Measuring Interaction Bandwidth During Physical Human-Robot Collaboration

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Abstract—**An assistive robot can augment human performance by providing physical assistance or motion guidance. In human-robot collaboration, it is important to know the bandwidth of an individual's ability to generate motion in response to external stimuli, such as visual or haptic cuing. This becomes particularly relevant in timing-sensitive tasks, such as walking or catching a falling object. In this work, we propose a frequency-based assessment of motion that enables us to measure the bandwidth of physical human-robot interaction (pHRI)—quantifying how fast individuals can respond to stimuli on a continuous basis. We introduce a robot-assisted virtual dynamic task with a tunable resonant frequency. A human subject study with seven participants shows that our task can elicit a dynamic response in a participant at frequencies of 0.5 Hz, 1 Hz, 1.5 Hz and 2.5 Hz at the arm. Using the virtual task, we test whether haptic cues improve motion timing. At all tested frequencies, we find that haptic stimuli help guide timing of dynamic movement and improve performance compared to visual-only cuing. By quantifying the interaction bandwidth for other pHRI systems—particularly when the human collaborators have neuromotor impairments—our method can help assistive robots adapt to an individual. Moreover, our results highlight the importance of incorporating haptic feedback into pHRI for dynamic tasks—haptics can provide guidance around motion timing, such as in assistive robots used for assessment and physical rehabilitation.**

Index Terms—**Haptics and haptic interfaces, human factors and human-in-the-loop, physical human-robot interaction, physically assistive devices, rehabilitation robotics.**

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I. Introduction

Physically interacting robots, such as an exoskeleton, can be useful in a number of ways: they can alleviate physical burden during manual tasks, help with learning or re-learning motor skills, or provide precise assessment of physical abilities. Although many relevant motor skills and daily tasks are highly dynamic, assistive robots largely operate in a static or quasi-static regime. As an example, robot-assisted assessment of motor skills typically uses tasks such as defining reachable workspace [1], [2] or tracking a pre-defined trajectory [3]. However, recent work shows interest in assessing motor coordination through dynamic tasks, e.g., a timing-sensitive hitting task with moving objects [4], because ability to generate dynamic movements plays an important role in one's ability to complete activities of daily living.

When the human-robot interaction involves dynamic movements, the human-robot pair benefits from continuous communication [5], [6]. Processing times of communicative cues and the ability to generate a motor response may vary between populations: younger vs. older individuals [7], able-bodied vs. physically impaired [8]. To increase collaborative success, it would be beneficial to understand the bandwidth of an individual to react to stimuli and generate motion as a response. Our prior work attempted to assess motor coordination during dynamic tasks post-stroke [9]. Here, we build on this work and propose a method for measuring interaction bandwidth during physical human-robot interaction (pHRI).

To measure interaction bandwidth, we use a virtual ball-in-bowl task, inspired by the real-world task of quickly moving a cup of water without spilling. The ball-in-bowl task has a specified resonant frequency (dependent on the size of the bowl), which defines the default movement frequency that is needed to succeed at the task. Because of this property, we can learn about an individual's bandwidth from the frequency content in their motion. Unlike in existing assessments, we do not assess motion quality through jerk [10], [11], error [3] or time to motion initiation [8], but rather we look at the frequency decomposition of motion. In particular, we quantify the energy exerted by an individual during task completion around task resonance. Evaluating frequency content in motion during the ball-in-bowl task (a dynamic task with a resonant frequency) while a person is physically coupled with a robot allows us to quantify the individual's interaction bandwidth with the robotic system.

Prior work shows that real-time perception and processing of sensory information is crucial for effective motor coordination [12]. While motor coordination is controlled by both visual and proprioceptive feedback loops [13], precise movements can overwhelm the visual sensory channel—motor tasks that demand a high degree of accuracy are consequently more dependent on kinesthetic information [14]. Thus, robot-mediated haptic feedback should be expected to improve human performance, particularly in highly dynamic tasks that require accuracy with respect to motion timing. We use our approach to study one's ability to generate dynamic motion when relying on two different modalities for sensory feedback: visual and haptic cuing.

There are a number of studies that show the value of haptic feedback in human-robot interaction. It is well-established that haptic feedback is beneficial for teleoperation in quasistatic/non-dynamic settings, such as robotic surgery [13], [15], a peg-in-hole insertion task [16] or a pick-and-place task [17], particularly in a cluttered environment [18]. Moreover, there is recent research that explicitly studies robotic assistance with haptic feedback during dynamic tasks. Ozen et al. found that training with haptic feedback enhances motor learning for the task of inverting a virtual pendulum [19]. Other work has shown positive impact of vibrotactile feedback on task performance during balancing an inverted pendulum [20] or while using a teleoperated robot to balance an object on a tray [6]. While prior work shows that haptic feedback is helpful in improving joint human-robot performance, no study to date has shown *why* haptic feedback improves performance. In this work, we show that haptic stimuli improve people's timing accuracy across a range of motion frequencies. Improved motion timing is likely a significant contributor to an increase in overall task performance during human-robot collaborative tasks.

In summary, we contribute a frequency-based method for assessing interaction bandwidth—individuals' ability to continuously generate a dynamic response (controlled and timing-sensitive movements in response to real-time stimuli). In a robot-assisted virtual environment, we assess dynamic response under two feedback conditions: visual and combined visuo-haptic cuing. We test the task on a group of able-bodied individuals (n = 7). Through our experiments, we show that:

- Using the ball-in-bowl task—a virtual task with resonance—we can elicit motion at a specific frequency.
- Frequency content in motion during this dynamic task can quantify interaction bandwidth.
- Haptic feedback improves motion timing.

Given the validation study presented here, our method can be used to assess motion bandwidth in individuals with neuromotor impairments as well as to inform the design of physically coupled human-robot systems.

II. Experimental Setup

We have developed a virtual task that elicits controlled, timing-sensitive movements. In our experimental setup, we couple the virtual environment with a stationary upper-limb exoskeleton, capable of rendering haptic feedback and translating forearm motion into activity in the virtual task (see Fig. 1).

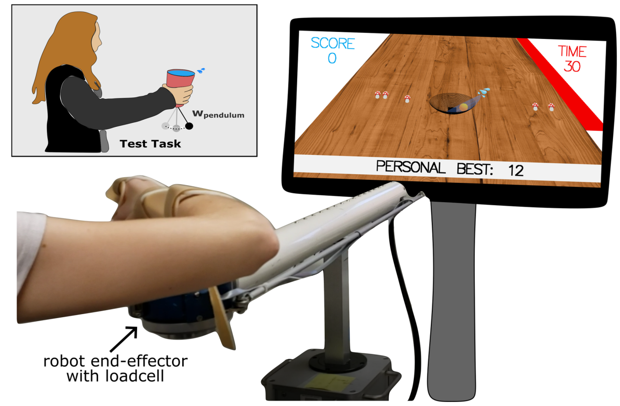

Fig. 1. Experimental setup and ball-in-bowl task. In the top left, we illustrate the real-world task of carrying a cup of water without spilling that served as inspiration for the ball-in-bowl task. In the bottom right, we visualize the experimental setup with the robot.

Using this setup, we conduct a human subject study with seven able-bodied individuals.

A. The Physical Environment

A haptic environment is created using the Arm Coordination Training 3-degree-of-freedom device (ACT-3D) [9]. The ACT-3D is the combination of an admittance controlled HapticMASTER robot, a 6-degree-of-freedom load cell (JR3 load cell, Woodland, CA) at the robot's end-effector, and a Biodex chair. The participant's forearm is attached to the load cell using a forearm-wrist-hand orthosis. This setup, as shown in Fig. 1, allows the participant to directly control the location of the end-effector with movements of their arm. Active movements are captured as force readings on the load cell and, using the robot's internal controller, translated into movements of the end-effector in 3D space.

The robot is able to provide partial or full support of the arm against gravity by modulating abduction loading at the shoulder. It is also able to render haptic objects and forces in the upper-limb workspace of the individual. The forces can be updated in real-time. Given that people can process haptic feedback at a temporal resolution up to 20 Hz [21], we chose 20 Hz as our update rate.

B. The Virtual Environment

A virtual task is visualized on a screen in front of the participant. We use a ball-in-bowl task, loosely inspired by the real-world activity of moving a cup of water without spilling. The task was introduced in our prior work [9] and modified for this study to incentivize dynamic motion. The current version of the task has been open-sourced and is available online under the MIT license [22].

In the ball-in-bowl task, the location of the robot end-effector is mapped to the location of a bowl on a virtual table. There is a virtual ball rolling around inside the virtual bowl and the participant experiences haptic feedback corresponding to the interaction force between the bowl and the ball. There is no friction in the simulated ball-in-bowl system—consequently only normal forces are rendered haptically to the user. While participants exert forces in a range of values throughout a trial (rarely exceeding 10 N), the haptic force feedback is scaled and consistently rendered as a 0.5 N vector in the xy-plane.

The motion of the ball is simulated using a modified dynamics model of a 3D pendulum, where the pendulum's acceleration $\ddot{\theta}$ is calculated using independent components $\ddot{\theta}_x$ and $\ddot{\theta}_y$ defined as

$$\ddot{\theta}_i = \left(\frac{g}{h} sin(\dot{\theta}_i) - u_i cos(\dot{\theta}_i)\right).$$

The variable $g = 9.81 \frac{m}{s^2}$ represents the gravity constant, h is the pendulum length, and i indexes the coordinate (either x or y). The variable u_i represents the individual's input to the system—in our experimental setup, it is the acceleration of the end-effector in the x and y directions, as calculated from load cell measurements of force. When the participant moves in synchrony with the ball, they amplify the ball's oscillations and allow it to gain energy. When the participant counteracts the ball's movements, they dampen out its energy and prevent it from falling out of the bowl. There is no damping or friction in the simulated ball-in-bowl system. This design choice disincentivizes the individual from waiting for the ball to lose energy and settle on its own. Only active movements of the end-effector can affect the ball's oscillations. Unlike in a real-world 3D pendulum, $\ddot{\theta}_i$ is only influenced by u_i—this simplification of the system dynamics was a design choice meant to improve explainability and participants' agency over the ball's movements.

Participants can move in 3 dimensions. Their xy-motion is mapped directly onto the location of the virtual bowl. In the z direction, participants start from a home position $z = 0$, resting on a haptic table. During task attempts, they are asked to keep their arm lifted anywhere above the haptic table to avoid imposing dynamic constraints on the ball-in-bowl system. In turn, to prevent fatigue, their arm weight is fully supported against gravity—the load cell readout in the z direction is near zero, making the arm feel buoyant in space. Movement in the z direction does not affect the simulation.

C. The Virtual Task

The goal of the virtual task is to collect as many targets as possible within a 30-second window. There are three conditions that have to be met for an individual to be able to collect a target: (1) The individual's arm must be lifted above the haptic table, indicated to the participant by the bowl turning blue. (2) The virtual ball's total energy must be low enough to be oscillating no higher than one third of the bowl's height, indicated to the participant by the ball turning green. (3) The center of the virtual bowl must be aligned with the target location.

At any given moment there are 5 target mushrooms spread out randomly on the virtual table within the participant's reachable workspace. During each attempt at the task, participants are instructed to manipulate the location of the virtual bowl to collect as many targets as possible in 30 seconds. Every time an individual collects a target, three things happen: (1) the participant receives a point, (2) a new target appears in a different location, so that 5 targets are visible at any given time, and (3) the ball is injected with a bit of energy, so that again the participant must generate movement to counteract the ball's oscillations and reduce its energy before collecting another target. The score and remaining time are visualized on the left and right side of the screen, respectively.

The simulated ball-in-bowl task has a software-defined natural frequency. We modulate the resonant frequency by changing the length of the modelled pendulum. There is an inverse correlation between the length of the pendulum h and task resonance f_{task}:

$$f_{task} = \frac{1}{2\pi}\sqrt{\frac{g}{h}}.$$

Modulating task resonance enables us to assess ability to generate motion at a specific frequency. In our experiment, we use pendulum lengths h = [0.995, 0.249, 0.111, 0.04] that correspond to natural frequencies $f_{task} =$ [0.5 Hz, 1 Hz, 1.5 Hz, 2.5Hz]. We chose 2.5 Hz as our maximum frequency, so that it would be achievable for all study participants [21]. Because we noticed that changes in frequency were not perceived by participants linearly—namely, a change from 0.5 Hz to 1 Hz was more perceptible than a change from 2 Hz to 2.5 Hz—we tested more frequencies near the lower bound of the range.

D. Study Participants

We recruited seven able-bodied individuals to complete the study. All participants expressed verbal and written consent to participate. The study protocol was approved by the Northwestern University Review Board under IRB STU00021840. Participating individuals were screened for physical disabilities and known abnormalities in motor control—none were reported. The group of tested individuals was 22–28 years of age (with an average of 26). There were 4 males and 3 females; all were right-hand dominant. We randomly assigned the arm with which individuals performed our experimental tasks—4 of our participants used their right arm while 3 used their left arm during the experiment.

E. Experimental Procedure

An experimental session starts with measuring arm weight, so that during the task we can support the arm against gravity. We then define the individual's reachable workspace by asking each participant to "clean" the virtual table. Participants are instructed to cover the biggest area on the table that they can reach without allowing their shoulder to leave the back of the Biodex chair. During later task attempts, targets are placed only within this reachable area.

We then proceed to a training period, when we explain the ball-in-bowl task. We allow numerous attempts at the task until the participant feels comfortable with the experimental setup and they seem to understand the task objective. We offer tips and guidance as well as encourage the participant to ask questions. The training period usually takes 15-20 minutes with at least 10 task attempts.

All individuals complete the ball-in-bowl task at four frequencies (0.5 Hz, 1 Hz, 1.5 Hz, and 2.5 Hz) and under four task conditions (with/without the ball moving, with/without haptic feedback). During trials without the ball moving, the ball rests at the bottom of the bowl, while the participant is asked to collect targets without needing to consider the ball's movements. The goal of the no-ball trials is two-fold: (1) without haptic feedback, to evaluate the baseline frequency spectrum of movement during the ball-in-bowl task, and (2) with haptic feedback, to confirm that the haptic forces themselves, without active participant movement, do not result in peaks at resonance. Each experimental set of conditions is attempted by the participant 24 times: 6 times at each task frequency in 2 sets of 3 in random order to control for potential effects of learning and/or fatigue. There is one exception: when the ball is stationary and no haptic feedback is provided, there is no notion of task frequency—participants attempt this experimental condition 6 times. Each study volunteer performs a total of 78 task attempts. We take two 5-minute breaks after 27 and 54 trials, as well as shorter breaks throughout the experiment as needed.

We end the experiment with a test of open-loop motion—motion that relies on internal proprioception without incorporating external stimuli. While coupled with the robot, participants are asked to move back and forth in the transverse plane as fast as they can, using small amplitude motion. Unlike during closed-loop motion in the ball-in-bowl task, they are not generating motion in response to any task-specific stimuli. We collect three 10-second efforts.

F. Motion Metrics

We assess motion by looking at the spectral properties of the forces introduced into the system by the participant. While the load cell measures forces in the x-direction and y-direction in the transverse plane, a discrete fast Fourier transform (FFT) is performed on each trial to obtain the amplitude of the signal for a range of frequencies up to 4 Hz. In a frequency spectrum, the relative amplitude of a signal at a certain frequency provides us with insight about participants' ability to switch movement direction at that frequency. The signal in the frequency domain is normalized by the energy introduced into the ball-in-bowl system by a participant throughout a task attempt. We use the following standard definition of a signal's energy: $E = \sum A(\omega)^2 d\omega$ where ω and A are the frequency and amplitude, respectively. After normalization by E, the total energy introduced into the system during each task attempt is equal to one, allowing us to do trial-to-trial and subject-to-subject comparisons. To obtain a single estimate of the frequency content of movement in the 2D plane, we add the x and y frequency spectra. The resultant spectrum is re-normalized and visualized throughout this letter.

The primary frequency metric presented in this letter is energy@resonance. It refers to the energy exerted by the participant at the task frequency ± 0.2 Hz (equivalent to a window size of $w_f = 0.4$ Hz). We compute the energy@resonance measure for each trial with a moving ball. Additionally, regardless of the task frequency, we compute an energy@frequency metric—the energy at 0.5 ± 0.2Hz, 1 ± 0.2Hz, 1.5 ± 0.2Hz, and 2.5 ± 0.2Hz—to validate that the game elicits movement at task resonance. For the last analysis, we compute the percentage difference in energy@resonance between trials with haptic forces and without haptic forces, i.e., $(e_{haptic\,feedback} - e_{no\,haptics})/e_{no\,haptics}$, where e is the energy at resonance.

Aggregate frequency spectra presented in this letter are averaged across participants, re-normalized, and filtered with a low-pass Butterworth filter (and a cutoff frequency of 5 Hz) for visual clarity. In creating the boxplot figures, we average across trials of a participant under the same trial conditions so that each boxplot demonstrates the spread in performance across the seven participants. All statistical analyses, except the window size analyses, are performed on unaggregated and unfiltered frequency spectra and metrics.

G. Study Design and Statistical Analyses

Our experiment aims to test two hypotheses: (H1) the ball-in-bowl game encourages participants to move at the task's resonant frequency, and (H2) haptic feedback further encourages movement at task resonance.

To assess H1, we perform two statistical analyses. First, we perform a set of one-way repeated measures ANOVAs (rm-ANOVAs) and post-hoc t-tests with Bonferroni corrections to determine whether the ball's resonant frequency affects the energy exerted by participants around specific frequencies when completing the task without haptic feedback. This determines whether, for example, participants completing trials using a ball with a resonant frequency of 0.5 Hz exert more energy around 0.5 Hz than while completing trials using a ball with a resonant frequency of 1 Hz, 1.5 Hz, or 2.5 Hz. We repeat the same analysis using trials with haptic feedback. For the second statistical analysis, we compare energy@resonance during trials with a moving ball to trials with a still ball (and hence, no incentive to move at the resonant frequency). We use a two-way rm-ANOVA with within-subject factors for the trial condition (moving vs. stationary ball) and ball frequency, followed by one-way rm-ANOVAs at each frequency with trial condition (still vs. moving ball) as the within-subject factor.

To assess H2, we perform two statistical analyses. First, we perform a two-way rm-ANOVA with within-subject factors for ball frequency and trial condition (with vs. without haptic feedback) across trials with a moving ball, followed by one-way rm-ANOVAs at each frequency with trial condition (with vs. without haptic feedback) as the within-subject factor. Secondly, we look at the percentage difference in energy@resonance between aggregated trials with haptic forces and without haptic forces. We perform a two-way rm-ANOVA with within-subject factors for task frequency and window size, followed by one-way rm-ANOVAs at each frequency with window size as the within-subject factor.

For each statistical test, we evaluate the assumptions using the Shapiro-Wilk test for normality and Mauchly's test for sphericity. If the sphericity assumption is violated, we report the Greenhouse–Geisser correction, indicated by p_{GG}.

III. Results

Using the ball-in-bowl task, we show that frequency decomposition of motion during a dynamic task can be used to assess motion quality, revealing information not easily obtained from the typically studied time-series data. In a small human subject study with able-bodied individuals (n = 7), we validate that the ball-in-bowl game is able to elicit active movement at specific

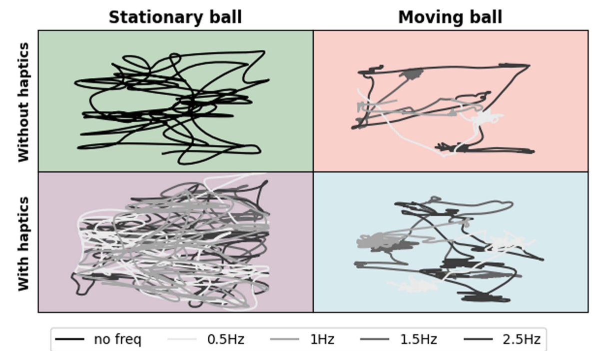

Fig. 2. Example trajectories across workspace (xy-plane) of a participant for 13 different trials. Each line represents one 30-second trial. Note that when the ball is stationary, participants traverse the workspace frequently to collect targets. When the ball is moving, participants alternate between moving quickly between targets and trying to settle the ball.

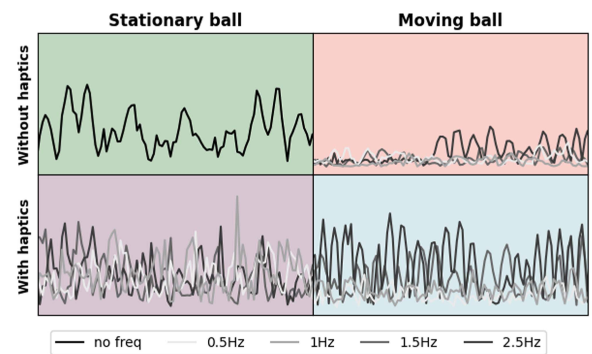

Fig. 3. Five seconds of time-series data of a participant's acceleration during 13 different trials of the ball-in-bowl task. Note that the time-series data is difficult to evaluate for success and comparison between trials. As we describe in this work, frequency content in motion can be used as a more informative, time-independent quantity to assess motion quality.

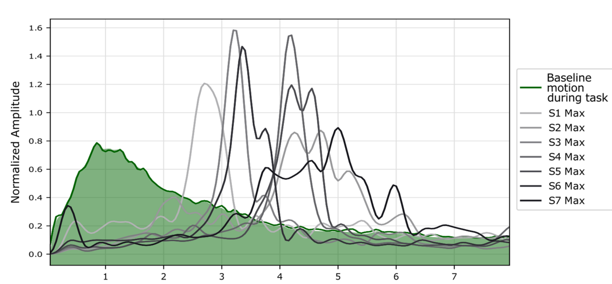

Fig. 4. Upper bound of motion bandwidth during open-loop movements (grey) in comparison to baseline closed-loop motion during the ball-in-bowl task (green). All tested participants are able to generate open-loop motion up to 2.5Hz—their maximum open-loop motion frequency ranges from 3 to 5 Hz. During the ball-in-bowl task, when collecting targets without a moving ball, most of participants' motion is exerted around 1 Hz.

frequencies. We show that haptic cues improve motion timing and increase frequency content in motion at task resonance.

A. Quantifying Motion Bandwidth During Open-Loop Movements

As a baseline, we evaluate open-loop motion. As visible in Fig. 4, participants generate open-loop motion at frequencies ranging from 3 to 5 Hz depending on the individual. Consequently, we conclude that all participants are physically able to generate open-loop motion up to 2.5Hz—the highest frequency in our experimental protocol. Given this result, the dynamic response we are measuring during the ball-in-bowl task is limited mainly by the capabilities of participants' reasoning about motion timing rather than a physical inability to move at the tested frequencies.

In Fig. 2 and Fig. 3, we illustrate the motion of one of our study participants during an example task attempt under each of the four experimental conditions. In Fig. 2, we visualize participant trajectories as a function of x and y. Note that when the ball is stationary, the participant moves quickly through their workspace, solely focused on collecting targets. This baseline motion has a characteristic frequency decomposition (green curve in Fig. 4)—if no other incentives are provided, the motion focused on collecting targets during the ball-in-bowl task largely centers around 1 Hz. When the ball is active, participants alternate between generating high-frequency movement to settle the ball and traversing the workspace to collect targets. The motion focused on settling the active ball introduces peaks around various frequencies, corresponding to the task's resonance, allowing us to assess an individual's interaction bandwidth in the physical human-robot system.

In Fig. 3, we illustrate participant movement as a function of time. Note that qualitatively it is difficult to compare participant's performance between experimental conditions and task frequencies. In contrast, by looking at the frequency content in motion, we can more easily reason about a participant's performance both quantitatively and qualitatively.

B. Measuring Interaction Bandwidth During a Dynamic Task

By using a task with a resonant frequency, we can quantify an individual's ability to generate a dynamic response at a specific frequency (see Fig. 5 for aggregate results). The energy exerted at the task's resonant frequency is consistently higher than energy exerted at that frequency during tasks with a different resonant frequency. Repeated measures ANOVAs reveal that, when only visual feedback is provided, task frequency significantly affects energy exerted at 0.5 Hz ($p < 0.001$, $F = 18.94$), 1 Hz ($p < 0.001$, $F = 15.28$), 1.5 Hz ($p = 0.009$, $F = 5.23$), and 2.5 Hz ($p < 0.001$, $F = 11.23$), respectively. The ANOVA is performed for the energy@frequency metric, delineated by different shades of blue in Fig. 5. Moreover, post-hoc t-tests with Bonferroni corrections reveal that for each task frequency, the energy@resonance metrics (red boxes in Fig. 5) are significantly higher than the energy@frequency metrics for the same frequency (grey boxes in Fig. 5) with all p-values less than 0.004.

The same analysis is performed for trials with a moving ball and haptic feedback. Again, we observe that individuals exert significantly more energy at task resonance (0.5 Hz ($p < 0.001$, $F = 72.10$), 1 Hz ($p < 0.001$, $F = 57.85$), 1.5 Hz ($p < 0.001$, $F = 8.57$), and 2.5 Hz ($p < 0.001$, $F = 15.19$)) than they would if the task did not encourage movement at this frequency. Moreover, post-hoc t-tests with Bonferroni corrections reveal that energy@resonance (energy under the blue curves in Fig. 6)

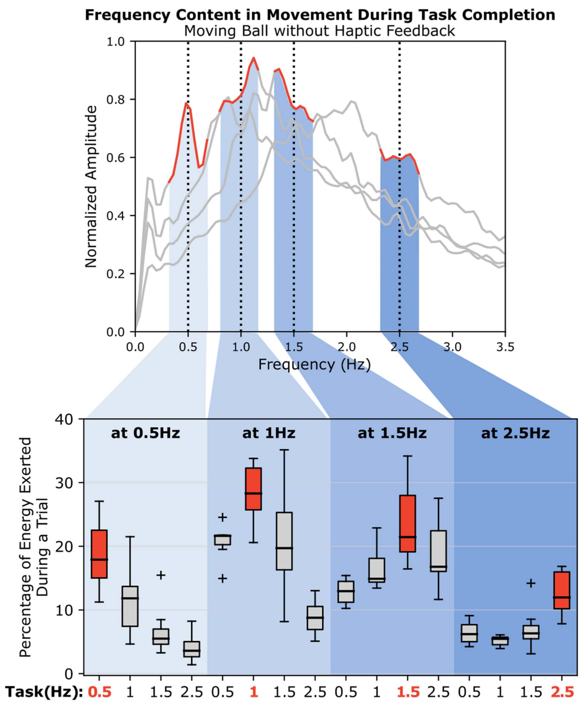

Fig. 5. Game elicits movement at task resonance. Energy@resonance (red boxes) is higher than energy@frequency (grey boxes) for all 4 tested task frequencies, denoted by the 4 shades of blue. Aggregate results (n = 7). Boxes in the bottom plot represent the area under the curve of sections in the top plot (highlighted in blue) across all participants.

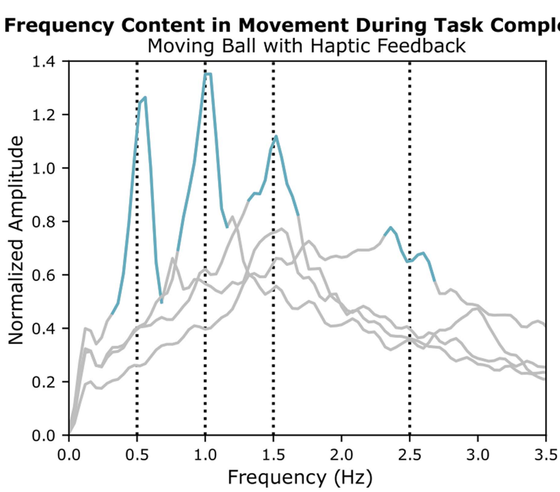

Fig. 6. Haptic feedback encourages movement at task resonance. The peaks at resonance (indicated with a blue color) are higher when haptic feedback is rendered to participants than when only visual cuing is provided. Aggregate results (n = 7).

is significantly higher than energy@frequency for trials with a difference resonant frequency, with all p-values less than 0.001.

When the ball is stationary, participants are no longer incentivized to generate movement at a specific frequency to settle the ball. Thus, we observe that participants produce significantly less movement at the ball's resonant frequency (see Fig. 7) when the ball is still. The repeated measures ANOVA shows that trial condition (still vs. moving ball) significantly affects energy@resonance ($p < 0.001$, $F = 78.92$) across frequencies and at each frequency—0.5 Hz ($p = 0.003$, $F = 22.59$), 1 Hz

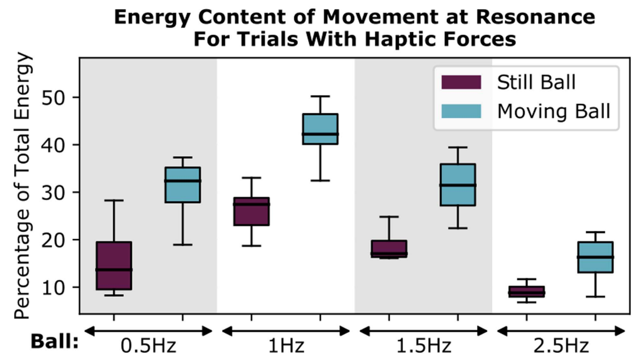

Fig. 7. Game is measuring active movement. Energy@resonance is lower when participants are not actively trying to balance the ball.

($p = 0.001$, $F = 48.53$), 1.5 Hz ($p = 0.030$, $F = 8.05$), and 2.5 Hz ($p = 0.045$, $F = 6.41$). Since haptic forces are present in both experimental conditions, this analysis confirms that a peak in the energy exerted at the task's resonant frequency cannot be fully attributed to an artifact of the haptic feedback. Instead, these results suggest participants are actively moving at the task's resonant frequency in order to settle the ball and succeed at the task.

Using the ball-in-bowl task, we are able to elicit a dynamic response at specific frequencies and quantitatively assess individuals' ability to perform movements at a chosen frequency. Results confirm that the game elicits active movement at the tested frequency.

C. Impact of Haptic Feedback on Motion Timing

The haptic feedback we provide during experiments makes the task more interactive and perceptually real. Moreover, in our results we find that haptic feedback improves the timing of individuals' motion—when completing the ball-in-bowl task, participants exert more effort near task resonance than during trials without haptic feedback.

When participants are provided both visual and haptic feedback, we observe that the frequency spectrum peaks (blue curves in Fig. 6) become more pronounced than when participants are provided only visual feedback (red peaks in Fig. 5). Accordingly, the statistical analysis reveals that participants exert more energy@resonance with haptic feedback compared to without haptic feedback (refer to Fig. 8). The repeated measures ANOVA shows that trial condition (haptic vs. no haptic feedback) significantly affects energy@resonance ($p = 0.002$, $F = 29.72$) across frequencies and at most frequencies individually—0.5 Hz ($p = 0.002$, $F = 26.43$), 1 Hz ($p = 0.012$, $F = 12.82$), 1.5 Hz ($p = 0.031$, $F = 7.85$)—with the energy@resonance at 2.5 Hz being marginally significant ($p = 0.067$, $F = 5.01$). There is also an interaction effect between ball frequency and trial condition ($p = 0.003$, $F = 3.81$), which may reflect a stronger impact of haptic feedback at lower frequencies compared to higher frequencies.

Lastly, we find that haptic feedback enables the participant to more closely match the task's resonant frequency with their motion. A repeated measures ANOVA reveals that window size ($w_f \in$ [0.2Hz, 0.4 Hz, 0.6Hz]) significantly impacts how

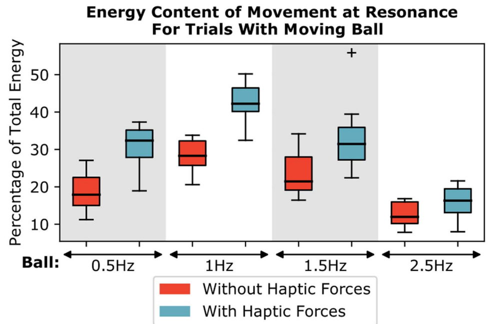

Fig. 8. Haptic forces improve movement timing compared to no forces. Energy@resonance is higher for trials with visuo-haptic feedback than with only visual cuing.

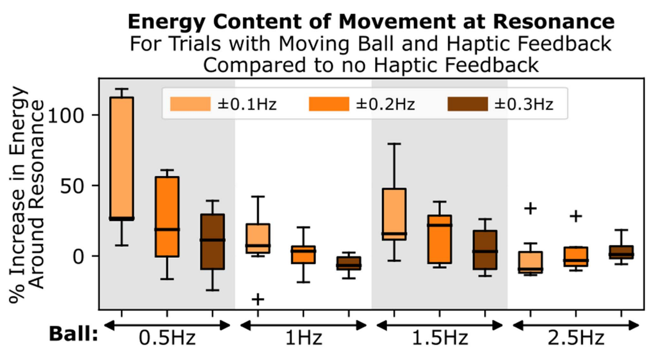

Fig. 9. Haptic forces guide precise timing of movement. Haptic forces improve energy@resonance more the smaller the window size w_f. The effect might only be true up to a certain frequency. At 2.5 Hz, we no longer observe this trend.

much haptic feedback improves the energy exerted around resonance ($p < 0.001$, $F = 15.83$) across frequencies (see Fig 9). Additionally, there is a significant interaction effect between window size and ball frequency ($p < 0.001$, $F = 9.71$), reflecting a stronger trend at 0.5 Hz ($p_{GG} = 0.003$, $F = 20.75$), 1 Hz ($p_{GG} = 0.107$, $F = 3.51$), and 1.5 Hz ($p_{GG} = 0.026$, $F = 7.93$) compared to a weaker trend at 2.5 Hz ($p_{GG} = 0.315$, $F = 1.23$). These results could indicate that people have a limited perception bandwidth for haptic feedback, meaning that the temporal resolution of haptic perception is not high enough to allow us to internalize haptic feedback above a certain frequency (between 1.5 Hz and 2.5 Hz). However, the results are not conclusive, because the within-frequency trends are statistically significant (with a p-value < 0.05) only at 0.5 Hz and 1.5 Hz. Moreover, visual feedback has been show to dominate proprioceptive feedback [23]—it would be interesting to do a follow-up experiment with haptic but no visual feedback.

IV. Discussion & Future Work

For effective human-robot collaboration, it is beneficial to understand people's bandwidth for motion and physical interaction. The scientific community outside of robotics has investigated these questions before. As an example, studies report that able-bodied individuals can generate a hand grasp with a delay of 200 ms in response to a sound. If these upper-limb reactions are generated repeatedly, a delay of 200 ms suggests an interaction bandwidth of 5 Hz. However, continuous interaction is mechanistically different from a one-off reaction in that it includes motion planning and re-planning in the motor cortices, cerebellum, and basal ganglia as well as motion termination and re-initiation at the level of the muscle. These processes may slow down interaction bandwidth in a complex, dynamic task.

Thus far, most research has investigated one-off reaction times [24], [25], [26], [27] rather than continuous interaction bandwidth. Using frequency analysis in a dynamic task, such as the ball-in-bowl task, we can evaluate the bandwidth of repeated interaction available to an individual in a specific context. In our experiments, we evaluate upper-limb movements in response to visual and haptic stimuli. By adjusting the feedback provided to the participant, we could further study interaction bandwidth under different modalities of sensory inputs. By using a different type of robot, we could study movements of other body parts, such as hands or legs.

In many neuromotor impairments, such as stroke, reaction times are delayed [27]. Our method can be used for quantitative assessment of motion and/or interaction bandwidth for individuals with neuromotor impairments. We can use it to examine deficits in receiving and interpreting sensory feedback due to a neuromotor disorder and determine how these deficits affect dynamic performance. Given this information, robotic systems focused on assistance or rehabilitation can tailor the interaction to the capabilities of that particular individual. In our ongoing work, we are looking at the impact of hemiparetic stroke on motion bandwidth post-injury.

While dynamic motion is part of many daily activities, such as walking, carrying a bag of groceries, or catching a falling object, current clinical assessments largely focus on static and quasi-static movements, because we do not have well-established methods for quantifying dynamic performance. A reliable, quantitative assessment of dynamic motion can have significant positive implications for translational research and clinical practice. In research, it can improve our ability to study the underlying causes of dynamic deficit. In clinical practice, it can be used for (1) precise tracking of disease progression, (2) studying therapeutic efficacy, and (3) early diagnosis of deficits in movement coordination and motion bandwidth. Long-term, our method can become the foundation of robot-assisted rehabilitation focused on re-training dynamic movements.

V. Conclusion

In this letter, we propose a method for measuring interaction bandwidth during pHRI. To validate the method, we run a human subject study (n = 7) and test frequencies 0.5–2.5 Hz—all within the normal range of a dynamic response for an able-bodied individual. We show that our game successfully elicits dynamic motion at the tested frequencies. Secondly, we show that haptic feedback helps guide the timing of participants' motion compared to only visual cuing. The method can be further used to analyze interaction bandwidth of human-robot systems, particularly to tailor interaction parameters to the individual capabilities of people with neuromotor impairments. Our ongoing work is

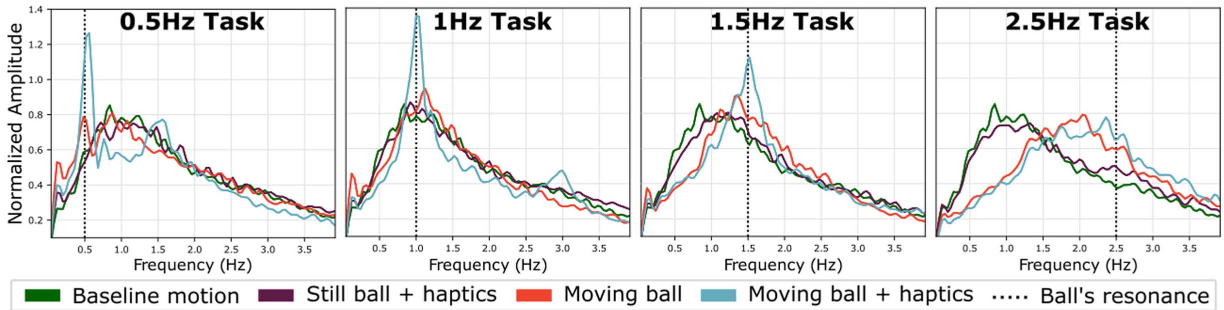

Fig. 10. Frequency decomposition of motion during ball-in-bowl task. Aggregate spectra for all subjects across four tasks and four experimental conditions.

applying the method to quantify deficiencies in dynamic motion after a hemiparetic stroke.

Appendix

Fig. 10 includes aggregate frequency spectra for all subjects across four experimental conditions and four tasks. The comparisons relevant to our study hypotheses are included in the main text of the letter. We include the aggregate data here to allow the curious reader to refer to it for context.

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