Abstract—Physical interaction can enhance motor learning, but it remains unclear what type of interaction is best suited to increasing the active effort put into a task, which should support learning. Here, we used the same interactive tracking task with different instructions to induce three training conditions: competition, collaboration, and self-improvement, where partners improve their own performance while interacting haptically with each other. The effort was gauged by measuring the total normalized muscle activity. Feedback of task performance and the haptic dynamics were identical in all three training conditions, so the effort needed to complete the task was the same. Only the instructions to ‘compete with the partner’, ‘improve your and your partner’s accuracy’ and ‘improve your accuracy’ were different among the competition, collaboration, and self-improvement conditions, respectively. Despite having the same goal of maximizing self-performance during competition and self-improvement, participants exerted significantly more effort during competition, and their tracking accuracy was highest during competitive practice. Least effort was put into collaboration but tracking accuracy during collaboration was comparable to self-improvement. Our results suggest that interactive haptic competition can induce higher active drive or effort than either collaborative training or self-focused practice.

Index Terms—Interaction, effort, competition, collaboration.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Imperial College Research Ethics Committee under No. 15IC2470, and performed in line with the Declaration of Helsinki.

Atsushi Takagi is with NTT Communication Science Laboratories, Atsugi, Kanagawa 243-0198, Japan (e-mail: atsushi.takagi@ntt.com).
Carlo Bagnato is with FRANKA EMiKA GmbH, 80797 Muenchen, Germany (e-mail: carlobagnato@gmail.com).
Alejandro Melendez-Calderon is with the School of Electrical Engineering and Computer Science, School of Health and Rehabilitation Sciences, The University of Queensland, St Lucia, QLD 4072, Australia, and also with Jamieson Trauma Institute, Metro North Health, Brisbane, QLD 4029, Australia (e-mail: alej.melendez@uq.edu.au).
Nathanaël Jarrassé is with the Institute of Intelligent Systems and Robotics, Sorbonne Université, 75005 Paris, France (e-mail: jarrasse@isir.upmc.fr).
Gowrishankar Ganesh is with the UM-CNRS Laboratoire d’Informatique, de Robotique et de Microélectronique de Montpellier (LIRMM), 34095 Montpellier, France (e-mail: ganesh.gowrishankar@lirmm.fr).
Etienne Burdet is with the Imperial College of Science, Technology and Medicine, W12 0BZ London, U.K. (e-mail: e.burdet@imperial.ac.uk).

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I. INTRODUCTION

HUMANS continually acquire new motor skills to physically interact with the environment. The physical interaction and assistance provided by other people play a vital role in learning new motor skills like when learning to ride a bicycle. Recent evidence has revealed how haptic communication (mediated by touch) yields superior motor performance [1], [2] and can boost learning [3], but the trainee needs to take an active role in the task and not be passively guided by the partner. The effort put into a motor task, which may be quantified by the total muscle activity [4], is a major factor in motor learning and improving the outcome of neurorehabilitation [5], [6], [7]. Thus, interactive practice may be beneficial to motor training and relearning [8], but the trainee should be exerting effort to reap its benefits.

Interactive practice can be subdivided into collaboration, competition, or self-improvement [9]. Self-improvement is where partners improve their performance while interacting haptically with each other [9], [10], which is different from solo training where the individuals practice alone and without interaction [11]. Collaboration is commonly used in interactive practice literature (see [12] for a review). A diverse set of motor tasks have been examined in the collaborative practice literature. Examples include reaching [13], [14] and tracking a common target [2], manipulating a common object [15], and tracing a common shape [16]. Competition is less studied relative to collaboration, but it is usually fostered by presenting conflicting goals to each partner [17], [18].

The goal of this study was to identify the haptic training condition (self-improvement, collaboration, and competition) that best enhances the trainees’ effort during practice. Previous studies faced difficulty in comparing competition with other modes of training because the competitive task usually required more effort to begin with. To illustrate this point, imagine a trainer competing with a trainee by opposing their motion whilst reaching for a cup. This competitive task clearly requires more effort than when reaching alone or if the trainer assists the movement [17], [18]. To have the same baseline effort needed to complete the task, the feedback provided to users and the haptic dynamics must be kept the same across all training conditions.

We propose a new interactive task wherein the three training conditions (self-improvement, collaboration, and competition) can be realized through instruction and without modifying the task or the target. This task consists of two partners following a common sinusoidal target trajectory whilst the hands are weakly repelled from each other like same-pole magnets. The repulsive
torque could be overcome easily and was not strong enough to prevent the partner from reaching the target. Thus, the only way of maximizing tracking accuracy was to stay near the target while absorbing the force perturbations from the partner. Prior to a trial, partners are instructed to either “improve your accuracy” (self-improvement), “compete with the partner” (competition) or to “improve your and your partner’s accuracy” (collaboration). These instructions were used to define the training condition in each trial. Since the feedback display, the type of feedback and the type of haptic interaction were identical across training conditions, only the instruction affects the total muscle activity. Therefore, we can assess which training condition is best suited to increasing the effort put into the task.

II. MATERIAL AND METHODS

A. Experimental Setup

The experiment and the procedure were approved by the Imperial College Research Ethics Committee (no. 15IC2470), with all participants providing written informed consent prior to participation. Sixteen participants (24 ± 2 years old denoting mean and standard error, all right-handed) were recruited in same-sex pairs, forming 4 male and 4 female dyads. Mixed-sex pairs were not tested as a difference in strength may have affected the results. Each individual’s right wrist was strapped to a robotic interface that measured the angle and the torque at 1000 Hz [19] (Fig. 1). Participants were seated side-by-side and separated by a curtain to prevent direct observation of the partner, which can influence the perception of the force [20]. They were also prohibited from verbally communicating with each other. They viewed the position of the target, their cursor and the partner’s cursor on their individual monitor.

Participants’ right wrists were attached to a robotic wrist interface [19] which could be moved by flexing and extending the wrist. The angle of the wrist was picked up by a position sensor and was displayed as a vertical bar on a monitor. This cursor bar moved horizontally along an arc on-screen, moving left for flexion and right for extension. A circular target was displayed along the same arc.

Surface electromyograms (EMG) of the flexor carpi radialis and extensor carpi radialis longus were measured at 1000 Hz (g.GAMMASYS, g.tec). The envelope of the EMG activity was extracted by filtering the raw EMG data using a second order high-pass Butterworth filter with a cutoff frequency of 5 Hz. This signal was rectified then filtered using another second order low-pass Butterworth filter with a 5 Hz cutoff frequency.

The target position  \( \theta_T \) was a sinusoid with a frequency of 0.25 Hz and an amplitude of 20°. Each participant had to move their wrist to match their cursor position (henceforth denoted as  \( \theta_1 \) for the first partner and  \( \theta_2 \) for the second) with the target as accurately as possible. Each trial lasted 12 seconds. The mean tracking error  \( e = |\theta_T - \theta| \) in degrees over a whole trial was calculated at the end of every trial for each participant (swapping  \( \theta_1 \) for  \( \theta_2 \)), and normalized to a percentage accuracy measure

\[
a = 100 \left( 1 - \frac{e}{e_0} \right) \quad \text{with} \quad e_0 = 10^\circ.
\]

The accuracy was negatively and linearly related to the tracking error. While  \( a \) can be negative if the tracking error is greater than 10°, in practice the tracking error was always below this value. The accuracy of both individuals was displayed at the end of each trial on each participant’s monitor (Fig. 1).

B. Training Conditions

Before the start of the main experiment, participants were instructed about the nature of the interactive task and the force they would experience through the following message on the monitor: “You will interact with the person next to you. You will both feel a repelling force field (like a magnet) when you are close to one another”. The interaction instruction was displayed prior to each trial. In self-improvement, each participant was instructed to “improve your accuracy”. During collaboration trials, a large banner with “collaborate” in green lettering was displayed with the instruction to “improve your and your partner’s accuracy” (Fig. 1). Finally, in competition trials a red “compete” banner was displayed together with the instruction to “compete with your partner”. The banner’s color was changed to draw attention to the change in training condition. These instructions were not visible during the trial. No additional explanation was given beyond these written instructions onscreen to avoid biasing the participants’ behavior. None of the participants asked for clarification beyond the given instructions.

Each dyad first completed 7 self-improvement trials and then experienced three blocks wherein each block was composed of 5 consecutive competitive trials and 5 consecutive collaborative trials. The ordering of the training conditions was counterbalanced such that four dyads (two male-male and two female-female) experienced the five competitive trials first, while the other dyads completed the five collaborative trials first in every block. Finally, every dyad completed 5 self-improvement trials in the final block.

\[
\theta = (100 - e) \quad \text{with} \quad e = 10^\circ.
\]
C. Haptic Dynamics

In all three conditions, the first partner experienced a repulsive torque

$$\tau_0 = 2 \text{sgn}(\Delta \theta) \left( e^{-0.1|\Delta \theta|} - e^{-0.15|\Delta \theta|} \right) \text{Nm} \quad (2)$$

that is a function of the relative displacement $\Delta \theta = \theta_1 - \theta_2$ between the first partner’s position $\theta_1$ and the second partner’s wrist position $\theta_2$. The second partner felt a repulsive torque in the opposite direction, i.e., $-\tau_0$. The parameters of the repulsive torque were determined heuristically based on preliminary tests to avoid excessive force and fatigue. The repulsive torque was not strong enough to push the partner away to one side, such that completely blocking off a partner from reaching the target was impossible (Fig. 2).

Since the repulsive torque was easy to overcome, partners often switched sides from being on the partner’s left to going to their right and vice versa. These ‘crosses’ were counted throughout each trial and the number of crosses in a trial was used to quantify the behavior during each training condition.

D. Normalization of Muscle Activity

The filtered electromyograms of the wrist flexor and extensor muscles, measured in volts, was normalized to relate them to the torque generated by each muscle prior to the main experiment. The normalization procedure consisted of linearly regressing the activity of each muscle as a function of the torque produced by the muscle during an isometric contraction task [21], and was carried out separately for each individual before the main experiment. Each participant produced a constant isometric flexion or extension torque of $\{1, 2, 3, 4\}$ Nm against the robotic interface whose position was locked in place by motors. Taking a wrist flexor muscle as an example, its activity $u_f$ was linearly regressed to estimate the flexion torque

$$\hat{\tau}_f = \alpha_f u_f + \beta_f > 0 \quad (3)$$

where $\alpha_f$ is the slope and $\beta_f$ the intercept parameter of the flexor torque function, respectively. A similar linear regression of the form $\hat{\tau}_e = \alpha_e u_e + \beta_e > 0$ was carried out for the wrist extensor muscle activity $u_e$. The goodness of fit was calculated and averaged across the two muscles, which yielded a value of $R^2 = 0.64 \pm 0.02$ for all participants.

The estimated torque from each muscle was used to calculate the reciprocal activation $\hat{\tau}_{RA}$, the cocontraction $\hat{\tau}_{CC}$ and the total muscle activity $\hat{\tau}$ using the formulæ

$$\hat{\tau}_{RA} = \hat{\tau}_f - \hat{\tau}_e$$
$$\hat{\tau}_{CC} = 2 \min(\hat{\tau}_f, \hat{\tau}_e)$$
$$\hat{\tau} = \hat{\tau}_f + \hat{\tau}_e.$$  

$$\text{E. Statistical Analysis}$$

The tracking error, the number of crosses, total muscle activity, reciprocal activation, and the cocontraction were calculated for each participant (or dyad in the case of crosses) every trial. The mean value in the first and last self-improvement, collaboration, and competition blocks, totaling 30 trials per participant, 5 trials coming from each block, corresponding to 10 trials from each training condition were used in the analysis. To counterbalance the effects of learning, the data from the first and last blocks were averaged per training condition. Anderson-Darling tests were conducted on each indicator (tracking error, number of crosses, total muscle activity, reciprocal activation and cocontraction) across all three training conditions to ensure that each indicator was normally distributed prior to further analysis. These tests showed that all indicators were normally distributed for every training condition (see Table I).

The pooled data was used to carry out a one-way repeated measures ANOVA that measured the impact of the training condition on each indicator. Multiple comparisons within each measure were corrected by using Tukey’s method, while multiple comparisons across measures were corrected by the Holm-Bonferroni method.

III. RESULTS

We first examined the wrist trajectories during collaboration, competition, and self-improvement (Fig. 3). Partners tended to stick to one side of the target and stayed away from their partner during collaboration, while on competitive trials their positions tended to crossover. This was also evident in the torque sensor time-series as it remained positive or negative for a longer duration during collaboration (Fig. 3). While the torque fluctuated more during competition, the torque magnitude was not dependent on the training condition (Fig. 3). Hence,
different across training conditions. Post-hoc comparisons using Tukey’s HSD revealed a significant difference in the tracking error between competition and collaboration (p = 0.02), and between competition and self-improvement (p = 0.002), but not between collaboration and self-improvement. The tracking error was thus lowest during competition.

Did partners purposefully avoid each other to realize collaboration, or was the tracking error higher in collaboration for another reason? To quantify the collaboration strategy, we calculated the number of crosses over a whole trial (Fig. 4, circles). The number of crosses was significantly affected by the training condition (Fig. 4). Tukey’s HSD showed that the number of crosses was smaller during collaboration than in self-improvement (p = 0.03), and smaller in self-improvement than during competition (p = 0.006). Crosses were fewest during collaboration (45.1 ± 3.4 crosses, mean and SEM), greatest during competition (56.5 ± 3.3) and in-between during self-improvement (49.9 ± 2.6).

Finally, we examined the total muscle activity in each training condition (Fig. 5). A normalization procedure prior to the main experiment was used to relate the envelope of the raw electromyograms to estimate the torque generated by each muscle. The total muscle activity was significantly dependent on the training condition. Post-hoc comparisons using Tukey’s HSD revealed that the total muscle activity was larger during competition than in self-improvement (2.5 ± 0.4 Nm compared with 2.2 ± 0.4 Nm, p = 0.01), and bigger in self-improvement than during collaboration (2.2 ± 0.4 Nm compared with 2.0 ± 0.3 Nm, p = 0.01).
The total muscle activity can be split into reciprocal activation, which generates joint torque, or to cocontraction that increases joint stiffness [21, 22]. The reciprocal activation was weakly dependent on the training condition, while the cocontraction was significantly influenced by it. Tukey’s HSD showed no significant difference in the reciprocal activation between any of the training conditions. However, the cocontraction was significantly larger during competition relative to both self-improvement (p = 0.02) and collaboration (p < 0.001). The cocontraction during self-improvement was also bigger than during collaboration (p = 0.01). Thus, most of the increase in the total muscle activity came from the cocontraction.

We also looked for indications of a difference in motor learning between each training condition by carrying out a one-way ANOVA on the difference between the first and last block to see its dependence on the training condition. For this analysis, we excluded the self-improvement condition as its ordering of being the first and last block of the experiment for all dyads may bias the results. The reduction in the tracking error, total muscle activity, reciprocal activation and cocontraction were all comparable between collaboration, and competition (see Table III). However, the number of crosses reduced by a larger amount during competition in comparison to collaboration (p < 0.03). This difference likely comes from the larger number of crosses in the first competition block.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Training condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking error</td>
<td>F(1,30)=0.02, p=0.89</td>
</tr>
<tr>
<td># of crosses</td>
<td>F(1,14)=5.5, p&lt;0.03</td>
</tr>
<tr>
<td>Total muscle activity</td>
<td>F(1,30)=0.34, p=0.56</td>
</tr>
<tr>
<td>Reciprocal activation</td>
<td>F(1,30)=0.7, p=0.41</td>
</tr>
<tr>
<td>Cocontraction</td>
<td>F(1,30)=0.1, p=0.74</td>
</tr>
</tbody>
</table>

The goal of this study was to identify the training condition that promoted the greatest amount of effort during interactive practice. We developed and tested a novel interactive task wherein the haptic dynamics and the feedback was kept the same whilst inducing collaboration, competition, and self-improvement through instruction alone. Individuals were most active during competition and least active during collaboration. Competition boasted the highest tracking accuracy and the largest muscle activity overall. The tracking accuracy was comparable between collaboration and self-improvement, but the total muscle activity and the cocontraction was greater during self-improvement [23]. Our finding that competition promotes active effort is consistent with previous reports of higher movement velocity during competitive training relative to both collaborative practice and self-improvement [24].

There exist other ways to fairly compare the effort during collaboration and competition. For example, the feedback gain could be estimated in each condition to assess the strength of a participant’s response to tracking errors [25]. However, this method requires an accurate estimate of each person’s force which is difficult to obtain during haptic interaction. Furthermore, the feedback gain methodology ignores cocontraction, which is critical to stabilizing the arm during movements and interactions [26, 27]. Our analysis showed that the cocontraction increased during self-improvement relative to collaboration, and it was overall the largest during competition. The increase in the cocontraction was likely due to the instability of the repulsive torque field, particularly its changing sign that was evident in the torque time-series. Since the force switched directions rapidly and was difficult to predict, our participants stabilized their movement by coactivating their flexor and extensor muscles. Thus, an analysis based purely on the feedback gain could have missed the effort put into stabilizing the wrist.

Cocontraction is known to gradually decay with practice as motor learning progresses [28, 29]. Such a decay was observed in our experiment, but it reduced by comparable amounts between competition and collaboration. This suggests that the motor learning between these two conditions progressed at comparable rates. However, the number of crosses decreased by a larger margin during competition compared with collaboration. It remains unclear why the number of crosses was so high in the first competition block. One possibility is that participants may have explored a strategy to try and actively sabotage the partner by using the repulsive torque to prevent the partner from approaching the target. However, the repulsive torque field was not strong enough to accommodate such an antagonistic strategy, and so participants may have realized that the best way to compete was to outperform their partner by tracking the target as accurately as possible.
Did the repulsive haptic dynamics necessarily make all training modalities antagonistic, thereby making both self-improvement and collaboration competitive? While this possibility cannot be ruled out entirely, the difference in the number of crosses, the total muscle activity and in the cocontraction suggest that the participants did not consider all conditions to be equally competitive. When instructed to collaborate, our participants tried to track the target while disturbing the partner as little as possible by staying away from them and sticking to one side of the target. In contrast, the instruction to compete caused partners to increase cocontraction to stay as close to the target as possible, simultaneously tracking the target while preventing the competitor from approaching. One may argue that the partner’s behavior could have been different in each condition, which would necessarily change the haptic dynamics of the task. However, the magnitude of the torque was similar in all conditions, so a difference in the partner’s behavior alone cannot explain the differences between the training conditions.

Did the instruction to ‘compete with your partner’ confuse our participants such that they adopted different strategies during competitive training? To rephrase, did participants compete by aiming for a higher tracking accuracy than the partner, or did they resort to an antagonistic strategy wherein the repulsive torque field was used to destabilize the partner’s movement or block them from reaching the target? Our analysis suggests that the participants focused on improving their tracking accuracy to compete with their partner. An antagonistic strategy would likely decrease the pair’s tracking accuracy because at least one person is not focused on the tracking task. Since the tracking accuracy was overall greatest during competition, this supports the view that participants tried to achieve the highest possible tracking accuracy to compete with their partner.

Could participants have compromised between tracking error and effort in response to each condition? The analysis of the tracking error and the total muscle activity suggests otherwise as the tracking error during collaboration did not drastically decrease relative to self-improvement, even though the total muscle activity during collaboration was lower. Thus, the strategy undertaken during collaboration was not to relax and become lazy at tracking the target. Instead, partners actively tracked the target while staying away from the partner to prevent the repulsive torque from disturbing the partner’s movement as much as possible.

The analysis of the kinematics and the EMG showed that the effort put into competition was significantly higher than during collaboration and self-improvement. Our results suggest that competitive practice could be a suitable method in increasing the active drive during physical training.

REFERENCES


Atsushi Takagi received the M.S. degree in physics and the Ph.D. degree in computational neuroscience from Imperial College London, London, U.K. He is currently a Distinguished Researcher with NTT Communication Science Laboratories, mainly interested in motor control, using a mix of behavioral experiments, and computational modelling. This knowledge is applied to human-human and human-robot interaction.

Carlo Bagnato received the B.Sc. degree in bioengineering from the Polytechnic of Turin, Turin, Italy, the M.Sc. degree in neuroengineering and cognitive sciences from the University of Genoa, Genoa, Italy, and the Ph.D. degree from the Human Robotics Group, Imperial College London, London, U.K. He gained insight into human-human interaction and the influence of pain on human sensorimotor control and learning with Imperial College London. He currently specializes in managing design projects end-to-end, from early discovery and conceptualization to product development and launch – with a focus on users.

Alejandro Melendez-Calderon received the Ph.D. degree in bioengineering from Imperial College London, London, U.K. He has a transdisciplinary background in engineering, rehabilitation sciences and neuromechanics with research and industry experience in human augmentation technologies used in rehabilitation medicine, including robotics, wearable devices, and computational approaches to understand human neuromuscular control, including unimpaired, stroke, and SCI population. He leads the NeuroEngineering, Rehabilitation and Medical Robotics Group at the University of Queensland and the Jamieson Trauma Institute, Brisbane, QLD, Australia. His group integrates engineering and rehabilitation sciences to discover effective ways to maximize functional recovery after neurological injury and co-design of rehabilitation technologies.

Nathanaël Jarrassé received the M.Sc. degree in industrial systems engineering from Arts et Métiers ParisTech, Paris, France, and the M.Sc. and Ph.D. degrees in robotics from University Pierre and Marie Curie, Paris, France. He has been a Postdoctoral Research Associate with the Human Robotics Group, Department of Bioengineering, Imperial College London, London, U.K., and is currently a Tenured Researcher of the National Center for Scientific Research, ISIR, Sorbonne Université, Paris, France. His research interests include physical human-robot interaction for medical applications, and aims at developing robotic interaction systems, including prostheses, exoskeletons, and instrument objects, to study and characterize the human sensorimotor system, and to improve assistance and rehabilitation of individuals affected by motor skill loss.

Gowrishankar Ganesh received the Bachelor of Engineering (first-class, Hons.) degree in mechanical engineering from the Delhi College of Engineering, New Delhi, India, in 2002, the Master of Engineering degree in mechanical engineering from the National University of Singapore, Singapore, in 2005, and the Ph.D. degree in bioengineering from Imperial College London, London, U.K., in 2010. Since 2004, He was an Intern Researcher with Computational Neuroscience Laboratories, Advanced Telecommunication Research, Kyoto, Japan, and through his PhD. Following his PhD, he was with the National Institute of Information and Communications Technology as a Specialist Researcher till 2013. Since 2014, he has been a Senior Researcher with the Centre National de la Recherche Scientifique (CNRS), and is currently with the the Laboratoire d’Informatique, de Robotique et de Microélectronique de Montpellier in Montpellier. He is a Visiting Researcher with the University of Tokyo, Tokyo, Japan, National Institute of Advanced Industrial Science and Technology, Tsukuba, Japan, and The University of Electro-communication, Tokyo. His research develops the science of human-machine interactions by integrating core research in robot control and learning with human sensori-motor control and cognitive neuroscience.

Etienne Burdet (Member, IEEE) received the M.S. degree in mathematics, the second M.S. degree in physics, and the Ph.D. degree in robotics from ETH Zurich, Switzerland. He is currently a Professor and the Chair of Human Robotics with Imperial College London, London, U.K. His main research interest include human-machine interaction. He uses an integrative approach of neuroscience and robotics to investigate human sensorimotor control, and to design efficient assistive devices and training systems for neuro-rehabilitation, which are tested in clinical trials and commercialized.