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Equipping the Baxter Robot with Human-Inspired Hand-Clapping Skills

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***Abstract*— Human friends and teammates commonly connect through handshakes, high fives, fist bumps, and other forms of hand-to-hand contact. As robots enter everyday human spaces, they will have the opportunity to join in such physical interactions, but few current robots are intended to touch humans. To begin investigating this topic, we sought to discover precisely how robots should move and react in hand-clapping games, which we define as interactions involving repeated hand-to-hand contacts between two agents. We conducted an experiment to observe seven pairs of people performing a variety of hand-clapping activities. Their recorded hand movements were accurately described by sinusoids that have a constant participant-specific maximum velocity across clapping tempos. Behaviorally, people struggled most with hand clapping at fast tempos, but they also smiled and laughed most often during fast trials. We used the human-human experiment findings to select, modify, and program a Rethink Robotics Baxter Research Robot to clap hands with a human partner. Preliminary tests have demonstrated that this robot can move like our participants and reliably detect human hand impacts through its wrist-mounted accelerometers, thereby exhibiting promise as a safe and engaging interaction partner.**

I. INTRODUCTION

Social robots that physically contact humans hold great potential for emotional connection and engagement. Both social robotics and physical human-robot interaction (pHRI) are well established fields of human-robot interaction (HRI). Their intersection, social-physical human-robot interaction (spHRI), will let us leverage the crucial sense of touch in social scenarios. We chose simple hand-clapping games as an initial focus for our novel investigations of robots as social-physical agents. Here, the term "hand-clapping" refers to tempo-matching hand-to-hand contacts between two agents. In everyday spaces, it is easy to find people playing hand-clapping games on the playground, in ice-breaker activities, in cultural oral traditions, and to combat boredom in passing time. Accordingly, we believe that a mastery of hand clapping will outfit social-physical robots with a potentially useful tool for similar scenarios that range from getting to know students in a classroom setting to keeping older adults active in their homes.

After discussing related work (Section II), this paper describes how we developed a capable robotic system for hand-clapping HRI applications by carefully observing human-human interactions (Section III), analyzing results with robot design in mind (Section IV), and implementing our findings on Rethink Robotics's Baxter Research Robot (Section V). We will leverage the resulting robotic system to run user studies that will help answer questions in the space of spHRI. Through this work, we aim to help shape design processes for socially relevant pHRI involving joint action.

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II. RELATED WORK

Our work sits at the intersection of social robotics and pHRI. The field of social robotics studies robots in social scenarios, usually without having the robot contact human participants [1]. Within this field, the subtopic of socially assistive robotics leverages unique robot strengths in areas such as education and healthcare [2], the main two target environments for our investigation. In contrast, pHRI is focused more on interaction safety issues than social design [3]. pHRI might also be used to help a robot stay safe while navigating an unknown environment [4]. Less frequent investigations of pHRI consider social applications like subjective human responses to a robot's touch [5]. Experiments at this social-physical intersection, such as our work and the following related topics, will elucidate how people perceive and how we can appropriately apply spHRI.

Haptic Subfield of Social Robotics and pHRI: We are energized by prior research that combines social robotics and pHRI because touch is an essential pathway for human connection and emotion [6]. In particular, physical interaction with the hands greatly aids human understanding and serves as a channel for complex sensation and expression [7]. A few instances of spHRI appear in the haptics literature. The Haptic Creature Project, for example, explores an expressively actuated robotic companion that humans can physically contact [8]. Haptic feedback has also been leveraged to explore the subjective and objective results of physical human-robot collaboration [9], [10]. Our work explores a new area of haptic spHRI.

Inspiration from Haptic Teamwork: Further aspects of our hand-clapping robot research draw on the area of social motor coordination (also commonly known as joint action). This area is being actively explored not only in HRI, but also in human-human interaction research [11]. One research space similar to our human-human experiment is the investigation of human-human joint action through hand-to-hand contact in video games and workplace social interaction [12], [13]. Similarly, our inspiration for a jointly-acting hand-clapping robot is the popular PR2 demo entitled "Please ~~do not~~ touch the robot," during which people are able to high five, fist bump, and hug the Willow Garage PR2 robot [14].

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Precedents in Haptic spHRI: Other areas of spHRI shaping our current and future work include human-robot play, handshakes, and object passing. Investigations of robot play activities like hugging [15], dancing [16], and performing magic [17] inform our interaction design and analysis strategies. Studies of human-robot handshakes have illustrated a way to model human haptic behaviors [18] and shape human-like robotic handshake algorithms [19]. Human-robot handover experiments have found that robots equipped with basic sensing can execute successful joint action [20] and robots that move in a human-like way are most effective in this type of interaction [21]. These play, handshake, and handover investigations influenced how we processed data and designed motion in our work.

III. Human-Human Experiment Methods

We conducted an experiment studying human-human interactions to inform the design of our hand-clapping robotic system. Here, we were especially interested in encapsulating typical human *hand trajectories*, understanding how *acceleration features* relate to hand trajectories, and generally discovering what items qualify as *key aspects of hand clapping*. Accordingly, we gathered quantitive data about the movement of participants' hands during hand-clapping interactions as well as qualitative survey responses and behavioral reactions. Past studies have similarly used human movement to design robot behavior for ballroom dancing [16], shaking hands [18], object passing [20], [21], and manipulating objects together [9]. The Penn IRB approved all experimental procedures under protocol 818801. Fourteen participants between 22 and 48 years of age enrolled in our study, gave informed consent, and successfully completed the experiment.

A. Experiment Setup

Each randomly selected pair of participants came to the lab for a single sitting that lasted about 30 minutes. As shown in Fig. 1, the back center of one participant's left hand and one participant's right hand was outfitted with a magnetic tracking sensor (Ascension trakSTAR 3D Model 180 6DOF) and a three-axis accelerometer breakout board (Sparkfun MMA7361). The experiment activities involved only the instrumented hands. Because all but one of the enrolled participants were right handed, we randomized which hand to outfit with sensors.

B. Experiment Phases

This experiment centered on palm-to-palm hand-clapping motions executed repeatedly, in the style of hand-clapping games. We chose to examine only this one type of hand-clapping motion to decrease the likelihood of errors in hand clapping execution and increase the participants' ability to focus on synchronization with their partner. The specific experiment trial tasks were designed to explore human *engagement* and *challenge* during different gameplay tempos and tempo changes. An understanding of these topics could enhance human-robot gameplay and also inform other human-robot collaboration design.

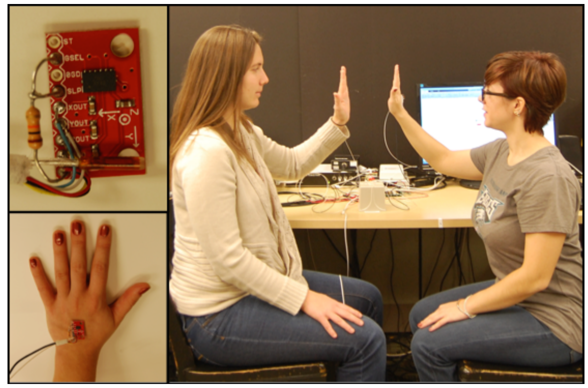

Fig. 1. The experiment setup. Upper left: closeup view of sensors. Lower left: sensors mounted to a participant's hand. Right: participants sitting face-to-face and hand clapping with opposite hands.

Hand-clapping cues (target tempos or tempo changes) were presented to the participants either through headphones or via cues written on index cards, as indicated in the phase descriptions below. The experimenter specified a hand-clapping task in each trial and asked the participants to carry out this task for data recording. We asked participants to rest briefly after each recording, to move and interact in as natural a manner as possible, and to communicate the tempo through haptic information only (not by verbal description, hand gestures, foot tapping, etc.) The three phases of the experiment increased in difficulty as follows:

- **Phase 1:** Five hand-clapping trials. Both participants could hear a target (randomly ordered) hand-clapping tempo stimulus (60, 110, 160, 210, or 260 beats per minute (BPM)) and attempted to clap hands at that tempo for 20 seconds.
- **Phase 2:** Ten hand-clapping trials. During each trial, only one of the participants could hear the target (randomly ordered) hand-clapping tempo stimulus (60, 110, 160, 210, or 260 BPM). The participant listening to the tempo led the other participant in making contact at that tempo for 20 seconds. Each participant had opportunities to be the tempo leader, and the randomized selection of the tempo leader was balanced between the participants.
- **Phase 3:** Eight hand-clapping trials. During each trial, one participant saw a written cue to speed up, slow down, or remain at a constant tempo and led the other participant in that activity for 20 seconds. Each participant had opportunities to be the tempo leader, and tempo leader selection was randomized and balanced.

Because we explore only constant tempo hand-clapping interaction in our initial Baxter investigations, the findings discussed throughout this paper draw mostly from Phases 1 and 2. We plan to use Phase 3 data when we endow Baxter with the ability to adapt to a human's gameplay tempo.

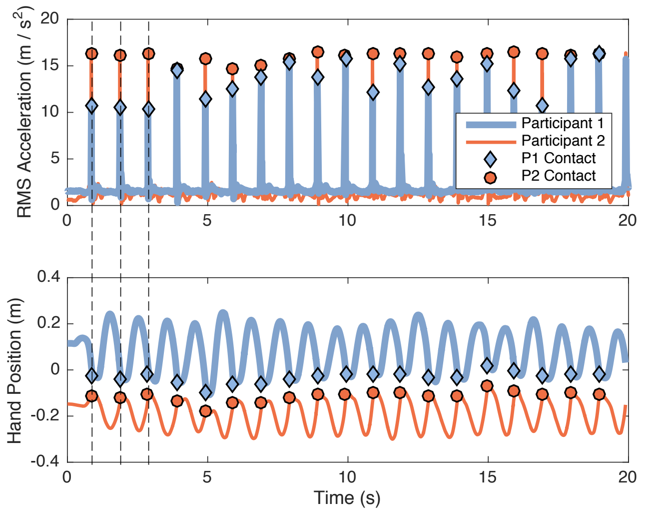

Fig. 2. Sample plot of acceleration and position recordings in the human-human experiment, with acceleration peaks and corresponding hand contact locations labeled. The three dashed lines emphasize that the acceleration peaks coincide with the location of hand contact.

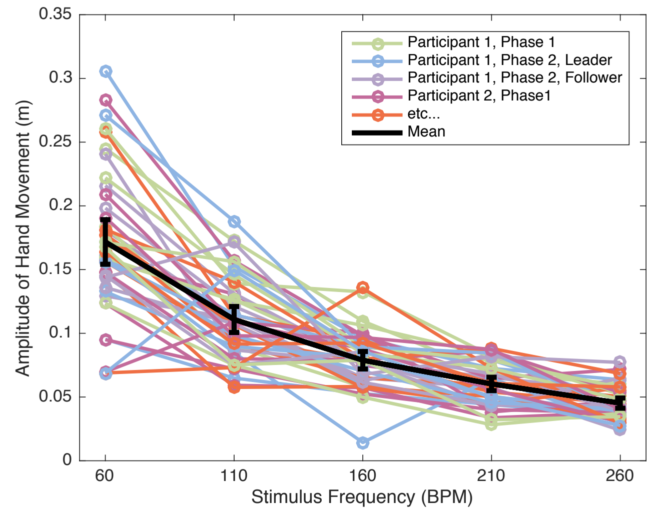

Fig. 3. Amplitude vs. frequency relationship for participant hand movement during Phases 1 and 2 of the experiment. The error bars represent a 95% confidence interval of the population mean. Colored lines show three amplitude measurements for each participant: Phase 1, Phase 2 leader, and Phase 2 follower.

C. Data Collection

We recorded 20 seconds of position tracker and accelerometer data for each mentioned experiment trial and gave participants three types of surveys: (1) a single-question Likert tempo rating survey after each trial of the first experiment phase, (2) a Likert and free-response concluding survey after the final trial of the experiment, and (3) a basic demographic survey after the concluding survey. All Likert-type questions used seven-point scales. The concluding survey was designed to capture participant reactions to the experiment and evaluate the difficulty level of the experiment using questions based on the NASA Task Load Index (TLX). The experiment was also videotaped to enable subsequent analysis of the participants' reactions throughout the experiment, especially smiling, laughter, and failures during a trial.

IV. Human-Human Experiment Findings

Analysis of the human-human interaction data yielded useful insights on the design of *engaging activities* for a hand-clapping robot with human-inspired *end-effector trajectories*, hand-clapping *impact detection*, and *state machine behaviors*. We break down the most relevant design insights into notable findings from motions, surveys, and behaviors. As discussed in Section V, the results of this study led us to select a robot platform and implement informed hardware and software modifications toward making it a safe and engaging hand-clapping partner.

A. Motion Results

Our analysis of recorded hand position and acceleration data sought to identify suitable robot *motion trajectories* and *contact detection logic* for hand-clapping games. An initial review of this data revealed that participants moved primarily in the y-direction of the magnetic position tracker's reference frame, which was parallel to the z-axes of the accelerometers. Participants' hands underwent little rotation about any axis. Accordingly, the position analysis in this paper focuses on movement only in the tracker's y-direction. The effects of gravity were removed from the accelerometer data by subtracting the mean acceleration value from the accelerometer readings in the vertical direction. We then calculated the root mean square (RMS) of the remaining acceleration vector at each time step. Figure 2 displays a sample trial recording after this initial processing.

Overall Trajectory Fitting: One of our key experiment goals was to identify a suitable waveform to describe the participants' hand motions. After considering several periodic and kinematically-inspired models that could explain the hand motion, we selected a few top contenders that closely resembled recorded data shapes, represented hand movements easily reproduced by a robot, and were unlikely to overfit: a triangular waveform model representing a constant speed motion, a piecewise parabolic model representing a constant acceleration motion, and a sinusoidal model representing the periodic oscillation of a simple harmonic oscillator.

To select the most representative model, we fit these models to each participant's motion in the Phase 1 and Phase 2 recordings. The sinusoidal model had the lowest average root mean squared error (RMSE) and also the best fit for over 90% of all Phase 1 and Phase 2 motion recordings. Accordingly, a sinusoidal hand motion model was our top choice for representing typical human hand movement.

Participant-Specific Amplitude Fitting: Figure 3 illustrates another clear relationship seen in the Phase 1 and Phase 2 data recordings and experiment video footage: a negative correlation between hand-clapping tempo and amplitude of hand movement. In the interest of adapting our hand motion model to reflect this trend, we created three versions of the sinusoidal model. Each version had a constant participant-specific maximum position, velocity, or acceleration parameter that we could tune to select the best model fit across all trials for a given individual. The models yield the following

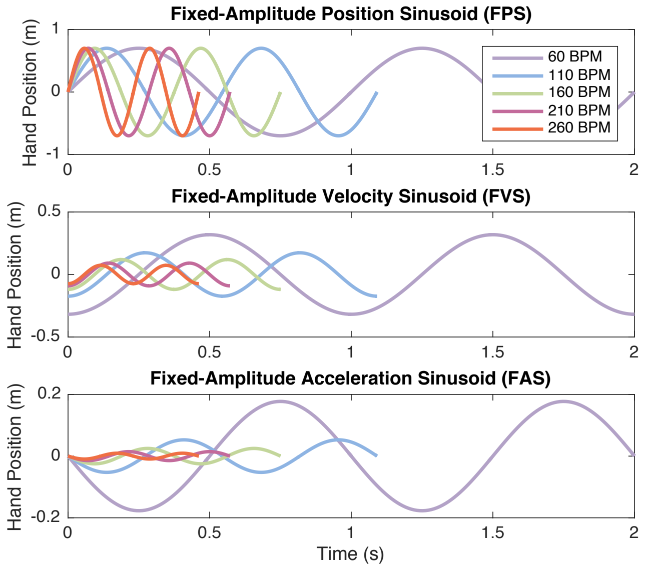

Fig. 4. Illustrative trajectories at the experiment stimulus frequencies for the three proposed sinusoidal human hand motion models.

relationships between hand-clapping frequency and the amplitude of hand movement, using variables for peak-to-peak amplitude (A), position (y), velocity (v), acceleration (a), and temporal frequency of hand contacts in Hz (f):

- Fixed-Amplitude Position Sinusoid (FPS) model using a position amplitude y_{fixed} as the parameter:

$$A = 2\, y_{\text{fixed}} \tag{1}$$

- Fixed-Amplitude Velocity Sinusoid (FVS) using a velocity amplitude v_{fixed} as the parameter. The velocity sinusoid is then integrated once to get a position sinusoid:

$$A = \frac{2}{\left(\frac{2\pi \text{ rad}}{\text{cycle}}\right) f} v_{\text{fixed}} \tag{2}$$

- Fixed-Amplitude Acceleration Sinusoid (FAS) using an acceleration amplitude a_{fixed} as the parameter. The acceleration sinusoid is then integrated twice to get a position sinusoid:

$$A = \frac{2}{\left(\frac{2\pi \text{ rad}}{\text{cycle}}\right)^2 f^2} a_{\text{fixed}} \tag{3}$$

Figure 4 demonstrates how the FPS amplitude is constant, the FVS amplitude varies inversely with clapping frequency, and the FAS amplitude varies inversely with frequency squared.

We used least squares optimization to identify the best parameter for each combination of model and participant. Figure 5 shows the RMSE between the data recordings and the best-fit version of each proposed model per participant in Phase 1, in Phase 2 as a tempo leader, and in Phase 2 as a tempo follower. Overall, the model that fits best is the fixed-amplitude velocity sinusoid model. Because of its simplicity, continuous nature, and replication of experiment data trends, this is the motion model we later implement on our hand-clapping robot. Note that four of the 42 lines reflect a best fit with the fixed-amplitude position model because one pair moved very little regardless of tempo during Phase 2.

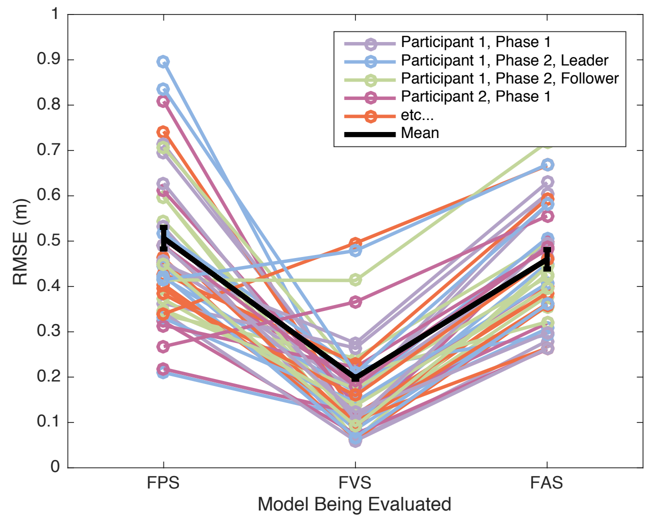

Fig. 5. RMSE between the amplitude of the best-fit version of each motion model and the recorded hand-clapping amplitude in Phases 1 and 2 of the experiment. The error bars represent a 95% confidence interval of the population mean.

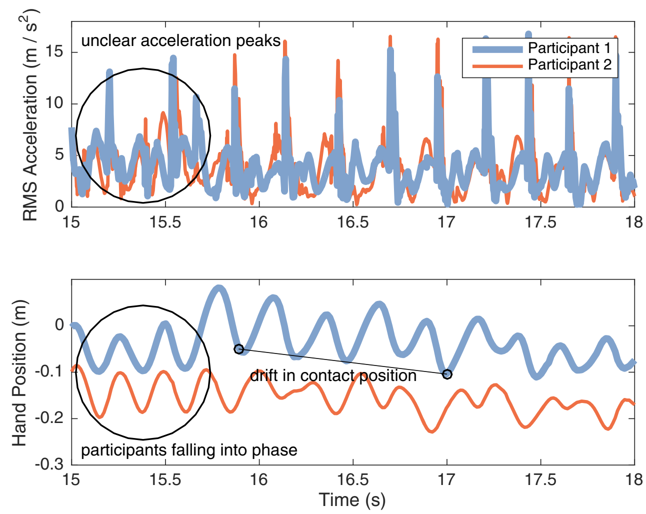

Fig. 6. An illustration of participant hand movement at fast tempos where some errors occurred, such as participants falling into phase with one another or experiencing drift in contact location.

Acceleration Peaks: Another result clearly illustrated in Fig. 2 is that peaks in the RMS acceleration occur consistently and exclusively at moments of hand impact. Local maxima detection on the RMS acceleration signal with set minimum peak spacing proved a reliable way to identify successful hand-clapping impacts and their corresponding hand positions throughout the entire dataset. Occasionally, we encountered brief periods without RMS acceleration peaks when participants were failing to successfully execute the hand-clapping game, such as Participant 2 at the beginning of Fig. 6. This finding means that a hand-clapping robotic system can use accelerometer signal processing to both detect handclaps and predict if its partner is having trouble.

Participant Performance: The position and acceleration recordings also demonstrated that the participants generally succeeded at the requested tasks, although some errors were evident in the recorded data. For Phase 1, the RMSE value

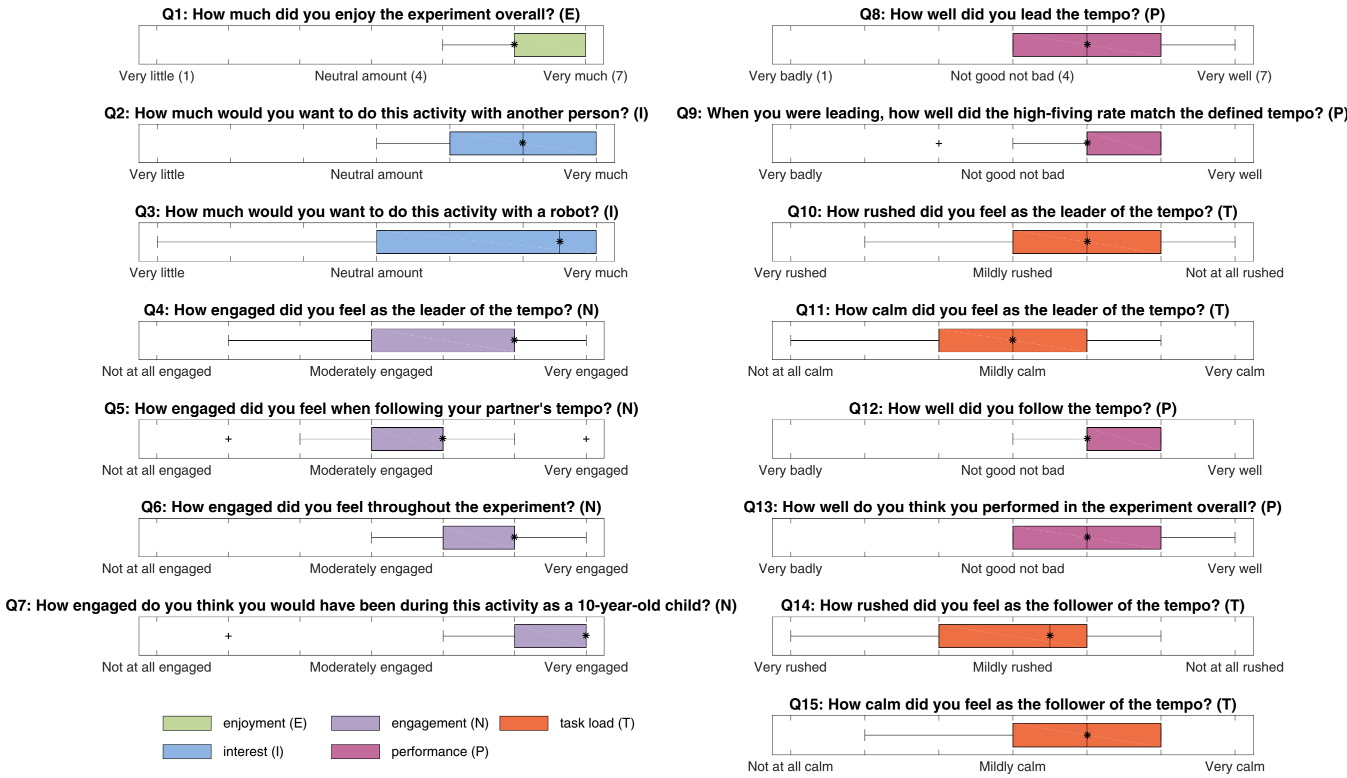

Fig. 7. Survey responses to each concluding survey question. Stars represent the median value for each question, pluses represent outliers, and box edges are the 25th and 75th percentiles. Color- and letter-coding indicate groupings of questions; the enjoyment, interest, and engagement topics were meant to inform our future research action, while the performance and task load questions were meant to capture the challenge level of experimental activities.

representing the difference between stimulus tempos and achieved tempos was 10 BPM. For Phase 2, the RMSE was 13 BPM. These results represent reasonable tempo errors, especially for the fastest two tempos, during which participants sometimes struggled. For Phase 3, 95% of the tempo change cues were executed successfully. Since participants were usually successful at the requested tasks, this set of activities may be a good starting point for our spHRI studies.

Failure Modes: Although participants generally succeeded at the requested tasks, they occasionally struggled with other aspects of hand clapping and exhibited various failure modes throughout the experiment. Errors such as drift in hand contact position throughout the trial and participants' hands falling into phase with each other were readily visible in the data recordings. These errors occurred because we chose a challenging range of tempos similar to those used in hand-clapping games. Samples of the error types visible in the data recordings are labeled in Fig. 6.

B. Survey Results

Written survey results gave us valuable feedback concerning participant *engagement* and *challenge* during the experiment. Preliminary survey responses reported in [22] include some participants excluded here due to data recording and eligibility issues. Surveys after each trial of Phase 1 revealed that our stimuli covered a rich range of tempos. Tempo ratings ranged from 1 (very slow) to 7 (very fast) with a median of 5 and an interquartile range of 3-6.

The concluding survey responses illustrated in Fig. 7 indicate that participants had a positive experience doing the experiment. The Q8, Q9, Q12, and Q13 box plots show that participants accurately perceived their general success in carrying out experiment tasks. Since the concluding survey data are nonparametric, we used Kruskal-Wallis tests to compare other pairings of responses in an effort to answer the following interaction questions:

- Would participants prefer to do this activity with a human or robot? (Q2 vs. Q3: $\chi^2 = 0.15$, $p = 0.70$)
- Did participants have a better experience as tempo leaders or followers? (Q4 vs. Q5: $\chi^2 = 1.22$, $p = 0.27$)
- Is this type of activity better suited for adults or children? (**Q6 vs. Q7:** $\boldsymbol{\chi^2 = 8.1}$, $\boldsymbol{p < 0.05}$)
- Did participants feel more rushed as leaders or followers? (Q10 vs. Q14: $\chi^2 = 0.75$, $p = 0.39$)
- Did participants feel calmer as leaders or followers? (Q11 vs. Q15: $\chi^2 = 1.23$, $p = 0.27$)

Participants saw the experiment activity as better suited for children than adults, but otherwise they displayed no statistically significant preferences. Thus, we are justified in designing a robotic playmate, and we have flexibility in the corresponding interaction design decisions. Another important trend to note is the wide range of responses to Q3, stemming from worries about the safety of clapping hands with a robot. We kept these concerns in mind as we developed our robotic system.

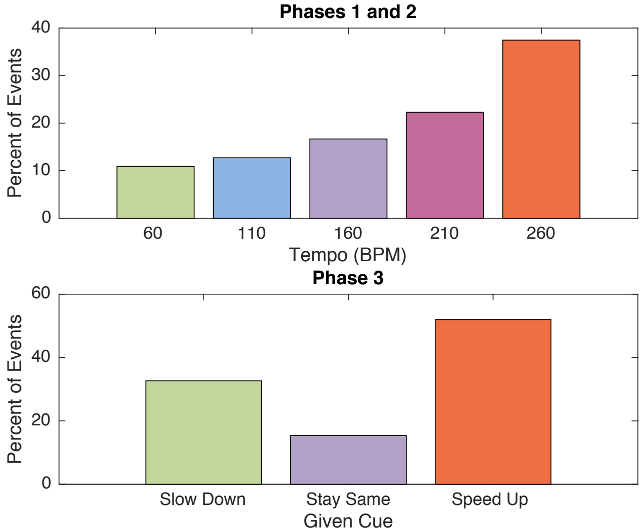

Fig. 8. The percentage of smiling and laughter events that occurred during each stimulus tempo in Phases 1 and 2 (top plot) and during each stimulus cue in Phase 3 (bottom plot).

C. Behavior Results

Behavioral results from the experiment provided useful insights into the ways participants reacted to hand clapping and how we could apply those results to hand-clapping robot *state machine design*. Our quantitative behavioral data was gathered by an experimenter who watched the session videos and tallied key events, in a similar style to the investigations in [23]. We found a significant relationship between hand-clapping tempo in Phases 1 and 2 and the occurrence of participant smiling and laughter, which we will henceforth call "mirth." As Fig. 8 demonstrates, 37% of all mirth happened at the fastest tempo (260 BPM). Similarly, in Phase 3 of the experiment, tempo change cues resulted in more mirth than constant tempo cues.

While searching for an explanation for these trends, we discovered that failures were strongly correlated with mirth and with fast tempos. Every participant pair had trouble with at least one of the trials at 260 BPM, and the video rater recorded failures during 58% of the overall trials at this tempo. Interestingly, these trials also led to abundant mirth; 38% of all recorded smiling and laughter events occurred during failures. Throughout all experiment sittings, there were only two failures (out of 69 total) during which neither person in the pair smiled or laughed. Accordingly, our robot state machine design should include not only practical hand-clapping motion sequences, but also lighthearted and encouraging responses to hand-clapping difficulties.

V. Robotic System Implementation

From the findings discussed in Section IV and a consideration of our resources, we decided to implement our newfound hand-clapping design insights on a robot that was human-sized, anthropomorphic, low cost, and safe for physical contact. Survey feedback from participants indicated that robot safety and collaborative ability were especially important. In accordance with these design criteria, we selected a Rethink Robotics Baxter Research Robot, a human-sized humanoid robot designed for physically interactive tasks in factory settings. Baxter offers several advantages over traditional industrial robots for developing playful human-robot interaction: a rich sensor suite including 360-degree sonar, joint torque sensing, and cameras; safe mechanical features like series elastic actuators, fully backdrivable joints, and impact-absorbing shells; a humanoid anatomy that makes the mapping of game motions to the human body intuitive; a standard Robot Operating System (ROS) framework; and a relatively affordable price (∼$25,000).

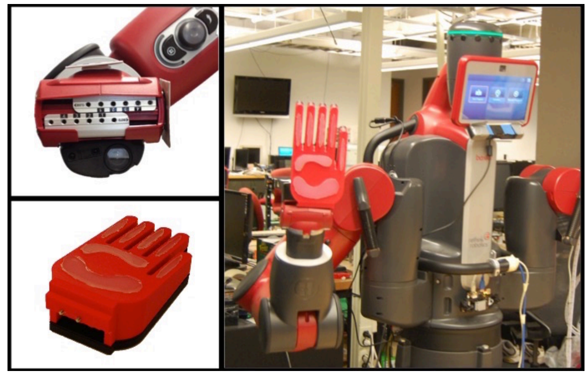

Fig. 9. Upper left: Baxter's built-in finger alignment rails with regularly spaced threaded holes. Lower left: Our fabricated Baxter hand with the compatible M4×0.7 screws. Right: Baxter with its custom-built end-effector. Depressions in the hand are filled with silicone rubber to soften contact.

With careful updates, we have advanced Baxter toward being able to carry out safe, compelling, and enjoyable hand-clapping interaction with humans. This process included *physical modification* of the robot, design of its *end-effector motion*, and use of its onboard sensors for *contact detection*. These adaptations readied the robot for the end goal of playing hand-clapping games. *Preliminary piloting* proved promising, and future studies with Baxter will help us explore aspects of hand-clapping games ranging from successful execution and timing to the public's overall perception of a robot that performs this type of activity.

A. End-Effector Modification

The commercially available hands for the Baxter robotic platform proved insufficient for comfortable hand contact with a human gameplay partner. As a result, one of our first steps toward transforming Baxter into a capable hand-clapping teammate was designing and fabricating new end-effectors that allowed for safe and satisfying hand contact. Human-human study results showed that humans perceived the safety of interacting with a robot as very important and also identified the sound of a handclap as an indicator of interaction quality. Consequently, our current hand design is an anthropomorphic but non-articulated 3D-printed plastic hand. It includes depressions filled with silicone rubber to imitate the properties of human tissue and facilitate a safe and satisfying-sounding interaction. M4×0.7 screws spaced to fit threaded holes in Baxter's finger alignment rails joined our custom hand to Baxter's arm, as illustrated in Fig. 9.

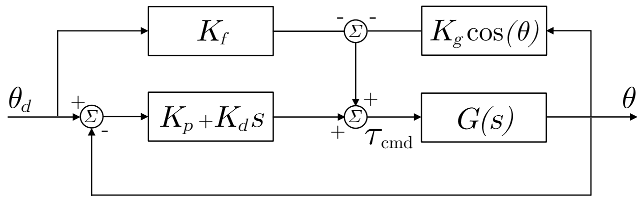

Fig. 10. Block diagram illustrating how the wrist pitch joint of Baxter's arm was controlled throughout pilot experimentation. $G(s)$ represents the forward transfer function of the system, K_g is a gravity compensation gain, and all other symbols are elements of the arrays defined in Eqn. 4 below.

B. End-Effector Motion

Data collected in our human-human experiment showed that human hand-clapping motion could be modeled well by sinusoids that have a constant participant-specific maximum velocity across clapping tempos. Accordingly, our initial design for Baxter's motion is a control strategy that moves the robot's end-effector along these trajectories using the typical profiles exhibited by participants in the study.

Successful execution of these human-inspired hand-clapping trajectories is possible with Baxter's built-in joint torque control mode but not the more commonly used position controller. We computed the desired input torques at each time step using a PD controller with feedforward and gravity compensation terms, as illustrated by the block diagram in Fig. 10. The overall time-domain control law is

$$\boldsymbol{\tau}_{\mathrm{cmd}} = \mathbf{K}_d(\dot{\boldsymbol{\theta}}_d - \dot{\boldsymbol{\theta}}) + \mathbf{K}_p(\boldsymbol{\theta}_d - \boldsymbol{\theta}) - \mathbf{K}_f\boldsymbol{\theta}_d + \boldsymbol{\tau}_{\mathrm{gc}} \quad (4)$$

where $\boldsymbol{\tau}_{\mathrm{cmd}}$ is a vector of torques commanded to each Baxter arm motor, $\mathbf{K}_d$ is a diagonal matrix of derivative gains, $\boldsymbol{\theta}_d$ is a vector of desired arm joint angles, $\boldsymbol{\theta}$ is a vector of actual joint angles, $\mathbf{K}_p$ is a diagonal matrix of proportional gains, $\mathbf{K}_f$ is a diagonal matrix of feedforward gains, and $\boldsymbol{\tau}_{\mathrm{gc}}$ is a vector of gravity compensation torques.

Once we implemented this control scheme, we had to decide where in its workspace Baxter should execute the desired trajectory. We obtained possible start poses by physically moving Baxter's arm and querying for the current joint angles from Baxter's ROS topics. From one start pose, we discovered that Baxter could move through a near perfect approximation of the human-inspired sinusoidal trajectory using only the wrist pitch (W1) joint. The resulting hand-clapping motion was almost exclusively in the x-direction of Baxter's Cartesian workspace and the x-direction of the inbuilt wrist accelerometer. Figure 11 illustrates the achieved motion and corresponding accelerometer readings in these key axis directions during interaction with a human partner.

C. Hand Contact Detection

Hand-clapping games typically end when one of the players fails to perform the correct motion. Thus, Baxter should expect a particular contact input at each action state to continue gameplay, and any incorrect contact input or absence of awaited contact input should trigger the end of the game. To accomplish this gameplay model, we had to find a reliable way to detect contact. Of Baxter's many built-in ROS

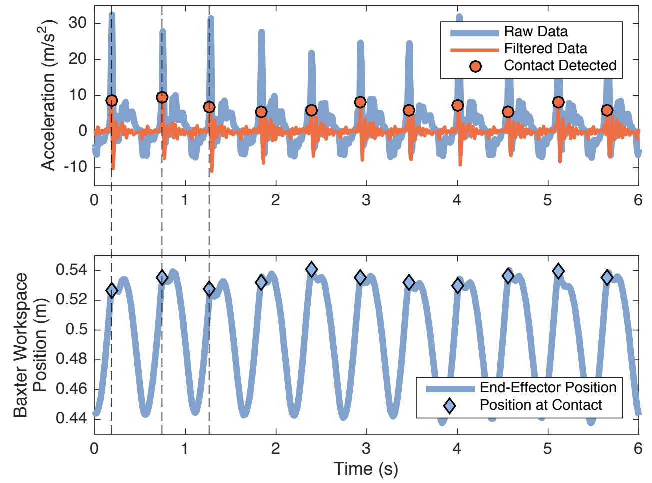

Fig. 11. Sample plot of acceleration and position recordings from Baxter during human-robot gameplay. The upper graph includes the high-pass filtered acceleration values thresholded to predict times of hand impact on the robot. The three dashed lines emphasize that times of predicted hand impact coincide well with hand contact artifacts in the position plot.

topics, we found the robot's wrist-mounted accelerometer to give the best information for detecting hand impacts. Although previous results demonstrated that acceleration local maxima-finding was sufficient for detecting hand contact in human-human hand clapping, Fig. 11 illustrates that the robot ego-vibrations during gameplay forced us to seek a new contact detection strategy.

Instead, we filtered accelerometer readings to discriminate between extraneous features and actual hand contact with the robot. We obtained the best results when filtering raw readings from only the x-axis of the accelerometer, which is aligned with the impacts. As illustrated in Fig. 11, a discrete-time first-order Butterworth high-pass filter with a cutoff frequency of 25 Hz is effective for helping us to discriminate acceleration peaks caused by hand contact with Baxter from other accelerometer signal features. This strategy is consistent with contact detection results from related work on humanoid robot gripper contact detection [24]. To prevent false positives from secondary peak artifacts appearing shortly after actual hand contacts, we also introduced a 0.1 second timeout period after each detected hand impact. Thresholding the filtered accelerometer signal allowed us to find all hand contact instances during hand-clapping interactions with several pilot users.

D. Pilot Investigation

Baxter successfully completed a pilot study playing hand-clapping games with a human user under Penn IRB protocol 823886. This participant carried out one hour of interaction trials with Baxter. These trials were basically identical to the 60, 110, and 160 BPM Phase 1 trials of our human-human experiment. He reported comfortable contact with the custom Baxter end-effector throughout the entire hour. Our motion control scheme worked well enough that this individual perceived the robot to be making a trajectory error only one time out of all 947 human-robot hand-clapping cycles (0.001% of interactions), when Baxter's ego-vibration triggered a false positive register of hand contact. Overall, the robot's contact detection logic correctly identified over 97% of the human-robot contact occurrences, displaying less than 3% misses. The pilot participant was satisfied with the interaction and felt safe contacting the robot.

VI. Discussion and Conclusions

The results of our human-human experiment provided abundant information to help create an *engaging* hand-clapping robot, including many essential *motion trajectory*, *contact acceleration*, and *behavioral* patterns. Participant motion trends indicate that a robot playmate should exhibit an inverse relationship between hand-clapping frequency and amplitude. Study results inspire us to pursue a simple and continuous sinusoidal model of robot motion with a participant-specific constant maximum velocity across all clapping tempos. Survey responses indicate that this type of activity is perceived to be engaging, especially for children, thereby motivating us to continue developing robot hand-clapping abilities. Additionally, participant responses to hand-clapping failures suggest that it will be important to design our robot to react to failure in a lighthearted and encouraging manner, like our study participants tended to.

We decided to use a Rethink Robotics Baxter as our hand-clapping robot because of its human-like size, low cost, and safety features. Our work with Baxter so far has involved creating *new end-effectors* and implementing our human *trajectory* and *contact detection* findings on the robot after iterative investigations of Baxter's inbuilt sensors and SDK API. Baxter has safely and successfully completed a *pilot study* playing hand-clapping games with a human user throughout one hour of interaction trials similar to those in Phase 1 of our human-human experiment. We plan to formally evaluate the robot's hand-clapping performance, as well as participants' general reactions to and opinions of this type of activity, with a future user study. Overall, this robotic system serves as a gateway to many explorations and instantiations of social-physical human-robot interaction using Baxter and other robots.

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