Power Chess

Robot-to-Robot Nonverbal Emotional Expression Applied to Competitive Play

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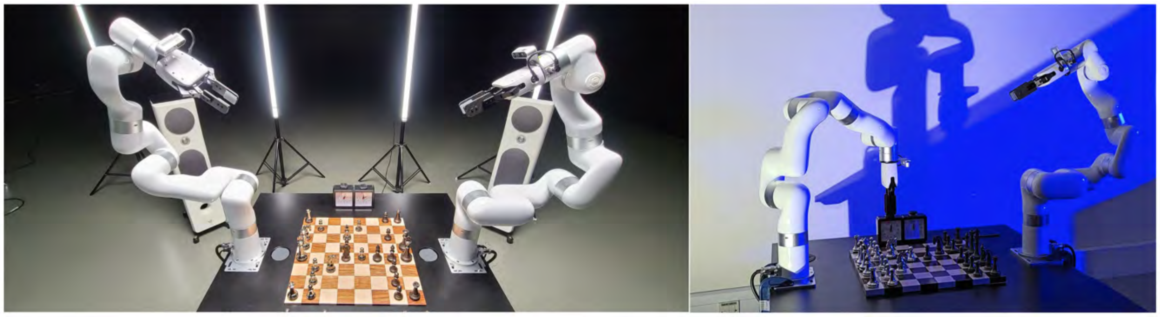

Figure 1: Power Chess (2021) (Left) is a robotic installation consisting of a robot playing a high-stake narrative chess game against another robot, expressing emotionality through physical movement gestures and rule-based game play. (Right) One of the arms play the piece while the other observes, both using the end effector either as a hand or as a head.

ABSTRACT

Human-machine communication has evolved from one-to-one to multi-agent systems where the interplay between machines themselves interacts with human perception and behavior, complicated by unconstrained emotion-based variables in social systems. To investigate Human-Robot and Robot-Robot-Human interaction while constraining the interaction variables in a rule-based system, we developed an artistic intervention using competitive game performance between robotic arms. Two robots play chess with each other while expressively making gestures like thinking, examining, hesitating, shows of satisfaction and bewilderment, breathing, etc. These nonverbal behaviors and evolving rules between games tell a narrative of power struggle between two robots of aggressive vs. reflective personalities. We used recorded videos to assay audience interpretations of individual and robot-to-robot expressions, finding that gestures like standing and confirming were perceived as aggressive, while head turns, deliberation, and audience alerts were seen as curious. Human perception of robot play-style and their own intended play strategies were influenced by robot-robot interactions, such as holding defensive strategies when the robot was deemed aggressive. Robotic movements caused audiences to attribute personality characteristics to them, modifying their intended strategy in patterns like pretending to be friendly first to lull the robot opponent. Our work uses artistic metaphors to study multi-agent environments that cannot be easily controlled for in scientific settings.

CCS CONCEPTS

• **Human-centered computing** → Interaction design; Empirical studies in interaction design; • **Computer systems organization** → Embedded and cyber-physical systems; Robotics.

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KEYWORDS

Robot gestures, machine art, robot-robot-human interaction, behavioral design, interactive storytelling

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1 INTRODUCTION

For ordinary factory robots, the most efficient movement in accomplishing a task is the one using the shortest distance from one point to another without compromising safety and the intended action. The key factors are speed, reliability, and precision. As robots become more intertwined in the human workspace, their nonverbal behaviors become social gestures, making body language and expressivity main considerations in the robot's design. In this paper, we discuss an artistic work illustrating expressive motions of two robotic arms engaged in the human milieu of competitive chess.

Unlike previous work on robot chess [19, 27, 31], we examine: (1) the way robots can employ nonverbal behaviors like movements and expressions to affect audience perception, and (2) the way two interacting robots shape perception of in-game strategies and intended play strategies of the audience.

Using two robotic arms interacting not only with the chess pieces but also with each other and with the public, we interpret their behaviors not in terms of efficiency, but rather in terms of body language, movements, and their ability to affect audience perception of game dynamics and narrative flow. This work applies the idea of machine-subject as art-subject to the interaction between machines, their environment, and their human counterparts [2].

2 BACKGROUND

The use of robotic systems for demonstrations of competitive play has previously focused on pitting human participants against autonomous robots in games like real time first-to-answer trivia [9], competitive sports [34], trust-based card games [5], and physically-based tabletop games like chess [19]. These systems attempt to fit robots into the ecosystem that humans created, as a companion or adversary as opposed to an independent general manipulator. They also show machines as inanimate entities whose role is to create the next move, as opposed to considering from the machine's perspective the type of emotional expressions that make them relatable to humans. Instead, we examine robot-robot interaction from a movement-gesture perspective, beginning with a look at the game of chess itself.

Chess has provided a playground for engineering problems, starting with the mechanical Turk constructed by Wolfgang von Kempelen, which nods to visually express its "emotion" when it checkmated. Chess-playing programs first used heuristic rules based on human player reaction. When IBM's Deep Blue team beat Garry Kasparov in 1997 [22], the gains were due to increased computing capacity and opening "book" knowledge. In the realm of Go, AlphaZero used a neural network approach repeatedly playing itself given the rules and goal states [29]. In chess, these advances have changed how top players train, for example learning how to defend positions previously considered lost [24].

More empathic interactions between humans and machines necessarily utilize nonverbal communication such as gestures, postures, and sounds, much as in human-human communication [20]. Instead of showing machines as technical specimens, this social robotics approach allows us to tell stories by evoking emotional response in audiences by interactively adapting the robot's response to the audience [7, 15]. In this vein, work has been done to convert the prosodic elements of human speech into arm gestures that provoke emotional response [1].

Nonverbal behaviors make up the majority of interpersonal communication [12]. Leveraging nonverbal communication in robots like movements and sound can facilitate human-like emotional communication [11]. In particular, humans can categorize and interpret simple arm and head movements of robots as one of the basic Ekman emotions [17]. When such human-like gestures are introduced into the robot movement, they significantly raise the perceived animacy of the robot and positive effect of the participant's emotional state compared to only robot-specific movements [23]. Appropriate robotic arm gestures also raise the extent to which they are anthropomorphized and lead to greater future contact intentions by human participants [25].

To go beyond human-robot adversarial games into nonverbal expressivity in multi-agent systems, it is necessary to investigate how robots can play with robots. Like humans in the classic Asch experiments, robot groups can lead participants to conform to suboptimal choices [26]. Robot groups can also ostracize human subjects by interacting amongst themselves in a collaborative game with humans [8]. This suggests that robot groups can behave like human groups to socially influence individuals. Robot group membership also affects human behavior. For example, humans choose robotic teammates based on previous experience, level of competition, and performance [6]. The level of coherence within a group of robots also affects human perception and willingness to interact with these machines [10].

How can robot-robot nonverbal behaviors be used to drive audience perception? One study showed that when one robot makes a request of another robot, using social behaviors as opposed to direct request increases the likeability of the requesting robot, indicating that robot-robot gestures affect our perception of their personality characteristics [33]. Recent work has used sounds associated with expressive movements to build robust nonverbal robot behaviors [3]. To study these nonverbal behaviors, video prototyping has been used to evaluate human responses and effectiveness of particular gestures without in-person testing [4, 35].

3 TECHNICAL IMPLEMENTATION

Installation of the work involves nonverbal behaviors of the robot arms, movement with sound, and interaction between two robots, which are driven by the chess engine in real-time. On the software level, the two arms (uFactory xArm 5) and the sound system are connected to a macOS with the chess engine developed with python 3 scripts and Stockfish13. Game status, the movement of a chess piece, and robot's internal evaluation of possible lines are sonified

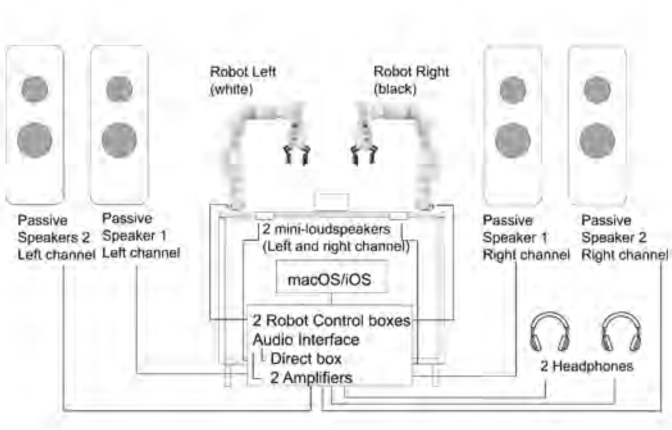


Figure 2: Installation overview. A chessboard is centerd at the tabletop. The left robot plays white and the right robot plays black. A chess clock is placed at the right-hand side of the black player. The distance between a robot and the nearest chessboard edge is 123 mm. Two mini-loudspeakers are embedded into the table in front of each robot. Four loudspeakers are placed further away in a quadraphonic setup. Headphones reproduce the same surround sound.

with a program written in Max (Cycling 74 & Ableton), receiving real-time data from the chess engine over OSC.

On the hardware side, two sets of speakers and two headphones are directly connected to a macOS through an audio interface PreSonus Studio 1824c, while a MCD2 Pro Direct Box is needed to transmit two audio channels from the audio interface to two mini-loudspeakers. The grippers' fingertips are extended to 80mm long. Scripts are modified based on its control GUI app and API. Signals are sent to Max msp for sound generation in real-time.

The custom chess engine utilizes the neural network (NNUE) [21] in Stockfish13 for quick position evaluations. Compared to chess engines relying on linear methods like Monte Carlo Tree Search (MCTS), NNUE recognizes winning patterns without searching through all possibilities. This CPU-based architecture enables the program to run without requiring an independent GPU for real-time match evaluation. The evaluations and ply expectation in different depths are computed simultaneously and used for motion and sound generation, in order to visualize and sonify the thinking process. The chess engine uses the latest Chess960, allowing all self-defined rules and starting conditions.

3.1 ROBOT MOVEMENT

Two 5-axis robot arms, xArm Lite 5 (uFactory, Shenzhen, China), along with xArm Grippers are used in this project. The built-in software for robotic movement, xArm Studio, is re-programmed for designing nonverbal behaviors not only with the other robot, but also with the audience. Human-to-human chess playing video footage, video game character's animations and robot-based cartoons are used for visual and movement reference during motion design. Unlike human and biped robots, they are base-fixed, referencing movement with pace and angle adjusted to fit the physical limitation.

The robotic arm expresses its movement mainly before and after moving a chess piece (Figure 3 left). For example, a "thinking" gesture we term Deliberation is sometimes played before deciding a chess move. The arm will lower its head perpendicular to the chess board and move horizontally indicating a scanning and thinking process. This explicitly shows a thinking process of a chess player doubting with her hand before deciding a move. Another example would be the "your turn!" gesture we term HeadUp after moving a piece of chess indicating the arm is provoking the opponent with confidence. After finishing a chess move, the head of the arm will tilt up quickly to create an up-nod gesture, showing this robot's confidence.

3.2 Robot sounds

Sonification is the translation of non-verbal data into sound [13] with functional or aesthetic goals [18]. The sonified aspects are the game status, robot moving a piece, and robot internal evaluation. The game of chess is a mental structure that develops in time, which we show using looped real-time musical structures representing present configuration of the pieces on the board. When the robot releases a moved piece, the musical pattern is updated.

The physical move itself is sonified with a reverberant sound that draws attention to the robot's gesture. The internal evaluation depends on the chess engine's analyzed sequence of possible moves, called a "line." Top human players who stream their games reveal their thought process by "thinking aloud," and by "banter" (telling

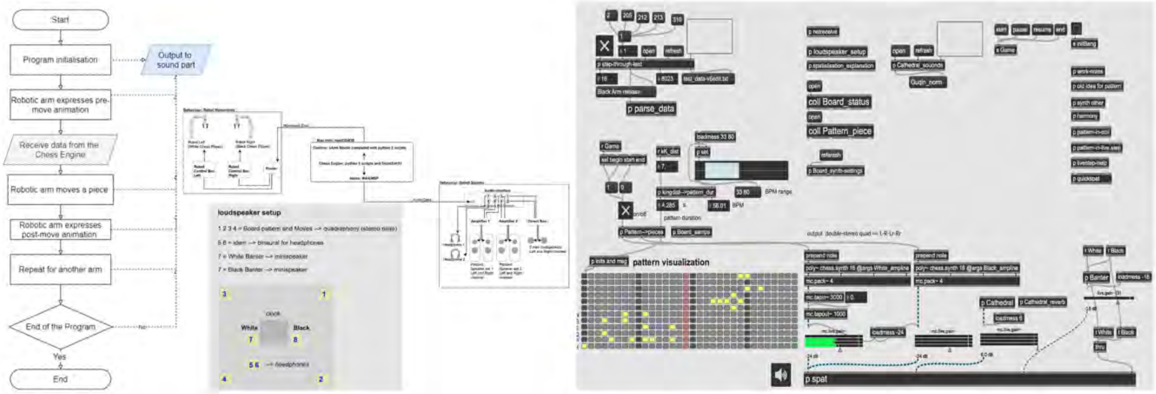


Figure 3: An overview of the system. The build includes two parts: "Robotic Arm" and "Sound". Customized python 3 scripts and chess engines (Stockfish) are used in the former part while the latter part is Max msp. Data generated from "Robotic Arm" are passed to "Sound" by OSC in real-time. Audio output from the sonification patcher (Lower middle). Note the quadraphonic "surround" sound to four loudspeakers. The same signal is also specialized to binaural surround for listening on headphones.

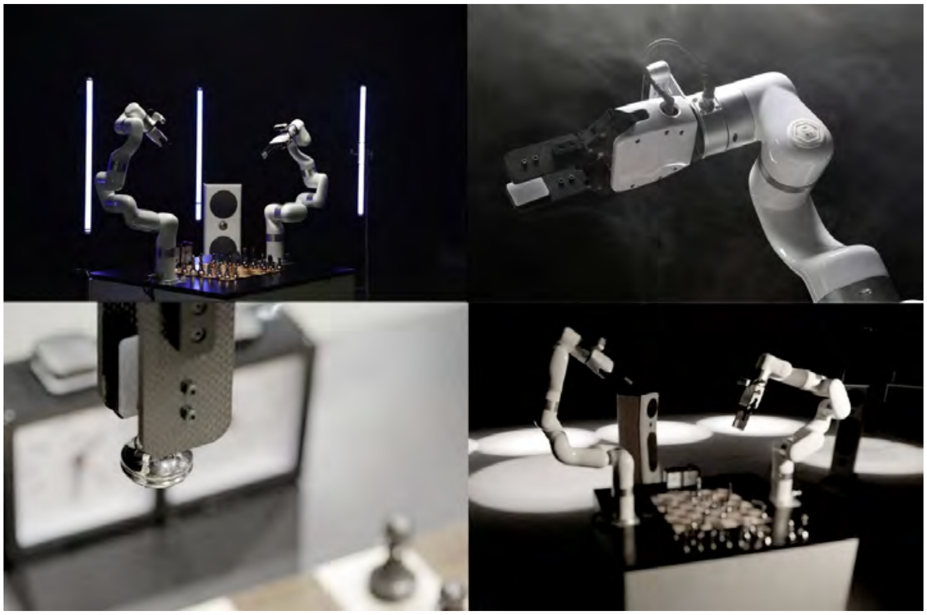


Figure 4: Power Chess (2021) completed system including the sound (upper left speakers), gripper specific for our chess pieces (lower left), 5-axis arm system (upper right), and presentation in dramatic form with chess board in a theatrical setting (lower right).

jokes and teasing). Here, we give each robot a voice that sonifies the lines that it considers before making move decisions.

4 EVALUATION METHODS

Due to social distancing restrictions, we adopted a video prototyping strategy [32, 35] to study audience perception of single robot movements, as well as game play dynamics in robot-robot interaction.

4.1 Single-Gesture Study

We used an online survey to collect participant perception of singular robotic arm gestures without the necessary context of chess. Participants were recruited via the Prolific platform and paid for their participation (n=33, 22 female). They were shown 11 GIFs looping the following designed movements 3 times each (Figure 5): HeadTilt (head of the arm moves up and down as in a nod), HeadUp (head moves upward like arrogant confidence), Breathing (small movement of the entire frame forward and backward at approximately 15 cycles per minute), HeadTurn (turning of the head of the arm to around 45 degrees clockwise then counterclockwise), Wiggling (tilting entire body side to side as in shifting weight), Bow (lowering the head of the arm in front of the other robot), Standing (straighten up entire robot body, Alert (at standing position perform HeadTurn towards audience), Confirm (look towards the other robot eye to eye after looking down at the board), Deliberation (move back and forward observing the board), and Hesitation (turn its head at 45 degree angles while staring down at the board).

Participants were asked to rank the gestures in terms of Expressiveness, Friendliness, Curiosity, Aggressiveness, Thoughtfulness, and Decisiveness on a 1-7 Likert scale. They were also asked "what do you think this gesture is trying to communicate?," the result of which is qualitatively coded post hoc into categories to summarize how participants perceive the shown gestures. The results were processed and analyzed in R and RStudio with the likert, dplyr, ComlexHeatMap, and dunn.test libraries.

4.2 ROBOT-ROBOT GAME PLAY STUDY

A study was conducted to explore participants' perception of robot-robot interaction and their influence on chess game play via an online survey. Participants were also recruited via Prolific (n=36, 18 female, 1 nonbinary). They were given a series of four videos which together show a continuous play through part of an entire chess game between the two robots (total approx 10 minutes). After each section, subjects were asked to describe how each robot appear to behave towards the other, to infer each robot's playing style, to narrate what is happening between the robots, to describe what strategy of play the subjects themselves would take if they were playing against each particular robot, and to describe the movements they find most salient in the video. Each video showed a segment of game play including periodic gestures by the arms, showing a top view indicating the chess piece positions, and a side view showing two robots engaged in synchronized play.

Responses were coded into categories to analyze participants' perceptions of playstyle and how participants would respond to such playstyle if they played against each robot arm. Robot's playstyle evaluated by participants were grouped into 9 categories: Aggressive, Careful, Casual, Competitive, Defensive, Experienced, Passive (not reactive), and Strategic. Robot's perceived behavior towards the other robot is grouped into: Aggressive, Calm, Casual, Cautious, Confident, Counter(wait for a counter), Defensive, Pretend (to be passive but really actually aggressive or setting traps for example), and Passive. Human intended strategies against the Robot was coded into: Aggressive, Competitive, Casual, Cautious, Counter, Situational (depending on the context), Foresight (planned ahead future moves), Defensive, Pretend, and Passive. Results are coded by two naive coders, with Cohen's Kappa Coefficient (k) calculated to ensure reliability.

4.3 Arm vs body perception

To study whether the robot is perceived as an arm or as a body, participants (n=25, 16 female) were asked: 1. An indirect question with two categories (acting as Head vs acting as a Hand) to assess what they think the robot would be likely to do, and 2. a direct question asking them to rate robot interpretation (Hand vs. Head and Arm vs. Body) using a likert scale. Participants were asked to provide the moment they thought the robots were perceived as arm vs. body.

5 RESULTS

5.1 SINGLE-ROBOTIC GESTURES

To examine how each perceptual dimension was rated differently for each robotic movement gesture, we ran a one-way Kruskal Wallis test for each perceptual dimension (n=33) followed by post hoc comparisons using Bonferroni corrected Dunn's Test. Individual movements were all rated as highly expressive, with the exception of HeadTilt (Kruskal p=0.006985), which was significantly less expressive than Bow and Standing (Dunn). Friendliness for each gesture was rated significantly differently (Kruskal p<0.0001), with high ratings particularly for Breathing, HeadUp, HeadTilt, HeadTurn, and Bow (Dunn). Curiosity was also quite different (Kruskal–Wallis test by ranks, p < 0.0001), with HeadTurn particularly high compared to other gestures (Dunn), perhaps due to turning of the head a movement associated with inquisitiveness. Aggressiveness was different across the groups (Kruskal p<0.0001), with Standing and Confirm significantly higher than the rest posthoc (Dunn), perhaps due to their explosive nature crossing typical movement boundaries in front and above the robot. Thoughtfulness was significantly different (Kruskal p=0.004107) due to Deliberation being interpreted as robot thinking (Dunn). Decisiveness was also rated differently across groups (Kruskal p=0.000923), with Standing as the main high-scoring gesture (Dunn). Summary of these points can be seen in the averaged median ratings across each group of movements and dimensions, scaled for every gesture (column) (Figure 6).

Looking at the Likert plots, we find that Standing is rated as a more extreme (aggressive) version of Confirm and Alert, as seen in the shifting of all ratings towards higher values. Similarly, Deliberation is an extreme version of Hesitation, and HeadTurn appears to score similarly to Breathing, but a bit more evocative. Wiggling appears to score across the dimensions similarly to Bow.

Based on the qualitative data, gestures involving simple head movement of nod (e.g. HeadTurn, HeadTilt) were more likely to be perceived as a sign of affirmation. Wiggling and Standing were perceived as "taunting" more frequently compared to any other gestures. Phrases like "mocking", "Show off", and "aggression" were used to describe why the Wiggling gesture makes them feel like taunting. Some descriptions were also found in the group of Standing. Both Alert gestures and Confirm were found to be the most "Unclear" gestures. However, the second perception of them was expressing "taunting" for Alert and "confusion" for Confirm. Without proper context, complex single robotic gestures appear difficult for participants to understand. Breathing was identified as a status of being "Idle" while waiting for orders or doing calculations. 40% of the participants recognized the "Bow" gestures and described it as a form of sending a message such as "respect." Over 60% of the participants rated HeadTilt and HeadTurn as the most friendly gestures. HeadTilt and Hesitation are the least expressive, while Wiggling and Bow appear to be the most expressive at over 80%. Example of the coded responses to how participants are perceiving the gestures is in Figure 7

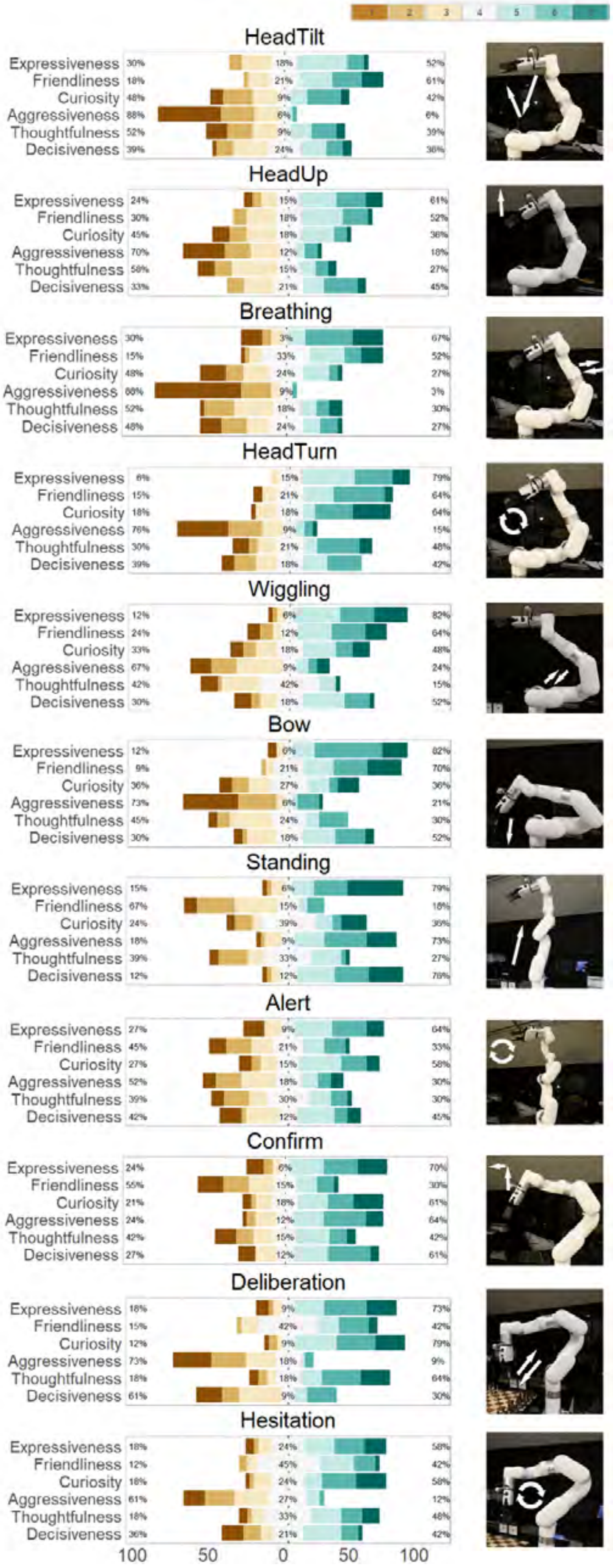


Figure 5: Individual robotic movements as interpreted by human participants by Likert scale rating (n=33). Videos are presented as looping animations to subjects in an online survey asking to assay each dimension.

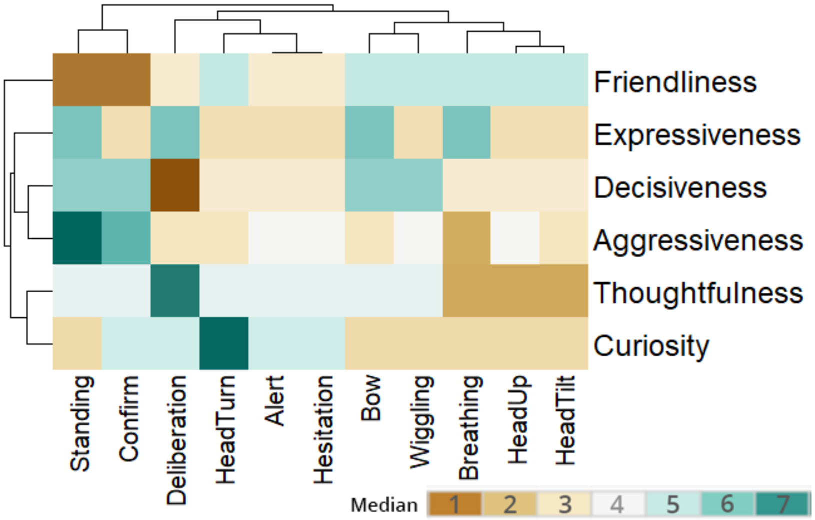


Figure 6: Summary of robotic movement perceptions on scales of expressiveness, friendliness, decisiveness, curiosity, thoughtfulness, and aggressiveness (Likert 1-7). Shown are scaled median scores across all subjects for each perceptual dimension (y-axis) and movement gesture (x-axis).

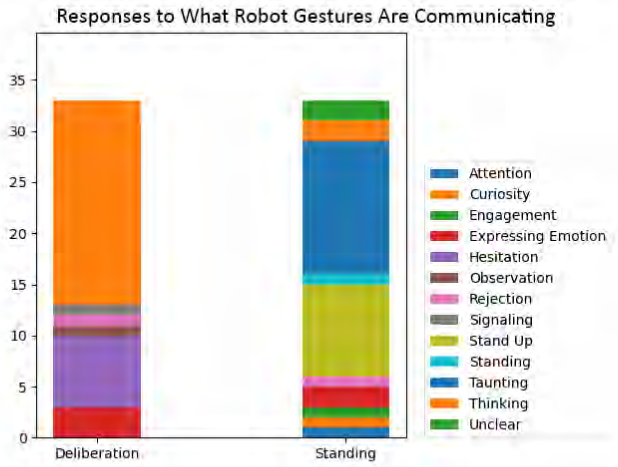


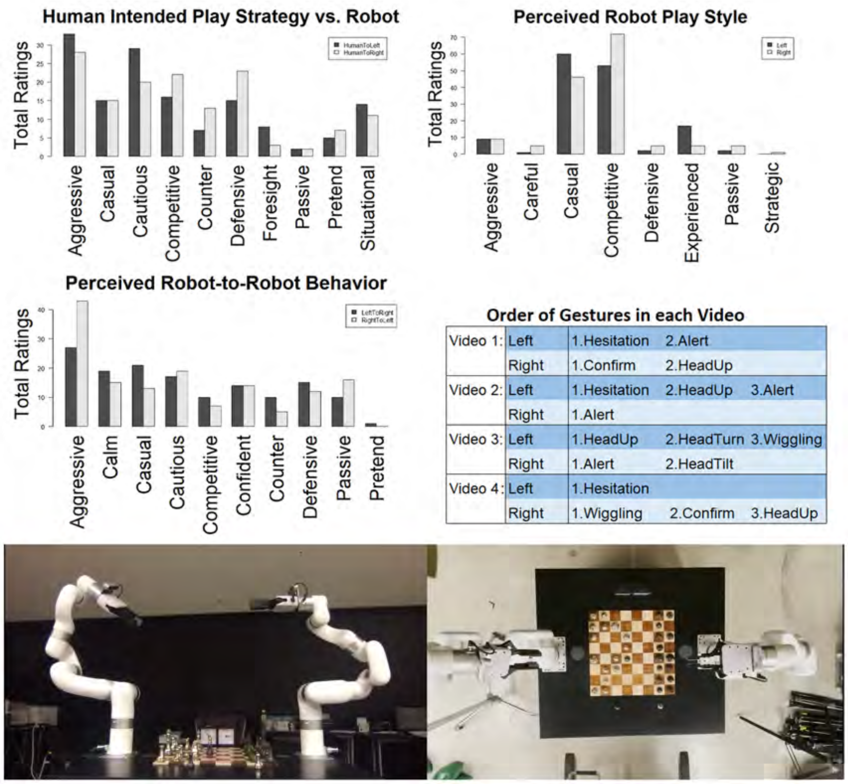
Figure 7: Coded responses to what the machines are communicating for the Standing and Deliberation gestures. Note that Deliberation is consistent with ratings of thoughtfulness, while Standing is perceived as highly aggressive, as seen in the rating section of the survey.

5.2 ROBOT-ROBOT INTERACTION

While single robot gestures can inform us of how audiences perceive movements in isolation, they don't provide data on how robot-robot interactions lead to a perception of game play dynamics and the relationship between the two robot arms. Qualitative coding of audience survey responses to videos of sessions of chess play between the robots show that the description of "competitive" was used the most frequently among all responses. Comparing the right arm and the left arm, right arm was interpreted as more aggressive and competitive than the left. Left arm was perceived as "experienced" with a "defensive" or "counter" playstyle. Indeed, the video game play showed the right arm doing aggressive gestures like Confirm more frequently, and the left arm performing Curious and Thoughtful gestures like Hesitation more (Figure 8), a la the Single-gesture study.

Coded answers (k=0.6318) to the questions reveal intricate relationships between perception of robot behavior and the game play dynamics. Significant difference was found between the right and left robot in perceived playing style ($x2$ test df=7, p=0.01461), with humans appearing to rate the right robot as more competitive and aggressive (Figure 8). This theme of the aggressive right robot and thoughtful left robot can be seen in the perceived rating of how left arm behaves towards the right arm vs. how right arm behaves towards the left arm though the aggregated robot-robot perceptions were not significant ($x2$ test df=9, p=0.2733). The right arm was perceived as behaving aggressively against the left arm, while the thoughtful left arm was deemed calm yet casual. The play strategies that humans would adopt against each robot did not differ ($x2$ test df=9, p=0.3959), but results indicate that participants wanted to adopt defensive strategies against the aggressive right robot and use foresight and planning against the calmer and strategic left robot (Figure 8). While some individuals wanted to adopt aggressive strategies towards either robot, a differential number of participants adopted defensive strategies against the aggressive right robot and cautious strategies against the thoughtful left robot. Thus the participants not only picked up on the different personalities of the left and right arm, but appeared to show some manner of different planned strategies for the game play based on those different perceptions.

Qualitative results emerge from other questions in our paradigm. For example, when asked about the play strategy, one participant



Video 1:	Left	1.Hesitation	2.Alert	
	Right	1.Confirm	2.HeadUp	
Video 2:	Left	1.Hesitation	2.HeadUp	3.Alert
	Right	1.Alert		
Video 3:	Left	1.HeadUp	2.HeadTurn	3.Wiggling
	Right	1.Alert	2.HeadTilt	
Video 4:	Left	1.Hesitation		
	Right	1.Wiggling	2.Confirm	3.HeadUp

Figure 8: Human perception of Robot-Robot interaction during continuous chess game play. Human interpretation of the playing style of a particular robot (upper left). Human interpretation of how one robot behaves towards the other (upper right). Human intended chess play strategy towards each robot (center left). List of gestures employed by each robot during game play (center right). Example of video shown to participants showing top/side view (bottom).

specifically stated a strategy of tricking the robot: "*I would be assertive and aggressive also, but I would first let the right robot think that I was being casual and friendly.*" Similar answers also mentioned robots could be trapped or fooled if actions were done correctly. This implies an understanding of the personality of the right robot, and then planning to address that personality by a specific play strategy. When asked to describe the game, they provide the setting as well as the perception of the expressions of the arms: "*It is a casual game of chess, but one robot is more competitive than the other.*" Interestingly, different participants focus on different aspects of the experience, not just the aggressive right arm, but rather examine their moves as part of the perceptual experience: "*the left robot seems to be watching the moves played by the right robot, and then responding accordingly.*"

People also read a lot into the robots' movements, ascribing to them human characteristics, stating in their responses that "*the right robot is playing assertively and quickly, decisively. The left robot is more unsure, moving slowly and is visibly distressed,*" and "*the left robot seems to straighten its body all the way, in a way to taunt the right robot,*" and "*its kinda like the left is an older one and the right is a young one.*" These interpretations border on storytelling: "*battle of wits, matching two strategies of counter attack and laying traps to find out who will be victorious*" and "*The Overly confident Left Robot meets the Silent Killer Right Robot*" and "*two lover robots love to engage with each other in all ways, competitively and playfully, these to like each other and they like to have a little fun without hurting each others feelings*" and "*Left had it all under control but now Right is on the top his game,*" and finally, the absurdist vent of "*two robots playing chess, but they aren't really getting anywhere.*" These comments reflect the willingness to ascribe human intentions to not only the movement-based gestures of the robots but also to the different styles of moves in the game the robots are making.

5.3 Arm vs Body Interpretation

For the indirect question, participants were asked to select which gesture is most likely undertaken by the robot as seen: "nodding to incoming visitors depending if it's the right arrival terminal" and "looking around the room for an intruder as museum security" as Head and "catching a fish by scooping it out of the water" and "throwing a ball to the catcher at a baseball game" as Hand. The idea here is to allow participants to more casually evaluate a hypothetical context for the robots instead of affecting their direct judgment. When asked this way, a binomial test showed significant difference (p=0.01463) in how participants perceived robots in the video as a head (19) vs a hand (6).

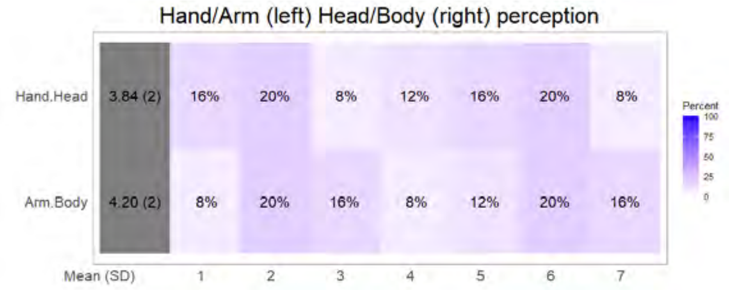


Figure 9: Likert scale ratings of human perception on Head vs Hand and Arm vs Body as direct question. 1 indicates separately Hand and Arm interpretations. 7 on scale indicates Head and Body interpretations.

Participants repeatedly referred to “Picking”, “Moving”, and “Tapping” combining with chess movements if they were asked what gesture made them think of the robots acting as an arm. In comparison with the arm interpretation, the majority of the participants took grip movements such as HeadTilt and HeadTurn as the sign of robots acting like a head with a body. One participant described the grip of both robots as “Bird Head” because the robot’s movements reminded him how birds act in real life. Head movements involving shaking, tilting, and nodding seemed to increase participants’ perception of taking robots as a body instead of an arm. There were also participants who pointed out that when the robots were executing the “Confirm” gesture, they sensed a mocking message was sent to the other robot.

6 DISCUSSION

Power Chess is a study of the human interpretation surrounding robots that not only compete in a game, but produce nonverbal behaviors like gestures and movements that tell a story about their interaction. While the game itself may have different rule sets played slow or fast, complex or simplistic, the sonic and movement designs still function by appealing to human instincts for assigning humanness to animate devices [14, 30]. We measured the way individual robots were perceived by naive observers, and also the way the robots’ interaction with other robot affects the way the activity they are engaged in is perceived by the audience, shifting the way audiences imagine stories about the robots and their own intended strategies if they were competing in the play.

While we have begun to examine the influence of Robot-Robot interactions on the way we perceive and interact with them, many questions remain to be explored. In our study, we focused on audience interpretation of the robots’ own interaction with each other, ascribing strategies and narratives to their actions that led to the human’s own modification of intended behaviors, we did not explore what would happen when the robot interacts with the audience. For example, what if the robots exclude us from the game [8], or cheat together and against us [28]? What properties of the robot gestures and sound can contribute to our reaction to the coordinated influence? The social influence of multiple-robot systems will rely on norms, appearances, and likeability, none of which we varied in our two robot arms for this study. An artistic perspective can investigate these complex questions within the context of audiences.

Beyond the technical challenge of developing behavioral expressivity adapted to a specific game, the original artistic objective of the Power Chess was to interrogate the logic of social conflicts in the current socio-political crises. The chess game provides a micro space-time model of social conflict. The variant rule sets allow the gameplay to serve as a model for tactical approaches to conflicts, via the distribution of pieces and respective power of these pieces. For example, in the “Power vs Number” variant developed, we leave one side with all 32 pieces (but limited to pawn’s moves – only one step) and the other with only 16 pieces (but can all move like Queens – all directions). This rule set is a class struggle: only certain people have stronger power. Another variant is “Gender Equality,” where the King acquires the power of the Queen. The “You Matter” variant delays the take of the opponent during one round, giving more time to deliberate.

In our workflow, we became aware of the similarity between animating a robotic arm to make it more expressive and creating animation, such as humanized animals (Disney) with anthropomorphic behaviors, and humanized objects like toys (Toy Story, Lasseter, J.), but industrial robots are usually dedicated to highly specific tasks that don’t take into consideration human-robot or robot-robot dialogue. The animation process itself may mimic traditional practices like key-framing (step by step predefined animation), motion-tracking (pre-recorded human movement to be interpreted by the robot as a skeleton animation, puppeteer animation (real-time human-driven guiding), or processual animation (a behavioral design that generates sequential motions based on algorithmic processes). When the end effector is a grip, its practical function become different from its symbolic-expressive function. When the arm moves a chess piece, the end effector becomes the human hand. When the arm breathes, nodes, or expresses curiosity, surprise, provocation, pride, the effector becomes a head. As a metaphor, the robot switches from a human arm to a snake, since animals with no hands use their mouth to grip things. We observed then that we were using the end-effector-hand to make robots communicate through the game, and the end-effector-head when they express themselves to the public.

7 CONCLUSIONS

This research led us to the conclusion that apparently indirect functional actions by a robot may play an important role in the quality of human-machine social interactions. Their nonverbal behaviors contribute to the way we interpret their fictional personality, and engage us in a narrative surrounding their actions, changing our perception of the activities they may be engaged in. Further studies will reveal the importance of humanized behavior, through complex nonverbal and even nonfunctional actions. Robots are becoming part of the human environment (see: domestic robots, AI assistants). Artworks provide a context for experimenting with human-machine social interaction without the constraints of purely functional work. In particular, we can naturalistically can ask people to describe their interpretations of events, yielding qualitative insights that allude strictly scientific investigation.

With machines increasing their computing capacities, evolution leads to interactions that include an expressive dimension, conveying the artificial intentionality desired by their designers. Logical intelligence gives way to emotional intelligence as part of the language of machine communication, promulgating richer modalities of agency based on divergence-convergence feedback loops. Classic game models like chess serve as case studies for improving machine perception, interpretation, decision, action... and manipulation. We may soon have robotic players expressing themselves beyond the usual poker face, so unnatural and challenging for humans, but so normal and expected for machines.

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