Humans Need Augmented Feedback to Physically Track Non-Biological Robot Movements

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Abstract— **An important component for the effective collaboration of humans with robots is the compatibility of their movements, especially when humans physically collaborate with a robot partner. Following previous findings that humans interact more seamlessly with a robot that moves with human-like or biological velocity profiles, this study examined whether humans can adapt to a robot that violates human signatures. The specific focus was on the role of extensive practice and real-time augmented feedback. Six groups of participants physically tracked a robot tracing an ellipse with profiles where velocity scaled with the curvature of the path in biological and non-biological ways, while instructed to minimize the interaction force with the robot. Three of the 6 groups received real-time visual feedback about their force error. Results showed that with 3 daily practice sessions, when given feedback about their force errors, humans could decrease their interaction forces when the robot's trajectory violated human-like velocity patterns. Conversely, when augmented feedback was not provided, there were no improvements despite this extensive practice. The biological profile showed no improvements, even with feedback, indicating that the (non-zero) force had already reached a floor level. These findings highlight the importance of biological robot trajectories and augmented feedback to guide humans to adapt to non-biological movements in physical human-robot interaction. These results have implications on various fields of robotics, such as surgical applications and collaborative robots for industry.**

Keywords: Physical Human-Robot Interaction; Human Factors and Human-in-the-Loop; Human-Centered Robotics

I. INTRODUCTION

Robots are transitioning from operating in isolated rooms to working in close collaboration with humans [1][2]. Human-robot interaction (HRI) introduces unique challenges for planning and control of robots to ensure the safety and comfort of the human partner while enhancing the overall task efficiency [3][4]. Optimal action planning [5][6], human intent recognition [7][8][9], and collision avoidance [10][11][12] are among the important challenges that need to be addressed. Physical human-robot interaction (pHRI), where the human and the robot work in direct contact with one another, adds even more complexity because it tightly couples the heterogeneous motor abilities of the two partners.

In pHRI, the interaction can be limited to a few seconds as in object handover [13] or it can be present throughout the entire task, e.g., collaboratively carrying an object [14]. In either case, the movements of the human and the robot directly impact the task execution. The interaction can be enhanced either by relying on the learning capabilities of humans to adjust their behavior to the robot, or by adapting the robot to move in ways that are intuitive for the human [15].

In the robotics literature, intuitiveness of a movement is often tied to its human-like aspects. To characterize trajectories as human-like, one must turn to human motor control studies that have tried to identify the core signatures present in human movement. Examining hand or end-effector trajectories, some robust features have been revealed: most notably the speed-accuracy trade-off in pointing tasks [16], [17] and the velocity-curvature relationship (two-thirds power law) in continuous trajectories [18], [19], [20]. These kinematic features have been replicated using optimal control with a variety of cost functions, such as minimum jerk [21], minimum endpoint variance [22], and minimum torque change [23].

Robot movements that are intuitive to humans have been explored in HRI tasks that do not involve physical contact. Bisio et al. [24] demonstrated that humans modulate their movements based on the robot movements as long as the kinematics is consistent with movements recorded from real humans. Conversely, when the robot violates the human-like features, the human does not adjust their own movement to those of the robot. A study by Kupferberg et al. [25] reinforced this finding in a contact-free interaction with a humanoid robot, showing that humans tended to perceive the robot as interaction partners as long as it exhibited minimum-jerk profiles, i.e., maximally smooth profiles. These results suggest that humans dissociate from their robot partner and do not execute the task collaboratively, if the robot displays non-human-like behavior.

However in physical interactions humans no longer have the option to dissociate themselves from their robot partner. This raises the question, how do humans react to non-human-like movements of a robot? Previous work showed that untrained subjects prefer interacting with robots that move in more biological patterns during collaborative tasks, such as point-to-point reaching [26], object handover [27], and exoskeleton applications [28]. A previous study of our group on a human-robot tracking task also showed that humans tended to follow the robot's movements if its kinematics obeyed the two-thirds power law. Specifically, humans exerted less force on the robot if its tangential velocity varied with the path's curvature with a specific power relation identified in humans [29].

Programming robots to elicit human-like movement patterns therefore seems the best approach to achieve seamless interaction and increase the usability and acceptance of the robot. But this is not always an option, as external constraints may

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be imposed by the task or the environment. In such cases, one could expect that humans are able to adapt if they are given enough practice. Indeed, humans have been shown to adjust to the robot behavior to increase the task efficiency [30] and they could learn to predict non-biological robot movements during visual interaction [31]. And, after all, humans seem to demonstrate a sheer boundless ability to learn new and complex skills in everyday and leisure time activities. But is this adaptability really without limits?

Maurice et al. started to examine human abilities in physically tracking a robot, and has reported first evidence that humans can adapt to robot movements that violated the velocity-curvature relation of the two-thirds power law [29]. Specifically, participants were instructed to hold a robot as it traced out an elliptical path with a constant (non-biological) velocity profile, while minimizing the force exerted against the robot. After 1.5-hour practice, participants who received visual feedback about their exerted force revealed some reductions in force, while those without feedback did not improve. But interestingly, despite this improvement, the performance reached was still less optimal compared to when the robot followed the power law. Performance in the biological condition remained superior even when subjects had no practice and no visual feedback. This suggested that the untrained performance of the biological profile is the best humans can do. However, the practice comprised only a single session and performance did not reach a clear plateau, hence real performance limits could not be assessed.

For the development of physical human-robot interaction, it is crucial to understand to what extent humans can learn and overcome the challenges posed by non-biological movement patterns. A related question is what is needed to facilitate learning. Therefore, the present study investigated to what extent humans can adapt to and learn the robot motion when violating human movement signatures. Using a paradigm similar to our previous study [29], we extended the practice over 3 days to assess whether performance with a biological profile without training remains a hard limit. Participants underwent practice with the same constant velocity profiles as in [29], but also with another non-biological profile to assess the generalizability of the findings. Extended practice with the biological profile aimed to scrutinize whether further improvement was possible even in this familiar condition.

Since our previous study suggested that visual feedback facilitated learning, half of the participants in the present study were provided with augmented feedback. In addition, to provide the best opportunity to learn, we modified the visual feedback to better match the elliptical hand-robot movements than the previously used display.

II. Methods

A. Participants

A total of 41 healthy college students (22 females and 19 males, aged 18-35 yrs) participated in the study. All participants were right-handed, did not report any biomechanical problems in their upper extremity, and were naive to the purpose of the study. All participants signed an informed consent form approved by Northeastern University Institutional Review Board prior to the start of the experiment (#10-06-19).

B. Two-Thirds Power Law in Velocity Profiles

Previous research in human motor control showed that human endpoint trajectories exhibit the so-called *two-thirds power law*, a systematic relation between the kinematic characteristics of the hand movement and the curvature of the associated path [18][19][20]. For trajectories with no inflection points, the power law can be written as,

$$v(t) = Kr(t)^{\beta} \tag{1}$$

with $\beta = 1/3$, where v is the tangential hand velocity, r is the radius of curvature of the path, and K is a gain factor that determines the tempo of the overall trajectory[1]. Hence, the kinematics scales with the geometric features of the endpoint movement. Essentially, this means that the movement slows down in more curved portions of the path and speeds up in straighter portions. Thus, this power relation can be used to characterize biological 'power law' profiles and non-biological profiles that violate this relation in robot movements.

C. Experimental Conditions and Procedure

A robotic manipulandum was programmed to trace out an elliptic path in a horizontal plane (major axis = 30 cm, minor axis = 10 cm) with its end-effector, moving in counterclockwise direction (Fig. 1A). The tangential velocity of the traversal was modulated according to the two-thirds power law. By varying the exponent β of the power law in (1), we created 3 different velocity profiles: *biological* ($\beta = 1/3$), *constant* ($\beta = 0$, profile used in the learning experiment of [29]), and *exaggerated* ($\beta = 2/3$). For the *biological* profile, the robot followed the power law, where the movement velocity decreased as the path curvature increased, and vice versa. The *constant* condition enforced a constant tangential velocity on the robot, similar to a control strategy commonly used for robot movements. The *exaggerated* velocity profile was an amplified version of the *power law* profile, where the robot significantly slowed down around curves and moved faster in the straighter sections of the ellipse. The K parameter in (1) was adjusted for each velocity profile to hold the ellipse period at 3 s across all conditions.

In each trial, the robot traced the ellipse 6 times without pause, with each ellipse lasting 3 s (18 s per trial). A 5 s break between successive trials allowed for rest to avoid fatigue. After 5 s, the robot automatically began the next trial. Each trial began and ended with a short sound. After a block of 10 trials, participants could rest for 2 to 3 minutes.

Participants were instructed to firmly hold the robot handle and move with the robot as it traced the ellipses, while exerting as little force as possible on the robot handle (Fig. 1B). Participants used their right-dominant hand to interact with the robot. The robot handle was free to rotate about its vertical axis which decoupled its orientation from the participants' wrist orientation (Fig. 1C). The elliptic robot and hand movements were confined to the 2-dimensional horizontal plane. The height of the robot was adjusted for each participant to ensure their forearm was approximately horizontal when holding the robot

[1]The name two-thirds power law comes from the original formulation with the angular velocity and curvature (instead of tangential velocity and radius of curvature), for which the value of the exponent is 2/3.

end-effector. Before starting the experiment, participants could find their most comfortable orientation and distance relative to the robot, but were instructed to maintain this position during the trials. A video of the experiment is available here: `https://youtu.be/t6VRMFxMxfs`.

D. Experimental Apparatus

1) Robot: Participants interacted with the HapticMaster, a 3-DOF robotic manipulandum (Motek Medical, The Netherlands) [32] (Fig. 1B). The robot was programmed through a custom C++ API and controlled using an impedance controller with high stiffness. Given the high stiffness, the robot continued to trace the predefined path even if the human applied resistive or assistive forces to its end-effector. The robot's desired position was updated at 120Hz. A 3-axis force sensor embedded at the robot end-effector measured the force exerted by participants on the robot handle. The force data and the position of the robot's end-effector were recorded at 120Hz.

An additional force sensitive resistor (FSR) afixed to the handle measured grip force (Fig. 1C) to test whether subjects firmly held the robot handle and were actively engaged in the task. The grip force sensor would trigger a buzzing sound, if participants loosened their grip on the handle beyond a threshold value. Without this check, participants may apply less force on the robot simply by loosening their grip on the handle during the experiments. This could be misinterpreted as compliance with the task. Note that the FSR was only used to ensure active participation, and not for analysis purpose.

2) Augmented Feedback: Since our previous study [29] suggested that additional feedback may facilitate learning, visual feedback about online performance was provided to half of the participants to give them the best opportunity to learn. This online feedback was shown on a projector screen in front of the participant with a cursor tracing the ellipse as the robot moved along its predefined elliptical path (Fig. 1B). The color of the cursor changed on-line to indicate the error in the force applied. Its shade changed between green (good) to red (bad) depending on the real-time error. Real-time error was quantified as the root mean square (RMS) of the magnitude of force in the horizontal plane that the participant exerted on the robot over a sliding window of 80 ms. The range of color was adjusted for each participant, based on their average force exerted in their *baseline* trials (see section II-E). The cursor was green if the force error was less than half of their *baseline*, and it was red if it was more than double of their force at *baseline*. In order to ensure subjects were continuously challenged to reduce their force on the robot handle, the reference force was updated after every 4 blocks of 10 trials. The reference force was updated to be the average of the most recent 10 trials. Participants who received visual feedback were instructed to ensure that the cursor color remained green.

For comparison, the other half of the participants were *blindfolded* and saw neither visual feedback, nor their hands or the robot. Hence, they had to rely on their proprioceptive and haptic feedback to smoothly follow the robot's motion without exerting additional forces against the robot.

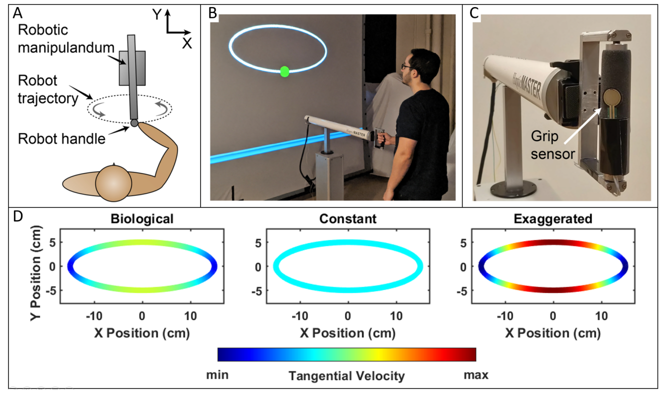

Fig. 1. **A.** Experimental setup. **B.** Participant performing the task with visual feedback of their performance. The cursor on the screen traced the ellipse simultaneously as the robot (HapticMaster) moved around its elliptical path. **C.** Grip sensor attached to the robot end-effector to ensure participants' engagement in the task. **D.** Tangential velocity across the ellipse for the three velocity profiles used in the experiment.

E. Experimental Design

Participants were randomly assigned to 1 of 6 groups, with 6 to 8 participants per group (Fig. 2). Three groups received visual feedback (*with-FB*) of their real-time force error throughout the training, as shown in Fig. 1B; 3 groups were blindfolded (*no-FB*). All participants received haptic and proprioceptive feedback through grip contact with the robot handle.

Prior to the training, all participants performed 2 blocks of 4 trials each, in which all groups were blindfolded: 4 trials of the biological profile determined *reference* performance; the second block of 4 trials presented the assigned velocity profile to determine *baseline* performance before introducing feedback. In the experiment proper, participants practiced their assigned velocity profile in 3 one-hour-long training sessions on 3 consecutive days. Every training session involved 8 blocks, with each block containing 10 successive trials. Hence participants practiced 24 blocks with 240 trials, for a grand total of 1440 elliptical movements.

F. Data Analysis

1) Data Filtering: The recorded data consisted of continuous forces in X and Y horizontal directions that a participant exerted on the robot end-effector during the interaction. The magnitude of the force at every point of the ellipse was calculated. In order to eliminate transient data, the first and last ellipse of every trial were excluded from the data analysis.

The human-robot interaction force data were filtered forward and backward (to avoid phase-shifts) through a 4th-order 6 Hz low-pass Butterworth filter. Over 90% of the original signal's power was maintained post filtering. Code and data are available here:
`https://gitfront.io/r/mahdiaredraki/YqQmHMJPnq1t/ICRA2023/`.

2) Performance Metrics: The explicitly instructed goal in all conditions was to minimize the magnitude of the force exerted against the robot, which therefore served as first performance metric. The force magnitude metrics *F-RMS* was calculated as the root mean square of force applied across the 40 ellipses of one block (10 trials per block and 4 ellipses per trial, since the first and last ellipse of each trial were excluded).

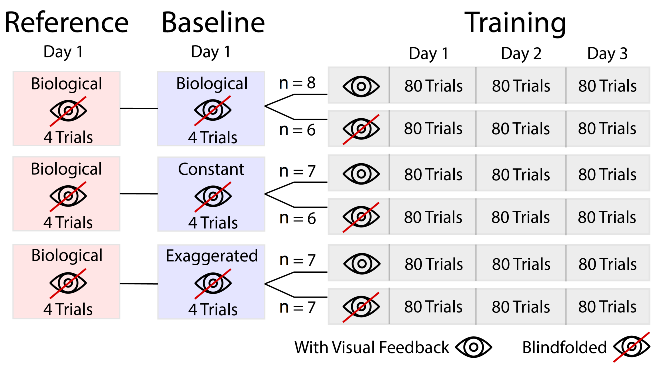

Fig. 2. Layout of the experimental design. Six groups of participants performed the 3 velocity conditions, either with or without visual feedback (n is the number of participants per group). The experiment began with recording reference and baseline performance (4 trials each, blind-folded). This was followed by 3 days of training, each day consisting of 8 blocks of 80 trials total.

As human performance is always variable and reduction of this variability has been shown a reliable characteristic of learning [33], the standard deviation of force *F-SD* was added as a second metric. This metric was calculated as follows: for each ellipse in a block (4 x 10 trials), force magnitude was computed at each spatial location across the ellipse (360 bins). At each spatial location, the standard deviation of the force magnitude was computed over the 40 ellipses. Finally, all location-dependent values were averaged.

3) Statistical Analysis: Performance across the training sessions was evaluated by fitting linear regressions to both the *F-RMS* and the *F-SD* values over the 24 blocks of the 3 days of training. Blocks rather than trials were used as regressors, because the calculation of standard deviations required aggregating trials of one block. The confidence intervals of the regression slopes served to determine whether each participant's performance significantly changed across 3 practice days. If the zero slope was not within the confidence intervals, the change was considered statistically significant (Fig. 3).

In the groups where improvements were detected, additional analyses were conducted to assess whether the performance reached after training was better than the *reference* performance (biological profile without visual feedback before any practice). This was done by comparing the 4 last trials of the training phase with the 4 *reference* trials, using a paired t-test.

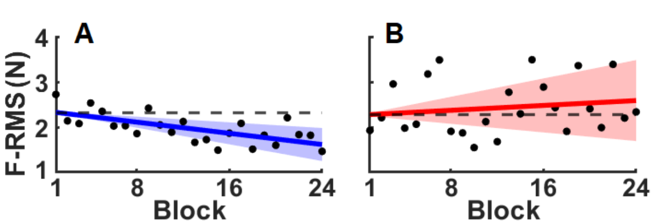

Fig. 3. Linear regressions for two representative participants. Black dots show block means across the 24 blocks. The shaded areas show the 95% confidence interval of the regression slopes. A: Linear fit for a participant that improved through practice as the confidence intervals did not include zero slope. B: Linear fit for a participant that did not improve as the confidence intervals did embrace zero slope.

III. Results

Based on the measured forces, this experiment aimed to evaluate whether extensive practice over multiple days with compatible and updating feedback could elicit performance improvements both in biological and non-biological conditions. We also assessed whether practice could take participants beyond baseline performance with the biological robot profile.

A. Elimination of Trials

Prior to data analysis, trials were scrutinized to assure that participants maintained a solid grip of the robot to prevent that low interaction forces only resulted from a loose grip of the robot. Trials where the buzzer was triggered for more than 10% of the trial duration (>1.8 s out of 18 s) were excluded from subsequent analysis. With this criterion, the data for 2 participants had to be excluded as they failed to follow the task instructions (reducing number of participants to 6 in 2 groups as shown in Fig. 2). In the remaining 39 participants, ∼4% of the trials across all participants were excluded.

B. Force Patterns Across the Ellipse

Fig. 4 illustrates the spatial and temporal pattern of the interaction force exerted by representative participants in the 3 velocity profiles. Different force patterns were elicited depending on the profile, highlighting how different segments of the ellipse posed difficulties to minimize the interaction force. Most notably, the forces were high at the highly curved segments in the constant condition, while the forces in the biological conditions were lowest and more distributed along the ellipse. In the exaggerated condition two peaks occurred at the linear portions where the speed was faster than the biological pattern. Except for short moments, the magnitude of force did not reach zero Newtons.

C. Force Magnitude and Variability Across Blocks

This analysis focused on how the force magnitude and variability changed across the 3-day-long practice in all 6 conditions. To this end, the values of *F-RMS* and *F-SD* of all participants over the 24 blocks were plotted for each condition in Fig. 5A and C. The linear regressions are also shown as lines. The R^2 values for all participants ranged from 0.19 to 0.77 with a median of 0.38 (see Fig. 3).[2]

Starting with the feedback conditions, the individual participants' regression slopes of *F-RMS* in the biological condition tended to be variable and without any visible trend to decline across blocks. This differed from the constant and exaggerated condition where the majority of participants exhibited negative slopes. This pattern was reinforced in the *F-SD* results, although less clear. In the no-feedback conditions, the individual regression slopes did not signal any consistent change with practice, neither for *F-RMS*, nor for *F-SD*. The slopes and their 95% confidence intervals for each group and participant are summarized in Fig. 5B and D, where the error bars indicate the boundaries of the confidence intervals. Table I summarizes the

[2]The R^2 metric evaluates the amount of variance explained by the linear fit in determining change in performance compared to mean performance for each participant. This makes it meaningless to report the R^2 values for regressions where the 95% confidence interval includes zero slope. Thus, only the R^2 of regressions with non-zero slopes are reported.

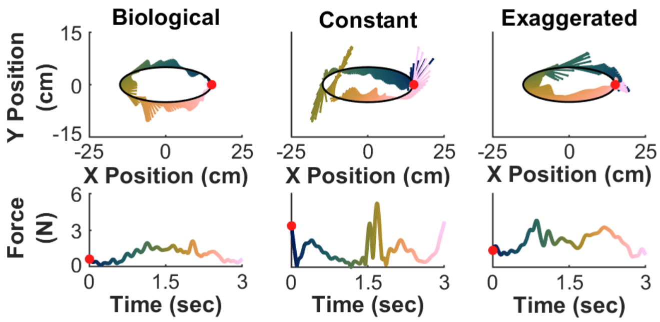

Fig. 4. Top row: Vectors representing the interaction force (direction and magnitude) exerted on the robot across one ellipse in the three velocity profiles, taken from 3 representative participants of the respective groups. The red dot marks the starting point of the ellipse. The color code indicates the progression of time matching the time series below. Bottom row: Time series of the magnitude of the interaction force around the ellipse of the same trial as shown above.

number of participants in each condition that show regression slopes different from zero, i.e., significant change across 3 days of practice. Overall, the data showed that participants learnt the non-biological patterns, but only when visual feedback was provided. Performance in the biological profile did not change, even when feedback was given. Hence, performance in the biological profile seemed to be at a 'hard limit'.

Given these results, the next question was whether performance in the non-biological conditions had also reached that limit. Using paired t-tests, the mean *F-RMS* in the last 4 trials was compared with the mean performance in the reference trials. These comparisons were only conducted for participants that received feedback in the constant and exaggerated conditions. Neither of the two comparisons was significant (p=0.068 for constant, p=0.265 for exaggerated condition). Therefore, even with practice, participants were not able to reduce their interaction forces beyond their untrained biological performance. When *F-SD* values were compared, the exaggerated condition showed no difference (p-value = 0.107), only the constant conditions showed a small difference (p=0.029).

Given the high initial force values in some of the feedback conditions, additional control tests were conducted to rule out that the introduction of visual feedback presented an initial difficulty. To this end, the first 4 trials of the training phase of all participants who received visual feedback were compared with the 4 trials at baseline with the same velocity profile, but blindfolded. For these 3 comparisons, both *F-RMS* and *F-SD* of all participants were compared by paired t-tests. None of these comparisons revealed a significant difference.

TABLE I

NUMBER OF PARTICIPANTS IN EACH CONDITION THAT IMPROVED VERSUS DID NOT IMPROVE THROUGH PRACTICE.

Performance Metric		***F-RMS***	***F-SD***
Condition		**(improved / did not improve)**	
with-FB	Biological	1/7	1/7
	Constant	5/2	5/2
	Exaggerated	4/3	4/3
no-FB	Biological	1/5	1/5
	Constant	1/5	1/5
	Exaggerated	0/7	2/5

IV. DISCUSSION

This study investigated to what extent humans can adapt to a robot motion in a pHRI task that violates human movement signatures, specifically the two-thirds power law, a human-preferred speed-curvature relation. Results showed that humans could improve their interaction with a robot moving in two non-biological velocity profiles, but only if augmented feedback was provided. This finding generalizes our previous findings [29]. However, even when given extensive 3-day-long practice with dedicated visual feedback of their performance, participants did not show any improvement in the biological profile. Additionally, improved performance with a non-biological profile never exceeded their untrained biological performance. This suggests that the untrained biological performance is a limit that humans cannot surpass.

A. Role of Augmented Feedback

It is noteworthy that participants who received continuous force feedback but were deprived of augmented visual feedback about their task error did not show any improvements in practiced velocity profiles, even after 3 daily practice sessions. This suggests that haptic feedback about the forces alone was insufficient to fine-tune their interaction with the robot. This inferior performance with haptic information alone suggests that humans may not have enough sensitivity to perceive the modulations of the relatively small forces. Visualization of force error, i.e., providing augmented real-time feedback, was evidently necessary.

These results were based on two main performance metrics that were regarded as two main indicators of performance and learning: While *F-RMS* expresses the error from the instructed zero force, variability *F-SD* is an independent metric of performance [34]. With one exception where variability in the constant profile was better than the biological condition, the current results showed parallel declines in the two metrics, therefore reinforcing the observations.

Note that both Maurice et al. [29] and a recent study by West et al. [35] also provided online visual feedback, but with mixed results. Not only was the practice duration in both studies much shorter, they also presented a different design of visual feedback. Their visualization of error was a horizontal bar deviating from a baseline representing the target force. Anecdotally, this vertical graphic arrangement proved difficult to map onto the horizontal elliptical pattern, i.e., showed little compatibility. Therefore, the present study presented the cursor moving online on an elliptical path and used cursor color to indicate force error. Note that augmented feedback can be of different degrees of 'compatibility' and therefore careful design of how feedback is provided is necessary [36].

In fact, feedback can also be detrimental if it is 'too complicated' because it can create an additional cognitive load. An increase in cognitive load due to feedback has been reported in surgical robotics applications, where novice surgeons could not benefit from additional haptic information and actually deteriorated in their performance accuracy [37]. Similarly, a study on object manipulation with a phantom robot showed that

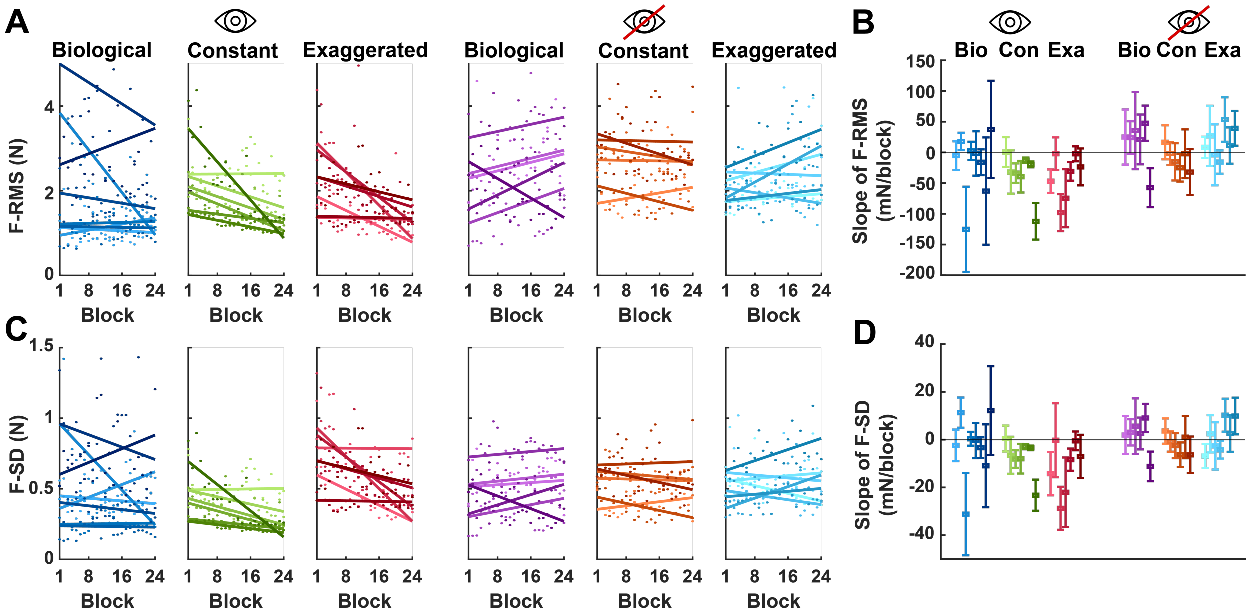

Fig. 5. Overview of participants' performance across the 3 practice days. **A.** Force magnitude *F-RMS* across blocks. Each point is the average value per block for each participant. The 6 panels correspond to the 6 conditions (3 velocity profiles and 2 feedback conditions). Within each condition, color shading within each condition denote different participants (consistently with panel B). The solid lines represent the regression slopes for each participant. **B.** Slopes (point) and their corresponding 95% confidence intervals (bars) of the linear regressions of *F-RMS* for each participant in the *biological* (Bio), *constant* (Con), and *exaggerated* (Exa) velocity profiles, with and without visual feedback. **C.** Same as panel A for variability of force *F-SD*. **D.** Same as panel B for variability of force *F-SD*.

the effect of haptic feedback on performance was dependent on the context [38]. To probe whether the introduction of feedback in our study did not require undesired attentional resources, we compared the blindfolded baseline trials with the first feedback trials. Results confirmed that this feedback did not introduce any noticeable extra load and, hence, the subsequent improvements were not a side-effect of the initial integration of feedback.

B. Limits of Human Performance in Biological Condition

The biological profiles did not show any improvements, even after 3 days of practice with enhanced feedback and regardless of whether augmented visual feedback was given. Note that the experiment also adjusted the visual force feedback to the current level of force error in order to maintain the challenge for participants. These efforts reinforced that participants have reached their maximum performance in the biological condition, even though the force errors were not reduced to zero.

This is in apparent contrast with a recent paper by West et al. [35] on a similar ellipse-tracking task that reported improvements in a biological profile. However, an important difference is that participants were instructed to apply a constant tangential force of 5 N against the robot. Further, the research focus was on force-motion or hybrid control. Hence, trial blocks with visual feedback alternated with blocks of no feedback, precluding direct inferences about learning.

C. Implications for Robotic Applications

The straightforward conclusion of our results is to program robots to move with human-like features to facilitate the interaction without requiring extensive practice. However, this may not be feasible in all pHRI applications. Some pHRI tasks have pre-set constraints on the types of motion that the robot can display. For example, Glogowski et al. developed a trajectory planning algorithm that allowed for the online adaptation of the robot velocity to satisfy constraints such as collision avoidance [39]. This may have traded off velocity with collision avoidance. In the same vein, robot control needs to avoid actuator torque saturation and prioritize stability and inertia compensation, all issues that may compromise the independent control of trajectory velocity [40]. For such situations where task constraints may prevent the robot to adopt human-like trajectories, the current study showed that humans do have the ability to adapt, at least in a limited way and if appropriate feedback about the interaction is provided.

V. CONCLUSIONS

This study examined the conditions in which humans could optimally track robot movements and learn to minimize undesired interaction forces. With extensive practice and real-time augmented feedback about the force error, humans could adapt to robot trajectories that violated human signatures. However, humans were unable to improve their performance when no additional feedback was provided. These results show that when humans have to interact with robots that move with non-biological profiles, they need proper guidance to master the interaction. Thus, training modalities have to be considered carefully when deploying such robots. Further, even in the most human-like trajectories, humans could not perfectly follow robot movements. Hence, future work should further probe into human preferences and their limited ability to interact with and adapt to robot motions. Feedback should be carefully designed to minimize additional cognitive load and to provide the best possible guidance to potentially push these human limits.

References

[1] Anas Abou Allaban, Maozhen Wang, and Taşkın Padır. A systematic review of robotics research in support of in-home care for older adults. *Information*, 11(2), 2020.

[2] Aslam Pervez and Jeha Ryu. Safe physical human robot interaction-past, present and future. *Journal of Mechanical Science and Technology*, 22:469–483, 01 2011.

[3] Henny Admoni, Julie Shah, and Siddhartha Srinivasa. Editorial: Special issue on human-robot interaction. *The International Journal of Robotics Research*, 36(5-7):459–460, 2017.

[4] Agostino De Santis, Bruno Siciliano, Alessandro De Luca, and Antonio Bicchi. An atlas of physical human–robot interaction. *Mechanism and Machine Theory*, 43(3):253–270, 2008.

[5] Kelsey P. Hawkins, Nam Vo, Shray Bansal, and Aaron F. Bobick. Probabilistic human action prediction and wait-sensitive planning for responsive human-robot collaboration. In *2013 13th IEEE-RAS International Conference on Humanoid Robots (Humanoids)*, pages 499–506, 2013.

[6] Behzad Sadrfaridpour and Yue Wang. Collaborative assembly in hybrid manufacturing cells: An integrated framework for human–robot interaction. *IEEE Transactions on Automation Science and Engineering*, 15(3):1178–1192, 2018.

[7] Przemyslaw A. Lasota and Julie A. Shah. Analyzing the effects of human-aware motion planning on close-proximity human–robot collaboration. *Human Factors*, 57(1):21–33, 2015. PMID: 25790568.

[8] Matthew Huggins, Sharifa Alghowinem, Sooyeon Jeong, Pedro Colon-Hernandez, Cynthia Breazeal, and Hae Won Park. Practical guidelines for intent recognition: Bert with minimal training data evaluated in real-world hri application. In *Proceedings of the 2021 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '21, page 341–350, New York, NY, USA, 2021. Association for Computing Machinery.

[9] Ravi Teja Chadalavada, Henrik Andreasson, Maike Schindler, Rainer Palm, and Achim J. Lilienthal. Bi-directional navigation intent communication using spatial augmented reality and eye-tracking glasses for improved safety in human–robot interaction. *Robotics and Computer-Integrated Manufacturing*, 61:101830, 2020.

[10] Woo Young Kwon and Il Hong Suh. A temporal bayesian network with application to design of a proactive robotic assistant. In *2012 IEEE International Conference on Robotics and Automation*, pages 3685–3690, 2012.

[11] Yitao Ding, Felix Wilhelm, Leonhard Faulhammer, and Ulrike Thomas. With proximity servoing towards safe human-robot-interaction. In *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 4907–4912, 2019.

[12] Hugo Nascimento, Martin Mujica, and Mourad Benoussaad. Collision avoidance in human-robot interaction using kinect vision system combined with robot's model and data. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 10293–10298, 2020.

[13] Patrick Rosenberger, Akansel Cosgun, Rhys Newbury, Jun Kwan, Valerio Ortenzi, Peter Corke, and Manfred Grafinger. Object-independent human-to-robot handovers using real time robotic vision. *IEEE Robotics and Automation Letters*, 6(1):17–23, 2021.

[14] R. Ikeura, T. Moriguchi, and K. Mizutani. Optimal variable impedance control for a robot and its application to lifting an object with a human. In *Proceedings. 11th IEEE International Workshop on Robot and Human Interactive Communication*, pages 500–505, 2002.

[15] Wesley P Chan, Chris Ac Parker, Hf Machiel Van Der Loos, and Elizabeth A Croft. A human-inspired object handover controller. *The International Journal of Robotics Research*, 32(8):971–983, 2013.

[16] Paul M. Fitts. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology: General*, 121(3):262–269, 1992.

[17] Réjean Plamondon and Adel M. Alimi. Speed/accuracy trade-offs in target-directed movements. *Behavioral and Brain Sciences*, 20(2):279–303, 1997.

[18] Francesco Lacquaniti, Carlo Terzuolo, and Paolo Viviani. The law relating the kinematic and figural aspects of drawing movements. *Acta Psychologica*, 54(1-3):115–130, 1983.

[19] Paolo Viviani and Roland Schneider. A developmental study of the relationship between geometry and kinematics in drawing movements. *Journal of Experimental Psychology: Human Perception and Performance*, 17(1):198–218, 1991.

[20] Stefan Schaal and Dagmar Sternad. Origins and violations of the 2/3 power law in rhythmic three-dimensional arm movements. *Experimental Brain Research*, 136(1):60–72, 2001.

[21] T Flash and N Hogan. The coordination of arm movements: an experimentally confirmed mathematical model. *The Journal of Neuroscience*, 5(7):1688–1703, 1985.

[22] Christopher M. Harris and Daniel M. Wolpert. Signal-dependent noise determines motor planning. *Nature*, 394(6695):780–784, 1998.

[23] Y. Uno, M. Kawato, and R. Suzuki. Formation and control of optimal trajectory in human multijoint arm movement. *Biological Cybernetics*, 61(2), 1989.

[24] Ambra Bisio, Alessandra Sciutti, Francesco Nori, Giorgio Metta, Luciano Fadiga, Giulio Sandini, and Thierry Pozzo. Motor contagion during human-human and human-robot interaction. *PLoS ONE*, 9(8), 2014.

[25] Aleksandra Kupferberg, Stefan Glasauer, Markus Huber, Markus Rickert, Alois Knoll, and Thomas Brandt. Biological movement increases acceptance of humanoid robots as human partners in motor interaction. *Ai & Society*, 26(4):339–345, 2011.

[26] B. Corteville, E. Aertbelien, H. Bruyninckx, J. De Schutter, and H. Van Brussel. Human-inspired robot assistant for fast point-to-point movements. In *Proceedings 2007 IEEE International Conference on Robotics and Automation*, pages 3639–3644, 2007.

[27] Markus Huber, Markus Rickert, Alois Knoll, Thomas Brandt, and Stefan Glasauer. Human-robot interaction in handing-over tasks. In *RO-MAN 2008 - The 17th IEEE International Symposium on Robot and Human Interactive Communication*, pages 107–112, 2008.

[28] Guoping Zhao, Maziar Ahmad Sharbafi, Mark Vlutters, Edwin van Asseldonk, and Andre Seyfarth. Bio-inspired balance control assistance can reduce metabolic energy consumption in human walking. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27(9):1760–1769, 2019.

[29] Pauline Maurice, Meghan E. Huber, Neville Hogan, and Dagmar Sternad. Velocity-curvature patterns limit human–robot physical interaction. *IEEE Robotics and Automation Letters*, 3(1):249–256, 2018.

[30] Stefanos Nikolaidis, David Hsu, and Siddhartha Srinivasa. Human-robot mutual adaptation in collaborative tasks: Models and experiments. *The International Journal of Robotics Research*, 36(5-7):618–634, 2017.

[31] Anca Dragan and Siddhartha Srinivasa. Familiarization to robot motion. *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, 2014.

[32] R.q. Van Der Linde and P. Lammertse. Hapticmaster – a generic force controlled robot for human interaction. *Industrial Robot: An International Journal*, 30(6):515–524, 2003.

[33] Dagmar Sternad. It's not (only) the mean that matters: Variability, noise and exploration in skill learning. *Current Opinion in Behavioral Sciences*, 20:183–195, 2018.

[34] Richard A. Schmidt, Howard N. Zelaznik, Gabriele Wulf, Carolee J. Winstein, and Timothy Donald Lee. *Motor control and learning: A behavioral emphasis*. Human Kinetics, 2019.

[35] A Michael West, James Hermus, Meghan Huber, Pauline Maurice, Dagmar Sternad, and Neville Hogan. Dynamic primitives limit human force regulation during motion. *IEEE Robotics and Automation Letters*, 2022.

[36] Robert W. Proctor. *Stimulus-response compatibility: An integrated perspective*. North-Holland, 1990.

[37] M. Zhou, D.B. Jones, S.D. Schwaitzberg, and C.G.L. Cao. Role of haptic feedback and cognitive load in surgical skill acquisition. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 51(11):631–635, 2007.

[38] Cara E. Stepp, Brian T. Dellon, and Yoky Matsuoka. Contextual effects on robotic experiments of sensory feedback for object manipulation. In *2010 3rd IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics*, pages 58–63, 2010.

[39] Paul Glogowski, Alexander Böhmer, Alfred Hypki, and Bernd Kuhlenkötter. Robot speed adaption in multiple trajectory planning and integration in a simulation tool for human-robot interaction. *Journal of Intelligent & Robotic Systems*, 102(1), 2021.

[40] Stephen P. Buerger and Neville Hogan. Relaxing passivity for human-robot interaction. In *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4570–4575, 2006.