Interaction with a reactive partner improves learning in contrast to passive guidance

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Many tasks such as physical rehabilitation, vehicle co-piloting or surgical training, rely on physical assistance from a partner. While this assistance may be provided by a robotic interface, how to implement the necessary haptic support to help improve performance without impeding learning is unclear. In this paper, we study the influence of haptic interaction on the performance and learning of a shared tracking task. We compare in a tracking task the interaction with a human partner, the trajectory guidance traditionally used in training robots, and a robot partner yielding human-like interaction. While trajectory guidance resulted in the best performance during training, it dramatically reduced error variability and hindered learning. In contrast, the reactive human and robot partners did not impede the adaptation and allowed the subjects to learn without modifying their movement patterns. Moreover, interaction with a human partner was the only condition that demonstrated an improvement in retention and transfer learning compared to a subject training alone. These results reveal distinctly different learning behaviour in training with a human compared to trajectory guidance, and similar learning between the robotic partner and human partner. Therefore, for movement assistance and learning, algorithms that react to the user’s motion and change their behaviour accordingly are better suited.

Which shared control strategy can ensure good performance and learning to drive a semi-autonomous car or assist a child on their first bicycle ride? To guide the user’s movement in robot-assisted applications, robotic interfaces traditionally use trajectory guidance (TG) with a spring-like force¹–³. Such an interaction control strategy ensures accurate tracking of the reference trajectory, but can provide erroneous haptic information if the trajectory planned from the robot’s sensors is not appropriate for the task. Training assisted by guidance considerably changes the learners’ motion patterns by restricting movement freedom⁴ and, therefore, can induce passive behaviour that can hinder the learning as well as its generalisation after the assistance is removed⁵–⁹.

Could robot-assisted motor learning be improved by incorporating the strategies used by humans during shared control? Humans routinely interact with each other e.g. to carry large objects together or during dancing. Although during such joint tasks partners communicate only by the exchange of forces, they can swiftly coordinate motions and adjust their movements to the partner. Recent studies investigated such haptic interaction in pairs of subjects connected by an elastic band and carrying out a tracking task¹⁰,¹¹, which revealed that human partners (HP) conspicuously exchange sensory information to improve their own performance¹²–¹⁴. Specifically, the benefits of haptic interaction in joint performance were revealed¹⁰ and subsequently shown to stem from the exchange of sensory information between the partners enabled by the haptic channel¹². The robotic partner (RP) introduced in¹⁴ to embody this haptic communication hypothesis was shown to provide similar performance and perception as human partners⁶.

The benefits of interactive control with a HP and a RP suggest that it may be used to boost performance in collaborative tasks such as shared driving, rehabilitation training and joint object manipulation. However, it is still unclear whether learning with a human or robot partner would offer any advantage over training alone. The previous publications studying human–human interaction report conflicting results on the effect of this type of motion assistance on learning. Some studies have reported benefits of human–human interaction on learning¹⁰,¹⁵, while in other studies no significant differences in performance were observed¹¹,¹⁶, or it was found that learning strongly depends on the partners’ skills during the interaction¹⁷. More importantly, these previous studies have only looked at the subject’s change in performance directly after the training session or at the differences within training, while sensorimotor performance can change with time¹⁸, thus it is crucial to assess motor performance after several days¹⁹.

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As interacting with a human partner will provide additional sensory information during interaction\(^9\), our first hypothesis (H1) is that this will lead to better performance and learning than when training without interaction. We further assumed that the robot partner, based on such sharing of sensory information\(^9\), will influence the learning in the same way as a human partner (H2). Finally, we anticipated from previous studies\(^8\) that trajectory guidance can impede learning when the interaction link is removed compared to training alone (H3).

### Results

#### Impact of interactive control.

We analysed the subjects’ performance during the training phase while being connected to one of the interaction agents, as well as how the performance changed over the course of the training. In every partner and stiffness condition, the tracking error and error variability decreased from the first connected trial relative to the familiarisation trial that was performed solo (all \(p < 0.0001\)) (Fig. 2B). Smoothness improved in the first training trial when interacting with both the RPg and the RPb at every stiffness level (all \(p < 0.02\)) (Fig. 2C). For the TG this strongly depended on the connection stiffness, where the TG with the medium and rigid stiffness immediately increased smoothness (\(t(308) = -2.533, p = 0.028\) for the medium,
Figure 2. (A) Experimental setup for the tracking task: participants were separated by a curtain and tracked a visual target presented on the monitor using handles of the dual robotic interface Hi5. (B,C) Learning analysis using the tracking error (B) and the SPARC smoothness metric (C). The different connection conditions were: “solo” (no connection), “soft” 0.29 Nm/rad stiffness, “medium” 1.72 Nm/rad, “rigid” 17.02 Nm/rad. The dots represent the average of the corresponding metric for a trial and the area around it represents the ±95% confidence interval estimated based on the least square fit of a second order polynomial. The horizontal yellow bars correspond to the metric’s value in the initial trial. Figures 2(B,C), 3, 4, 5 were created using RStudio (Version: 1.2.1335; https://www.rstudio.com/).

At the end of the training, all groups exhibited similar error levels for the soft connection (p > 0.59 for all pairwise comparisons for the averaged value over the last five trials) (Fig. 3A). However, clear differences appeared for the other stiffness levels. For the medium connection, subjects from the TG group followed the target more accurately than the HP (t(243) = −2.260, p = 0.044), RPb (t(167) = −3.032, p = 0.006) and S (t(167) = −5.306, p < 0.0001) groups. Furthermore, the RPg group showed less error than participants tracking the target solo (t(167) = −3.247, p < 0.014). With the rigid connection, the TG resulted in a higher accuracy than all other conditions (all p < 0.0001). Moreover, while rigidly connected, the HP and RPg conditions resulted in higher accuracy than conducting the task solo (t(167) = −4.371, p = 0.0003, S > RPg: t(167) = −4.347, p = 0.0003).

As expected, the TG decreased the error dramatically with a stiffer connection: the error was lower with the medium stiffness compared to the soft connection (t(308) = −2.254, p = 0.044) and with the rigid stiffness compared to less stiff connections (both p < 0.0001). In contrast, the error was relatively insensitive to the connection stiffness in the RPg and RPb groups (p > 0.097 for all pairwise comparisons between different stiffness levels for each group). Finally, the accuracy during the final trials with the HP was similar between the rigid and medium as well as between the soft and medium stiffness levels (both p > 0.2). However, the accuracy was lower for the soft compared to the rigid connection (t(308) = −2.273, p = 0.044). The average error for the HP tends to be as low as with the RPg over all stiffness conditions (t(154) = −0.321, p = 0.999).

A similar pattern was observed for the error variability at the end of the training: TG showed less variability than the HP (t(266) = −2.843, p = 0.013) and S (t(167) = −5.165, p < 0.0001) conditions with medium stiffness and less variability than all other conditions with rigid stiffness (all p < 0.0001). Furthermore, the RPg resulted in less error variance than S with medium (t(154) = −1.658, p = 0.221) and rigid stiffness (t(308) = −1.952, p = 0.1197) conditions including the solo condition (all p > 0.02), except for the RPb group with medium (t(308) = −1.952, p = 0.1197) and rigid stiffness (t(308) = −1.568, p = 0.221) (Fig. 2B).
Acquired behaviour in visuomotor tracking. To evaluate the effect of learning on individual performance, we analysed the influence of the stiffness and partner conditions on the accuracy, error variability and smoothness in the retention and transfer trials. Figure 4A shows the tracking error using the training trajectory in the three retention trials — immediately after training, after one day and after one week. The analysis showed a significant effect of the partner condition on the retention accuracy (F(3,153.45) = 4.027, p = 0.009). We observed that training with the TG resulted in a larger error than training with a HP over all stiffness levels and trials (t(154) = 3.408, p = 0.005). A small difference was seen between TG and RPg groups, however, this comparison was not significant (t(154) = 2.317, p = 0.065). The tracking error for the TG with the rigid stiffness was also larger relative to the S condition (t(167) = 3.649, p = 0.003) over all retention trials.

Error variability was also significantly impacted by the partner condition (F(3, 153.17) = 5.377, p = 0.0015). Subjects that trained with TG had significantly more variability in their retention trials than those with a HP (t(154) = 3.950, p = 0.0007) and the RPg (t(154) = 2.508, p = 0.0396) groups over all stiffness levels and retention trials. Moreover, the HP group showed less error variability in retention than S over all stiffness conditions (t(175) = −2.474, p = 0.0377).

The retention smoothness did not change for different partner conditions (F(3, 154.34) = 1.487, p = 0.220), but was significantly influenced by the connection stiffness (F(2, 154.35) = 3.176, p = 0.045). Participants that trained solo had smoother movements in retention than those that trained with the rigid connection (t(176) = −2.287,
p = 0.047). The rigid stiffness also tended to have lower smoothness than the soft (t(154) = −2.059, p = 0.062) and medium connections (t(154) = −2.282, p = 0.062), however these results were not significant.

Clearer differences between the groups were observed along the independent trajectory used to infer the transfer of learning (Fig. 4B): the partner condition (F(3, 153.53) = 5.551, p = 0.001) as well as its interaction with the test time (F(6, 299.10) = 2.745, p = 0.013) had a significant effect on the tracking error in the transfer trial. In particular, the TG resulted in more error than all of the other groups after one week (HP<TG: t(195) = −4.855, p < 0.0001; RPb<TG: t(198) = −3.333, p = 0.006; PRg<TG: t(198) = −4.016, p = 0.0008). Moreover, even immediately or one day after training the subjects that trained with the TG conducted their movements less accurately than those that trained with a HP (immediately: t(194) = −2.883, p = 0.016; after one day: t(198) = −3.063, p = 0.011) and than those in the RPg condition (immediately: t(194) = −2.436, p = 0.041; after one day: t(199) = −2.474, p = 0.041). The TG condition also had a larger error than the S condition for the rigid stiffness over all transfer trials t(167) = 3.291, p = 0.011). In contrast, the HP condition had a lower error than the S over all stiffness levels and retention trials (t(175) = −2.475, p = 0.037).

The error variability in transfer was also influenced by the partner condition (F(3, 152.24) = 3.800, p = 0.0116) and its interaction with the test time (F(6, 298.08) = 2.8681, p = 0.0099). The differences in variability between partner conditions were observed only in the transfer trial after one week: TG showed more variability than the HP (t(217) = 4.199, p = 0.0007), RPb (t(220) = 3.135, p = 0.0117) and RPg conditions (t(220) = 3.673, p = 0.0027).

The transfer smoothness, similar to the retention smoothness, was influenced by the stiffness (F(2, 154.32) = 4.512, p = 0.012) and its interaction with trial (F(4, 300.33) = 3.216, p = 0.013). Training with the rigid connection resulted in lower smoothness than with the soft stiffness in the first retention trial (t(227) = 3.299, p = 0.008) and then with the medium stiffness after one day after training (t(232) = 3.152, p = 0.008).

Discussion

Our experiment investigated how subjects perform a tracking task with wrist flexion/extension on a relatively complex trajectory. This task demands continuous planing based on incoming sensory information, in contrast to the widely studied reaching arm movements that can be carried out largely according to an initial plan28. By comparing representative interactive controllers with regards to performance and learning, we analysed their ability to assist movement for shared control, and the tracking performance they induce. This study is the first to analyze the long-term learning effect of training with a human partner (HP) and with the robotic partner (RP) of12 up to one week of retention, compared to solo performance (S) and training with trajectory guidance (TG).

During the shared control stage, when the subjects were connected to one of the partner conditions, the TG, HP and RPg all reduced the tracking error significantly relatively to the S condition when the connection between the partners was rigid. However, the manner with which the TG does so is distinctively different to the HP and RP conditions. The TG uses an elastic force to the known desired trajectory and thus results in more accurate tracking with increased connection stiffness. This results in a nearly perfect accuracy from the first connected trial, dramatically decreases error variability, and leads to higher smoothness. As a consequence, assistance from TG induces a considerable change of motion patterns compared to what a learner would exhibit during solo
training. In contrast, the HP and RP do not assume a-priori knowledge of the planned trajectory as they predict it\textsuperscript{12}. The HP’s or RP’s movement is different from the target trajectory and does not decrease with a more rigid connection. Moreover, the motions characteristics with HP and RP are similar to the solo condition, which indicates that these reactive agents help improve performance without changing the behaviour.

The effect of training with different interaction control modalities also separates the TG from the HP and RP as can be observed at the end of the training period, as is visualised in Fig. 5. The TG minimises the tracking error, error variability and smoothness while the connection is maintained. However, after it leads to deteriorating tracking performance as is particularly observed one week after training (Fig. 4B). This can also be observed from Fig. 5 where the TG had the stiffest slope in retention (b = 1.9639, t(12) = 4.894, p = 0.0004) and in transfer (b = 2.8225, t(12) = 3.542, p = 0.0041). Moreover, regression analysis revealed that the TG slope was different from all other groups in retention (all p < 0.027) and from HP and RP in transfer (both p < 0.45). This observation confirms the H3 hypothesis and previous findings, where despite improved training performance during connection, haptic guidance impedes learning and its generalisation in path-following\textsuperscript{31}, continuous rhythmic\textsuperscript{9} and timing-crucial\textsuperscript{6} tasks as well as to control an unstable inverse pendulum\textsuperscript{24}.

Interestingly, the performance after training solo remains stable after one week (Fig. 4A), arguably corresponding to learned task performance. Similarly, performance after one week did not deteriorate further after training with the RPs, where statistical comparison between the S and RP groups also did not exhibit a significant difference for the regression slopes. The HP, in contrast and in accordance with the H1 hypothesis, did show a tendency to improve after training relative to the S condition (Fig. 4B), which resulted in a more flat slope in Fig. 5 than other groups in retention (b = 0.5457, t(12) = 4.615, p = 0.0006) and transfer (b = 0.7387, t(12) = 3.210, p = 0.0076). These results might have been affected by the use of healthy subjects in a one-dimensional task and therefore need to be investigated further.

In this study we compared robot partners with high and low noise, which are different parameterisations of the RP, where the level of accuracy that the partner provides was varied. In this way we could test how the skill level of this human-like robot partner influenced learning. The RPg condition tended to lead to better performance during the training compared to the other conditions, however, after the training this effect disappeared and both RPs have a similar retention and transfer of the learned skills. The similarity of performance in retention and transfer regardless of the quality of the RP, suggests that for continuous tasks the accuracy of the robot partner might be not as important factor as the manner of how the partner interacts characterised by the intrinsic reactivity of the controller or its compliance. Since there is no difference between the robotic skill partner level and the learning with RPs is superior to TG, it is clear that assistance corresponding to the user’s ongoing movement is preferable over assistance through trajectory guidance, which agrees with recent results comparing compliant predictive control with TG\textsuperscript{24}.

While tracking error and error variability are mostly influenced by the interaction modality during the training phase, motion smoothness in retention and transfer depended on the connection stiffness of the training partner. Regardless of the partner condition, training while connected through a rigid link impacted the smoothness negatively compared to training solo or with the soft and medium stiffness levels. This may be linked to the
rigid stiffness reducing the subject's ability to freely move within the training, thereby not providing them with the opportunity to find more naturally smooth motions.

In summary, shared control with a human partner or the robotic partner of\textsuperscript{12} leads to a reduction of the tracking error when moving together and increases the movement smoothness without impacting the ability to perform the task when alone or reducing some error variability in the motion. With the exception of working with a HP no partner showed clear improvements in the retention or transfer trials compared to the S condition, where in particular TG resulted in reduced performance, which is likely due to slacking behaviour as was suggested in previous studies\textsuperscript{5,7,55}. This may be explained by the fundamentally different mechanisms of interaction: while TG physically guides the learner and restricts their own motion flexibility especially when the connection between partners is rigid as was shown in\textsuperscript{4}, the HP and RP benefit performance and learning by providing additional sensory information without interfering with the intended motion. Due to TG modifying behaviour, e.g. by invoking passive performance, and its inability to deal with intrinsic human variability, TG is only suited to applications where the human cannot perform the task actively, as in robot-aided stroke rehabilitation for severely affected individuals. Instead, in applications such as active neurorehabilitation, shared driving\textsuperscript{52} or co-pilot systems\textsuperscript{59}, an interaction with another human or RP is better suited. Furthermore, when learning is required, despite being widely used, the negative impact of TG on learning means again a HP or RP is more appropriate.

Finally, while the RPs generally exhibited similar behaviours to the HP condition during and after training, they present differences that are worth analysing. While a connection with RPs immediately improved the subjects' smoothness in the first training trial, interaction with a HP did not show this effect. Participants interacting with a HP also did not, in the medium stiffness condition, improve their accuracy during the training phase, while clear improvements were visible in all RPs conditions. Therefore, during the training the RPs showed a better performance than HP. It is however important to highlight that the HP was the only condition that showed a better accuracy than S in retention and transfer. This suggests that, contrary to the H2 hypothesis, there are unique characteristics of this human interaction that specifically possess the ability to improve motor learning. Identifying these characteristics and how to replicate them in human-like robot controllers as well as further generalisation of these results to robotic interfaces with higher degree-of-freedom and other tasks is therefore critical.

Conclusion

We evaluated different mechanisms for robot-assisted training. The results show that interaction with another human or with a human-like robot partner improves performance during interaction and learning up to one week. In contrast, trajectory guidance, which modifies the learner's behaviour considerably during interactive training, does not provide efficient learning. This suggests that a human-like robot partner is a suitable controller for automated training, since it enables the exchange of sensory information without interfering/restricting the motion during interaction.

Methods

Participants. The experiment was granted ethical approval by the Research Ethics Committee of Imperial College London (reference 15IC2470). The study was performed in accordance with all relevant guidelines and regulations. 180 healthy volunteers (66 females and 134 males, aged 17–41 years with an average age of 24.2 and standard deviation of 3.8) took part in this study. Twelve participants were left-handed, 167 right-handed and one ambidextrous. 129 participants reported some experience with haptic devices such as gaming controllers or joysticks and 138 regularly play or used to play computer games (from 0.1 to 40 h/week with a mean of 7.6 h and standard deviation of 3.8).

Experiment setup and procedure. Before beginning all participants gave their informed consent to carry out the experiment, then filled in the Edinburgh handedness form\textsuperscript{34} and a demographic questionnaire. They were instructed that within the experiment they might interact with a robot, another human, or complete the training without interaction. Subsequently, they were randomly assigned to one of the thirteen experimental groups. Altogether each group had 14 subjects, with the exception of the TG group with the soft stiffness condition, which had only twelve participants.

Subjects were seated in front of a monitor with their dominant hand connected to one of the handles of the Hi5 robotic interface. They used their hand to track the target trajectory shown on the screen, which was given (in degrees) by

$$q^*(t) = 18.5 \sin(2.031 t) \sin(1.093 t), \quad 0 \leq t \leq 30 \text{ s}.$$  \hspace{1cm} (1)

The interface yielded an elastic connection of the wrist flexion/extension $q(t)$

$$\tau(t) = k |q(t) - q^*(t)| \text{ Nm}, \quad 0 \leq t \leq 30 \text{ s},$$  \hspace{1cm} (2)

with the reference angle $q^*(t)$, which was differently set for each experimental condition, during 30 s long trials. The connection stiffness $k$ was set as one of \{0.29, 1.72, 17.02\} Nm/rad, since this parameter has been shown to impact the interaction behaviour as was detailed in\textsuperscript{4}. The Hi5 was operated in torque control, and enabled the interaction at 1000 Hz. Wrist angle data was simultaneously recorded at 100 Hz.

All subject pairs participated in three sessions as shown in Fig. 1B. On the first day, they completed one test trial without any interaction torque, followed by one of the interaction conditions for 20 30 s long trials with 10 s breaks in between. Learning was assessed immediately after training, after one day, and after one week.
Each of these assessment consisted of one retention trial without interaction, followed by one transfer trial on a different trajectory given by

\[ q^*(t) = 22.2 \sin(2.031(t + 1.2)) \sin(1.093(t + 1.2)), \quad 0 \leq t \leq 30s. \]  

**Experimental conditions.** The 13 experimental groups corresponded to one control group that performed the complete experiment without working with a partner plus groups for each combination of partner agent \{HP, TG, RPg, RPb\} and stiffness level \{0.29, 1.72, 17.02\} Nm/rad. Each subject completed the training in only one of the 13 condition (between-subjects study design).

For each different partner type the reference angle \( q_r \) was set differently. In the trajectory guidance (TG) condition, the subject performed the experiment connected to the reference trajectory such that \( q_r = q^* \). The interaction force \( (2) \) therefore acted as a proportional position controller.

In the human partner (HP) condition, two subjects simultaneously performed the tracking with trajectory \( (1) \) by holding their respective robotic interface with a virtual spring connection between them, such that \( q_r \) was given by their partner’s position. The subjects were not given explicit knowledge that they were working together but they were given indirect knowledge of their partners position through the interaction force \( (2) \).

Finally in the good and bad robot partner (RPg and RPb) conditions, the subjects were connected to a robot agent that tracked the measured target using the human-like partner algorithm of\(^{12}\). Here, the agent evolves \( q_r \) using a control input which is given by the linear feedback control law

\[ u = -L_p(q - \hat{q}^r) + L_v(\dot{q} - \dot{\hat{q}}^r), \]  

where \( L_p \) and \( L_v \) are the proportional and derivative gains and \( \hat{q}^r \) denotes the RP’s target estimation. To obtain this target estimate, the RP combines its own measurement of the target with the partner’s target estimated from the interaction force between them. This is achieved using a Kalman filter that uses the known dynamic model and a measurement consisting of both the partners own measurement and its estimation of the partner. The good and bad partners are achieved by altering the amount of noise in the RP’s partner estimation. The RPb was set so that the resulting tracking error

\[ \frac{1}{T} \int_0^T | q(t) - q^*(t) | \, dt, \quad T = 30s, \]  

where \( q^* \) is the target position. Two different RPs, “good” and “bad”, were considered which used different noise in their partner estimation: RPb had a 40% higher error compared to the subject’s initial performance and the RPg was set to 40% lower error.

**Statistical analysis.** Performance and learning were analysed using the tracking error defined by Eq. (5), the error variability defined as a characteristic of motion variability, calculated as a standard deviation of errors during each trial duration, as well as the SPARC smoothness metrics\(^{35}\) that evaluates the complexity of the movement velocity \( \dot{q} \). For all metrics the first 0.8 s of each trial was deleted to exclude the reaction time at the movement start and to analyse only the tracking performance. Metrics were analysed during the connection with a partner to estimate shared performance and after the link between partners was removed to evaluate the resulting acquired skills.

To examine the subjects’ initial skills level, we analysed the smoothness and accuracy using a 2-way ANOVA with two in-between predictors — partner and stiffness. We conducted tailored post-hoc contrasts to investigate the differences between the single factor levels. Moreover, a Dunnett test was conducted to compare each condition to a control group. The Benjamini–Hochberg adjustment was used to control the false discovery rate resulting from multiple comparisons. Since all 13 groups were not different in the performance (all \( p > 0.06 \)), in following analysis this skills baseline was not considered.

To investigate performance during the training we conducted a three-way mixed ANOVA with two in-between factors — partner and stiffness condition, and with one repeated measures predictor — training trial. We used tailored t-test contrasts with Benjamini–Hochberg adjustment to investigate the difference between the groups in the last five trials and within the same groups between different training trials. The differences between different trials in the solo group were analysed with paired t-tests. The comparisons between the S and other groups were realised using Dunnett tests.

To investigate how training with shared control influenced the learning, we analysed the smoothness and accuracy in the retention and transfer trials immediately, one day and one week after training. Due to the presence of missing observations in the data for some of the post-tests and non-normal data distribution in some of the conditions, we conducted an ANOVA using a linear mixed-effects model. For all dependent variables, we fitted a model with fixed effects on the stiffness, partner condition, test time (immediately after training, one day or one week after) and their interactions, and the random intercepts for the subject number. When one of the factors or their interaction was significant, post-hoc comparisons using t-test contrasts with a Benjamini–Hochberg adjustment were employed. A Dunnett test was conducted to compare each condition to the control group.

**Data availability**

All data generated or analysed during this study are included in this published article and its supplementary information files.
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Competing interests
The authors declare no competing interests.

Additional information
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