100 games with each of the six opponents. Eight end effector trajectory features are selected to quantify agent's gameplay styles: total displacement change on x, y, and z axis, average velocity, average acceleration, average jerk, total kinetic energy, and trajectory smoothness. These features are calculated for each of the games played by each of the protagonists. The quantified style of a protagonist agent is the averaged features across 600 games. The features of all protagonists are then compared via their three most significant principal components (less than 2% of information loss)[46], and the three most separable policies are selected for the user study. The protagonist's gameplay style for the warm-start policy and the three selected characterized policies are visualized in Fig. 3.

Algorithm 1: Iterative Two-Agent Learning

Input: Environment $\mathcal{E}$; Stochastic policies μ and ν; Instantaneous Reward Function *r(·)*
Initialize: Parameters θ_0^μ for μ and θ_0^ν for ν
for $i = 1, 2, ..N_{iter}$ **do**
  if *phase one training* **then**
    $\theta_i^\nu \leftarrow \theta_{i-1}^\nu$
  else
    $\theta_i^\nu \leftarrow \theta_{random_from_history}^\nu$
  end
  for $j = 1, 2, ..N_\mu$ **do**
    rollout $\leftarrow roll(\mathcal{E}, \mu_{\theta_i^\mu}, \nu_{\theta_{i-1}^\nu}, r(\cdot))$
    $\theta_i^\mu \leftarrow$ PPO_Update(rollout)
  end
  if *phase one training* **then**
    $\theta_i^\mu \leftarrow \theta_i^\mu$
  else
    $\theta_i^\mu \leftarrow \theta_{random_from_history}^\mu$
  end
  for $j = 1, 2, ..N_\nu$ **do**
    rollout $\leftarrow roll(\mathcal{E}, \mu_{\theta_i^\mu}, \nu_{\theta_i^\nu}, r(\cdot))$
    $\theta_i^\nu \leftarrow$ PPO_Update(rollout)
  end
end

4.3 Sim2Real

Due to the kinematic and dynamic mismatch between simulation and reality, policies that are trained solely on simulated data can perform poorly in reality. We use a combination of a Jacobian Transpose end-effector controller and a system identification (systemID) process to solve this problem. Instead of specifying the torque values for each joint, the policy outputs an offset from the current end-effector pose. The new desired pose is executed by the end-effector controller. We used the CMA-ES algorithm to optimize the following objective over the parameter space of both the controller and the robot model in the simulation.

$$(\theta_m^*, \theta_c^*) = \arg \min_{(\theta_m, \theta_c)} \sum_{t=0}^{T} (s_r^t - s_s^t)^2$$

Where θ_m represents the simulated robot model parameters: damping, armature, and friction loss. θ_c represents the proportional gains and derivative gains of the end-effector controller. T_r and T_s are trajectories sampled from the real robotic system and simulation respectively that result from the same control sequence. $s_r^t \in T_r$ and $s_s^t \in T_s$ are the robot's end-effector pose in reality and simulation at time t respectively. As a result, the difference in end-effector dynamics between the simulated robot and the real PR2 robot is reduced. The maximum controller output is bounded conservatively to prevent possible human injury.

Table 1: Subjective Ratings of the Modified TAM Questions

	1-Strongly Disagree	2-Disagree	3-Neutral	4-Agree	5-Strongly Agree
Perceived Usefulness	0%	6.25%	25%	37.5%	31.25%
Perceived Ease of Use	0%	18.75%	18.75%	62.5%	0%
Attitude	0%	6.25%	37.5%	25%	31.25%
Intention to Use	0%	18.74%	18.75%	25%	37.5%
Perceived Enjoyment	0%	6.25%	6.25%	31.25%	56.25%
Desirability	0%	6.25%	12.5%	31.25%	50%
Increase Engagement	6.25%	6.25%	31.25%	18.75%	37.5%

5 Experiments Procedure

An in-lab user study was designed to answer the following questions: 1. Is a competitive robot accepted by human users under the scenarios of physical games and exercise? 2. Can our system effectively create challenging and intense gameplay experience? 3. Can the robot interrupt the human learning effect by switching its gameplay style? The user study was conducted in accordance with the Institutional Review Board (IRB) review from our university. There were 16 human subjects recruited for our user studies, the demographic data is described in Appendix A.4..

Before the Experiment. Before the experiment, each subject was asked to sit for 3 minutes and then walk for 1 minute to record two averaged heart rate baseline values. In the experiment, both the robot and a subject held a polystyrene bat to play the games. A safety line was drawn on the ground, and every subject stood behind it to prevent a potential collision. Since the robot was not mobile, a subject also kept his/her feet planted on the ground during a game. The target area was not directly visible; an audible scoring feedback system notified a subject when his/her bat was placed within the target area. A high-frequency signal sound indicated that the human player was scoring, and a low-frequency signal sound indicated that the human player was getting penalization. Before the experiment, a subject had 5 minutes to explore this target area with their bat so that the target area's location and the scoring mechanism were clear to the subject. Afterward, the subject played two warm-up games with the robot to get further familiarized with the system. In these warm-up games, the robot's actions were slowed down and no data was collected.

Experiment and Questionnaire. The experiment contains four sections. In each section, a subject will play five consecutive games with the robot and rest for approximately 30 seconds between games. Subjects' heart rates will be recorded during each 20 second game. Due to the short duration of the games, our discussions in Sec. 6 use peak heart rate as a summarizing statistic of this recorded data. In the first section of the experiment, the robot will use the warm-start policy resulting from the phase one training. For the rest of the sections, the robot will load one of the three selected characterized policies in each section by following a random order. This ensures that all subjects will first learn to play with the robot at a regular speed, and then play with the robot with a new game style in each of the sections. After each section, a subject will be asked to describe the interaction in the last 5 games by selecting one or more of the following adjectives: 'Exciting', 'Joyful', 'Frustrating', 'Motivating', 'Amusing', 'Intimidating', 'Physically Demanding', 'Cognitively Demanding', 'Boring', 'Others (please describe:)'. Finally, when a subject finishes all four sections of games, they will complete the last part of the questionnaire that assesses their acceptance of the competitive robot, and their subjective feelings towards the games. We modified the technology acceptance model (TAM) [47] that assesses perceived usefulness, enjoyment, motivation, intention to use, system desirability, etc. Question design details can be found in Appendix A.3. Other than the open-ended question, all TAM questions were measured on a 5-point scale where 1 = "Strongly Disagree," 3 = "Neutral," 5 = "Strongly Agree".

6 Analysis and Discussion

Our experimental results show that participants would highly accept use of a competitive robot as an exercise partner. The majority of the subjects considered competitive games with our robot to be useful, entertaining, desirable, and motivating. Our system was able to provide a challenging and

intensive interactive experience that significantly increased subjects' heart rates. While competing against our RL trained robot, most subjects struggled to make significant performance improvement over time. Yet, a subset of subjects who constantly explored different strategies achieved higher scores in the long run.

User Acceptance. Table 1 summarizes the subjects' responses to the technology acceptance model. The majority of the subjects (*i.e.*, 68.75%) agreed that a competitive robot could improve the quality of their physical exercise. Moreover, 87.5% of subjects agreed or strongly agreed that competitive human-robot interactive games are entertaining, and 81.25% of subjects agreed or strongly agreed that a competitive robot exercise companion would be desirable in the future. Interestingly, the intention to use (62.5% agree + strongly agree) and increase engagement (56.25% agree + strongly agree) metrics are not as high as the strong agreement on perceived enjoyment and desirability. Some subjects who don't have strong intention to use our system explained their reasons in the open-ended question. They stated that it is not immediately clear how competitive robots can play a role in their routine exercises, such as jogging, and weight training. In fact, most subjects (*i.e.*, 71%) who exercise less than three hours per week agreed that a competitive robot partner will increase their engagement with physical exercise. Therefore, our competitive robot is more effective on motivating people who do relatively little exercise. Future research should explore how to effectively apply competitive-HRI to common exercises.

Increased Heart Rate. Most of the gameplay with our competitive robot increased the human subjects' heart rates significantly. Subjects' peak heart rates were higher than their rest heart rate in more than 99% of the games, and their peak heart rate in 92.6% of the games were higher than their walking baseline heart rate. Since the subjects were asked to keep their feet planted on the ground during a game, their body maneuverability was very limited. Despite this movement limitation, subjects' peak heart rates were significantly higher (*i.e.*, 20% to 58%) than their walking baseline in 29% of the games. We found that, other than physical effort, subjects' cognitive effort and reported emotions also corresponded to a rise in heart rate. Figure 4. b. shows that sections with higher average heart rate have more people feel cognitively demanding, motivated, frustrated, and intimidated by the robot. In short, playing competitive games with our robot can be cognitively demanding and can trigger noticeable emotional reactions.

The Human Learning Effect. As mentioned in Sec. 4, we wanted to test if changing the robot's gameplay style interrupts the human learning process and keeps the interaction challenging throughout the whole experiment. The hypothesis was based on our assumption that most human players can make significant improvement within five games given a fixed robot policy. Surprisingly, this assumption was invalidated by our user study data. Fig. 4. c. shows the average game scores and standard deviation of all subjects in the five consecutive games against each of the four robot policies. An analysis of variance (ANOVA) suggests that subjects have no significant performance increase between the five games for a given policy (Warm-start Policy: $p = 0.96$, Characterized Policy 1: $p = 0.74$, Characterized Policy 2: $p = 0.85$, Characterized Policy 3: $p = 0.43$). The red horizontal dashed line in each subplot of Fig. 4. c. represents the best mean score achieved by a subject, which approximates the performance of an observed best human policy. The averaged performance of all subjects were lower than (*i.e.*, much lower in most cases) the performance of the best human policies, and most subjects still have much room for performance improvement. Our assumption on human learning was based on evidence from noncompetitive HRI experiments. In contrast, our competitive setting creates a much more dynamical environment and resulted in a more challenging learning environment for the human. Glaze et al. [48] suggested that the human learning mechanism under highly dynamical environment is complex and varies with time and individuals. Future research that attempts to study the human learning effect in competitive-HRI will need much more data than five games for a fixed robot policy. Since no significant performance variance was observed across the four sections either (ANOVA $F = 1.51, p = 0.26$), our system was able to remain challenging to users throughout the whole experiment. However, more studies are needed to analyze how changes in gameplay style interrupt human learning.

Human Performance. Despite the fact that no significant learning effect was found in the subject population, we did observe that some subjects tried multiple strategies in the experiment, which could be interpreted as exploration within a learning framework. This observation motivated us to analyze the relationship between strategy exploration and performance, which we first quantified

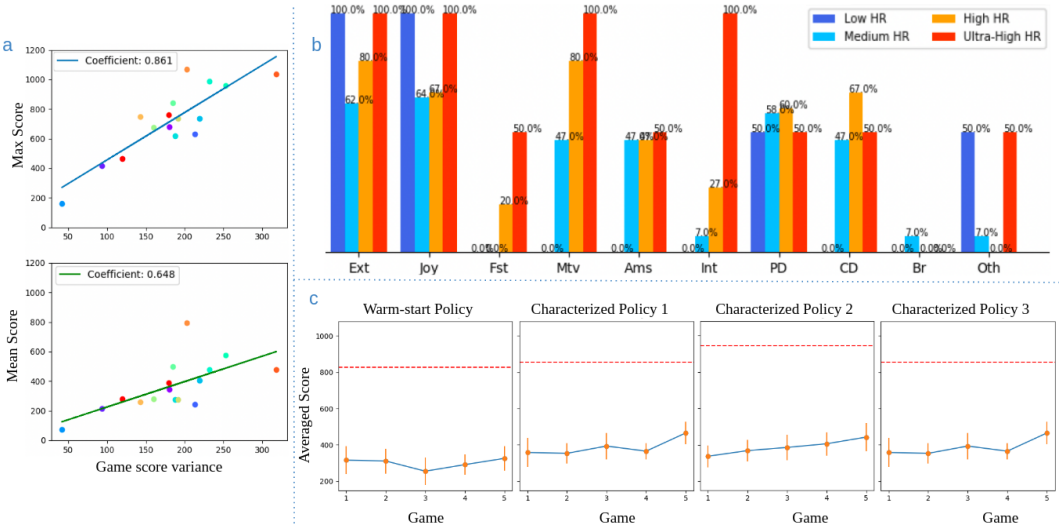

Figure 4: **a.** The 16 points in each subplot represent the 16 subjects. The variance of subjects' game scores is positively correlated to their achieved maximum and mean scores. **b.** Comparing subjective descriptions between sections with low, medium, high, and ultra-high averaged heart rates, the definition of each group is detailed in Appendix A.5.. The x-axis of each subplot shows the adjective describing each section of games (Exciting, Joyful, Frustrating, Motivating, Amusing, Intimidating, Physically Demanding, Cognitively Demanding, Boring, Others). The y-axis indicates the percentage of subjects in the corresponding group who selected the corresponding answer. **c.** Each subplot shows that averaged game scores of all subjects on the five games against each robot policy. The error bars indicate the standard errors over the samples. The red horizontal lines indicate the best mean score achieved by one of the subject against the corresponding robot policy.

as variance in game scores, and then as the featurized gameplay styles from Sec. 4. As shown in Fig 4. a., a larger variance in score corresponds to better performance in terms of achieving higher maximum and mean scores. We then compared the variance of the gameplay style between the five subjects with the highest maximum scores and the five subjects with the lowest maximum scores. For the sake of simplicity, we only compared the end-effector displacement change on x, y, and z axes and the averaged velocity. The result shows that the variance of each selected feature for subjects with high performance are at least 29% higher than subjects with low performance. This suggested that subjects who have high variance in score tend to take risks by constantly exploring different strategies, resulting in better rewards in the long run. Future research could examine whether a robot can help human users to achieve better performance by verbally or implicitly encouraging them to explore different strategies.

7 Conclusion

This work motivated research in competitive-HRI by discussing how competition can be beneficial to people and the technical difficulties competitive-HRI tasks represent. The Fencing Game, a physically interactive zero-sum game is proposed to evaluate system capability in certain competitive-HRI scenarios. We created a competitive robot using an iterative multi-agent RL algorithm, which is able to challenge human users in various competitive scenarios, including the Fencing Game. Our user study found that human subjects are very accepting of a competitive robot exercise companion. Our competitive robot provides entertaining, challenging, and intense gameplay experiences that significantly increases the subject's heart rate. Even though most human subjects struggled learning to make improvement in our experiment, subjects' exploration in various strategies can potentially improve their overall return.

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