Competition Increases the Effort Put Into a Physical Interaction Task

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***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.**

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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

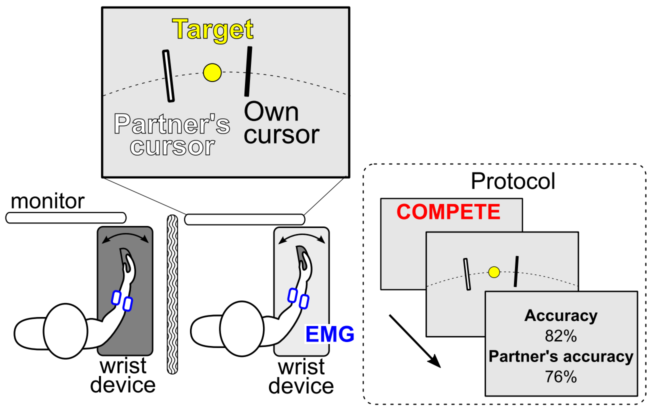

Fig. 1. Experimental setup. The target position θ_T (yellow), one's own cursor position θ_1 (solid bar) and the partner's position θ_2 (unfilled bar) were visible throughout the experiment. The right panel shows the experimental protocol. First, the instructions were displayed for 5 seconds prior to every trial. After the 12 second trial, the accuracy of both partners was displayed.

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 θ_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 θ_1 for the first partner and θ_2 for the second) with the target as accurately as possible. Each trial lasted 12 seconds. The mean tracking error $e = \|\theta_T - \theta_1\|$ in degrees over a whole trial was calculated at the end of every trial for each participant (swapping θ_1 for θ_2), and normalized to a percentage accuracy measure

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

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.

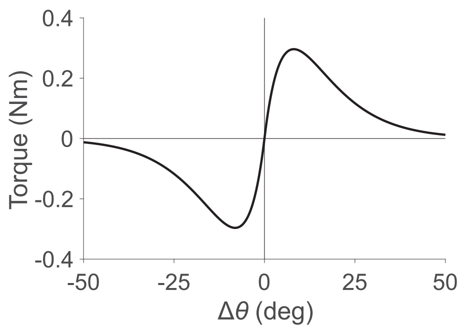

Fig. 2. Repulsive torque was centered on each person's wrist position θ_1 and θ_2, which disturbed the partner's movement but was not strong enough to prevent them from approaching.

C. Haptic Dynamics

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

$$\tau_\theta = 2\,\mathrm{sgn}\,(\Delta\theta)\left(e^{-0.1|\Delta\theta|} - e^{-0.15|\Delta\theta|}\right)\ \mathrm{Nm} \tag{2}$$

that is a function of the relative displacement $\Delta\theta = \theta_1 - \theta_2$ between the first partner's position θ_1 and the second partner's wrist position θ_2 The second partner felt a repulsive torque in the opposite direction, i.e., $-\tau_\theta$. 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

$$\hat{\tau}_f = \alpha_f u_f + \beta_f > 0 \tag{3}$$

where α_f is the slope and β_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.

TABLE I
SUMMARY OF ANDERSON-DARLING TESTS OF NORMALITY

	Self-improvement	Collaboration	Competition
Tracking error	p=0.29	p=0.18	p=0.77
Number of crosses	p=0.43	p=0.55	p=0.33
Total muscle activity	p=0.32	p=0.18	p=0.79
Reciprocal activation	p=0.35	p=0.30	p=0.43
Cocontraction	p=0.93	p=0.57	p=0.11

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 formulae

$$\begin{aligned} \hat{\tau}_{RA} &= \hat{\tau}_f - \hat{\tau}_e \\ \hat{\tau}_{CC} &= 2\min\left(\hat{\tau}_f, \hat{\tau}_e\right) \\ \hat{\tau} &= \hat{\tau}_f + \hat{\tau}_e. \end{aligned} \tag{4}$$

The total muscle activity is equivalent to the contributions from reciprocal activation and half the cocontraction, i.e., $\hat{\tau} = \hat{\tau}_{RA} + 0.5\,\hat{\tau}_{CC}$.

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,

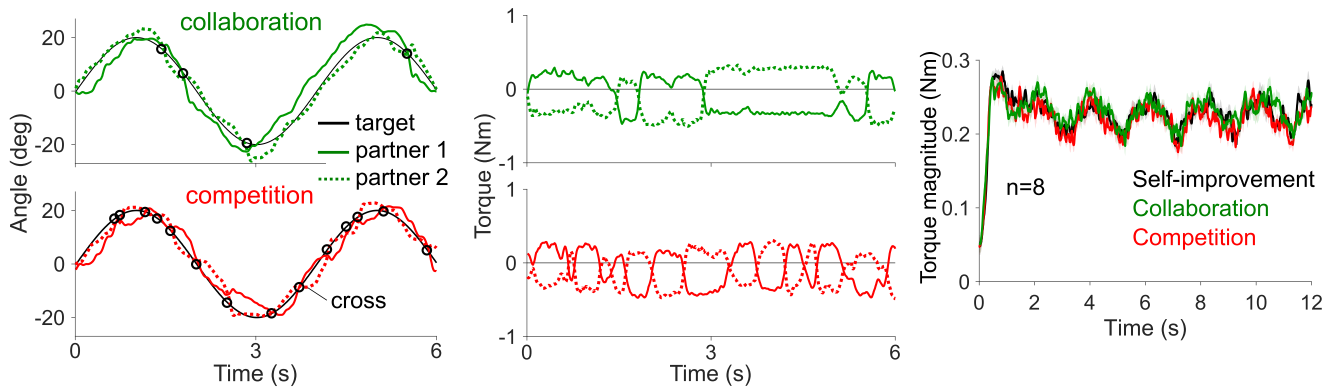

Fig. 3. (Left and middle) Time-series of the wrist position and the torque (from a torque sensor) from a sample collaboration and competition trial from the same representative dyad. Partners switched sides more often during competition, which is more noticeable on the torque sensor. During collaboration the measured torque remained positive or negative for longer. (Right) Time-series of the torque magnitude (absolute value of the torque sensor readings) from the repulsive torque field during the first and last blocks from all dyads, which was comparable across the three training conditions.

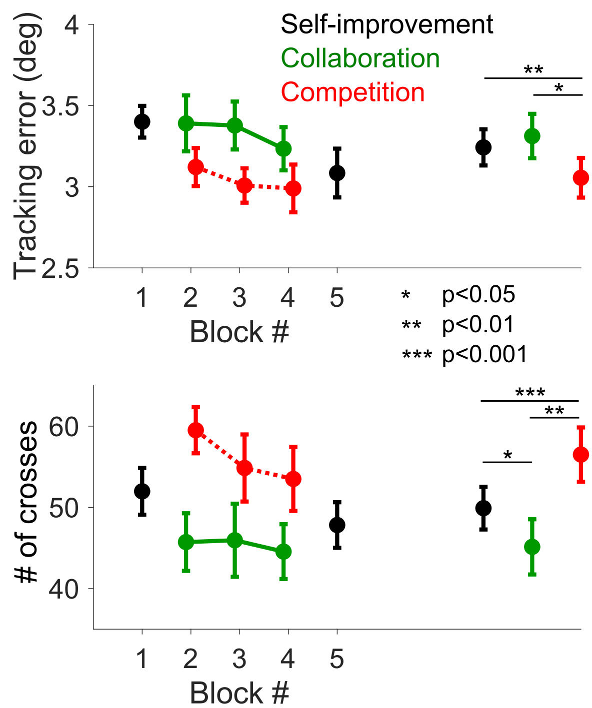

Fig. 4. (Top) tracking error, when averaged across the first and last blocks, was the lowest during competition, outperforming both self-improvement and collaboration conditions. Filled circle is the mean and the bar denotes standard error of the mean. (Bottom) number of crosses was smallest during collaboration and highest during competition, with self-improvement in between these two.

the magnitude of the force exerted by and against the partner was comparable between self-improvement, collaboration, and competition. A difference in behavior cannot be discerned from the torque magnitude alone.

We next examined how the tracking error, defined as the mean distance between the wrist and the target in a trial, changed with training and the training condition. The tracking error was calculated for each block consisting of five trials (Fig. 4). We compared the tracking error, averaged across the first and last blocks, in each training condition using a one-way repeated measures ANOVA with training condition as the factor (stats are summarized in Table II). The tracking error was significantly

TABLE II
SUMMARY OF ONE-WAY REPEATED MEASURES ANOVA TO EXAMINE THE EFFECT OF TRAINING CONDITION

Variable	Training condition
Tracking error	$F(2,30)=6.8$, $p=0.004$
# of crosses	$F(2,14)=29.0$, $p<0.001$
Total muscle activity	$F(2,30)=15.7$, $p<0.001$
Reciprocal activation	$F(2,30)=3.6$, $p=0.04$
Cocontraction	$F(2,30)=21.2$, $p<0.001$

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. 1, 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, $p = 0.01$).

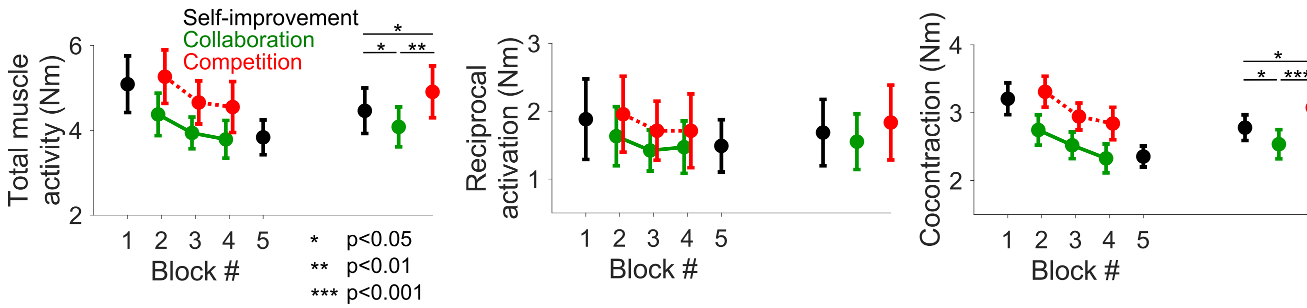

Fig. 5. (Left) total muscle activity reduced with block number and was greatest during competition, lowest in collaboration and in-between for self-improvement. (Middle and right panels) total muscle activity separated into reciprocal activation and cocontraction, plotted as a function of the block number. Both were larger during competition relative to collaboration.

TABLE III
SUMMARY OF ONE-WAY REPEATED MEASURES ANOVA TO EXAMINE DIFFERENCES IN MOTOR LEARNING

Variable	Training condition
Tracking error	$F(1,30)=0.02$, $p=0.89$
# of crosses	$F(1,14)=5.5$, $p<0.03$
Total muscle activity	$F(1,30)=0.34$, $p=0.56$
Reciprocal activation	$F(1,30)=0.7$, $p=0.41$
Cocontraction	$F(1,30)=0.1$, $p=0.74$

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.

IV. DISCUSSION

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.

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