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Physically interacting individuals estimate the partner's goal to enhance their movements

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From a parent helping to guide their child during their first steps, to a therapist supporting a patient, physical assistance enabled by haptic interaction is a fundamental modus for improving motor abilities. However, what movement information is exchanged between partners during haptic interaction, and how this information is used to coordinate and assist others, remains unclear[1]. Here, we propose a model in which haptic information, provided by touch and proprioception[2], enables interacting individuals to estimate the partner's movement goal and use it to improve their own motor performance. We use an empirical physical interaction task[3] to show that our model can explain human behaviours better than existing models of interaction in literature[4–8]. Furthermore, we experimentally verify our model by embodying it in a robot partner and checking that it induces the same improvements in motor performance and learning in a human individual as interacting with a human partner. These results promise collaborative robots that provide human-like assistance, and suggest that movement goal exchange is the key to physical assistance.

Humans are adept at physically interacting with and assisting each other, from helping children to walk, to the incredible feats of balance in acrobatics, and to synchrony during the tango. For over a decade, physical coupling has been documented to promote partners to adopt specialized roles[9–11] and enable pairs or dyads to improve in many joint tasks[3,9,12,13]. However, the underlying computational principle that enables movement coordination is still unknown[1]. The improvement in interacting partners has been shown not to be due to changes in attention or impedance of the interacting limbs[3], and is absent when the interaction is not physical[14,15] and when the interacting partners do not fully share control[16]. These results highlight the importance of haptics, the sensory modality related to tactile and proprioceptive senses[2], during continuous physical interactions, and suggest that individuals jointly coordinate with a partner by exchanging information haptically. However, what information is being exchanged, and how it is used to adapt one's behaviour, remains unknown. We hypothesized that haptically interacting partners can estimate and exchange sensory information about the task goal and the uncertainty of this information with their partner, and tested this hypothesis against competing models of haptic interaction during an interactive target tracking task.

Specifically, we first simulated the mechanical dynamics and control behaviour of individual partners during an interactive task in which two individuals, connected by an elastic band, plan their movement to track a randomly moving target. We considered our proposed 'interpersonal goal integration' model against three well-known models of interaction in literature that propose different information being exchanged between the partners. We compared the prediction of these four models with the empirical behaviour observed in our interactive tracking task to show that our model explains it best. Finally, we experimentally verified our model by embodying it in a robot partner and checking that the robot partner induces the same behaviour in a human individual as interacting with a human partner.

Our proposed 'interpersonal goal integration' model (blue panel in Fig. 1a) assumes that it is possible to estimate the partner's target from the haptic forces, and use it to improve one's own prediction of the target's movement. We compared this with models of interaction proposed in the literature. The 'no computation' model (red panel in Fig. 1a) proposes that the partners in a dyad track their targets independently without any exchange of haptic information[4], and that coordination is caused purely by the dynamics of their motion towards the target coupled by the elastic band. The 'follow the better' model assumes that the haptic forces enable one to estimate the partner's performance to judge who is better at the tracking task, and switch to following the partner when he/she is better. This model is motivated by previous work in collective decision-making in which the best partner's decision is taken by the collective[5,6]. Finally, the 'multi-sensory integration' model proposes that haptic forces enable one to estimate the partner's position and track a weighted combination of the partner position and the target, according to their reliabilities. Such sensory integration of vision and haptics has been reported in individual subjects[7,8], and could yield a better prediction of the randomly moving target if the partner is doing the same task. It should be noted that all four models have one observation variable, z, that represents what information partners use to plan their motion, and two free parameters that control the partners' strengths and the jerkiness of their trajectories, which were selected through a sensitivity analysis to best reproduce the empirical data (see Methods and Supplementary Information).

The prediction by the four models were compared against empirical data[3] obtained from the interactive tracking task (Fig. 1b; see Methods for details). Dyads completed 10 one-minute trials in our target tracking task. In half of the 10 trials, the partners tracked the target alone ('alone trials'). In the other trials, partners were haptically connected ('connected trials') by a computer-generated elastic band (of stiffness $120\,\mathrm{N\,m^{-1}}$, such that the force vanishes when the partners' hand positions coincide). The tracking errors e in the

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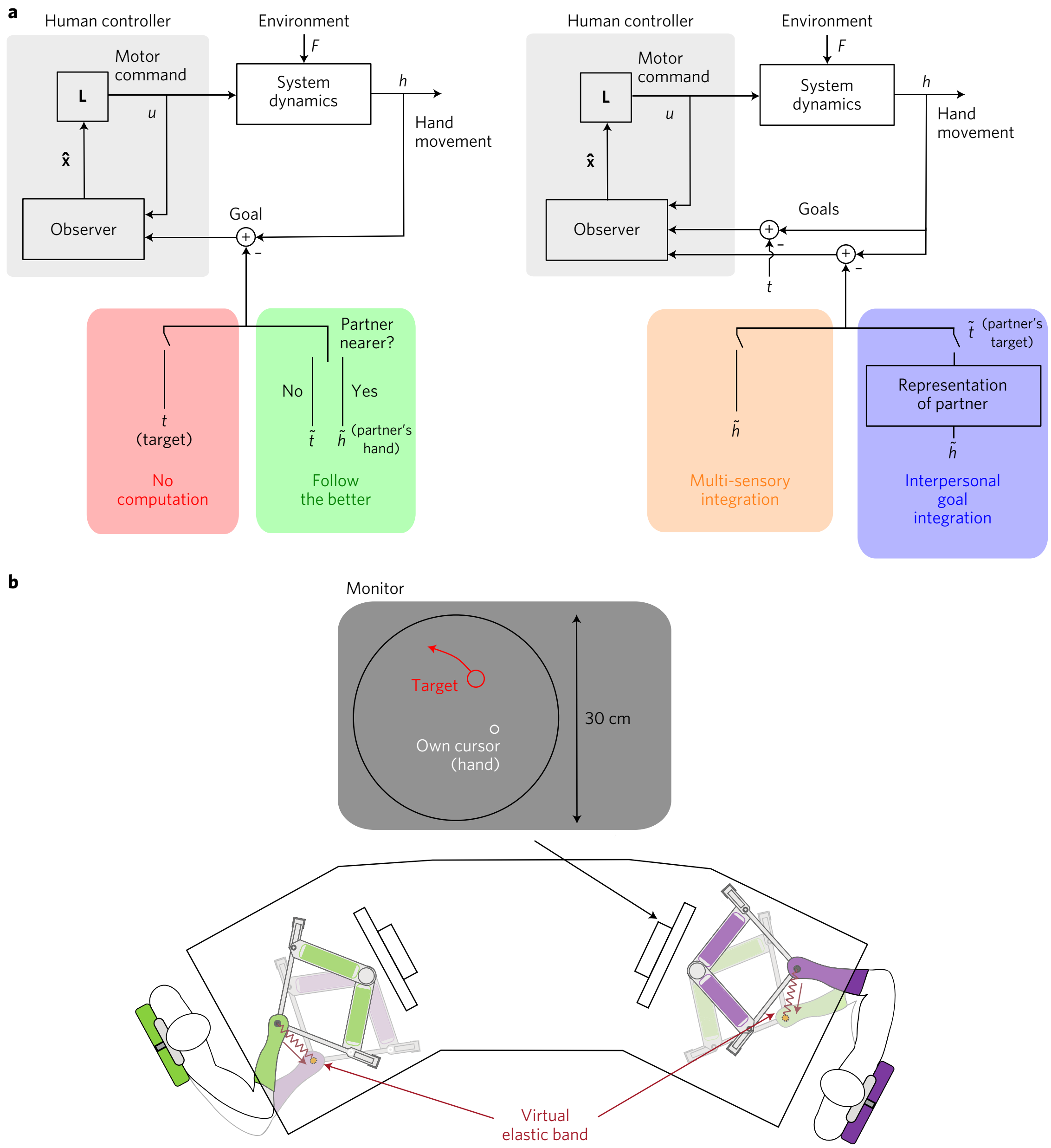

Figure 1 | Computational framework to test four models of haptic interaction for comparison against experimental data. a, Control scheme of the four proposed models of interaction. A human tracking a visual target with their hand is modelled as a sensorimotor estimation problem. All four models used the same control formulation to send motor commands *u* to a point-mass model of the arm, and only the sensory information of the goal was modified. In the 'no computation' model, partners track the target as individuals in 'alone trials' while under the influence of the physical coupling. In 'follow the better', the position of the superior partner is followed if they are nearer to the target, otherwise the target is tracked. In 'multi-sensory integration', the weighted average of the target and partner's positions is tracked. In 'interpersonal goal integration', a combination of the partner's target and one's own visual estimate of the target is tracked. For definitions of variables, please see Methods. **b**, Subjects each held the handle of their own robotic interface, and tracked the same randomly moving red target on their respective monitor with a white cursor representing their own hand position. Each subject could see the target, and only their own cursor on the computer screen. The partners' hands were connected by a virtual elastic band in some 'connected trials' for haptic interaction.

'alone trial' and e_c in the 'connected trial' were calculated as the root mean squared distance between the target and hand over one trial. As previously reported[3], motor performance (defined as $1 - e_c/e$) was improved for both partners in connected trials, regardless of their difference in skill at the tracking task (see black data points and trace in Fig. 2). Motor performance was improved through practice both with a superior partner, who had a lower tracking error than oneself at the task (one sample t-test, $t(8) = 13.5$, $P < 10^{-6}$; Fig. 2), and with an inferior partner, who had larger tracking error ($t(8) = 11.2$, $P < 10^{-5}$; Fig. 2). A model of haptic interaction should predict these improvements in motor performance during interaction.

The simulation of the 'no computation' model showed that although the inferior partner improved, the superior partner did not (Fig. 2, red trace). This demonstrates that the performance improvements in our interactive tracking task cannot be explained solely by the mechanical coupling of the two partners, and that partners were using haptic information to modulate their behaviour depending on the interaction with each other.

The 'follow the better' model (Fig. 2, green trace) was examined with a simulated dyad that could instantaneously judge and follow the partner nearer to the target (green panel in Fig. 1a). This mechanism predicted deterioration in tracking performance

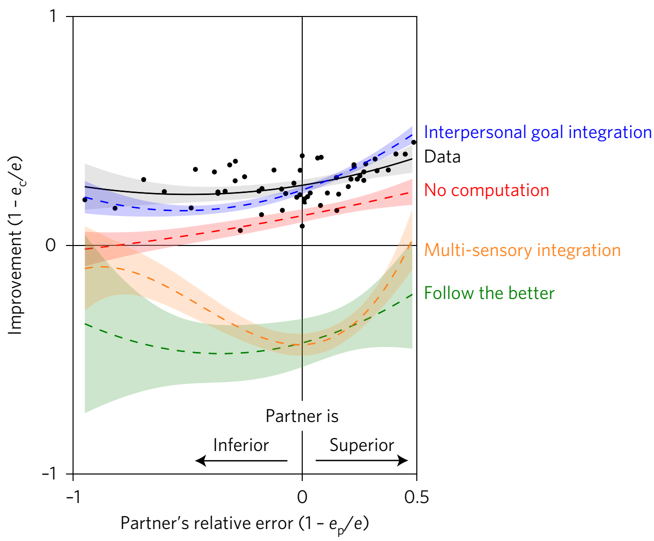

Figure 2 | Simulations of four representative models of haptic interaction reveal that the 'interpersonal goal integration' model has the most predictive power. Performance improvement during interaction as a function of the partner's relative performance from experimental data is plotted in black (shaded region shows the 95% confidence interval). The predictions from the four models of haptic interaction are each plotted with the best model parameters that minimize the squared error from the experimental data ($N = 18$). Improvement is defined as $1 - e_c/e$, where e is the tracking error in an 'alone trial' and e_c the tracking error in the preceding 'connected trial'. The horizontal axis plots the ratio of the partner's alone error e_p to own alone error e. 'No computation' (red trace) does not predict improvement for the superior partner. The 'follow the better' (green) and 'multi-sensory integration' (orange) mechanisms do not predict improvement for either partner. 'Interpersonal goal integration' (blue) predicts improvement for both the inferior and superior partners, and matches the experimental data best.

during interaction regardless of the partner's error, which contradicts the experimental data.

The 'multi-sensory integration' model was simulated with partners who followed a weighted combination of the perceived target position and the partner's position that was estimated from the haptic forces (orange panel in Fig. 1a). This model also predicted consistent deterioration in tracking performance and cannot explain the observed interaction behaviour (Fig. 2, orange trace).

Finally, in the 'interpersonal goal integration' model, we propose that the optimally weighted combination of the estimated partner's target (that is, the partner's movement goal) and one's own target is tracked (blue panel in Fig. 1a). The partner's target was estimated through an abstract representation of the partner's tracking behaviour, which relates the partner's movement in response to the movement of the target (see Methods). This model outperformed the other three models and explained the empirical data best, predicting motor performance improvement for both the inferior and the superior partners in the dyad (compare black data and blue model traces in Fig. 2).

Although our model captures the benefits of haptic interaction in simulation, can it really emulate the physical assistance provided by human partners during movement? To experimentally verify the 'interpersonal goal integration' model's ability to physically assist humans, we created a robot partner that embodied our model. We then assessed whether human users haptically interacting with it would also exhibit consistent improvements in motor performance. Twelve subjects interacted with the robot partner over three sessions of 10 trials each, which consisted of an equal number of 'connected' and 'alone trials'. By modulating the robot's performance across the three sessions, we were able to assess whether the subjects could improve with a superior, similar and inferior robot partner. We observed that human users consistently improved their performance irrespective of the robot's performance (Fig. 3a). They improved with a superior robot partner ($t(11) = 15.7$, $P < 10^{-8}$), with a similar one ($t(11) = 5.3$, $P < 0.001$) and, critically, with an inferior robot partner as well ($t(11) = 3.7$, $P < 0.005$). A linear mixed-effects analysis (see Methods) revealed that these improvements were similar to those observed between human partners ($\chi^2(3) = 1.75$, $P > 0.62$).

Although we have shown that a human partner and our robot partner improve a user's motor performance during haptic interaction, can partners learn from this interactive practice and retain the performance improvements even without haptic assistance? To address this question, we measured the progression of tracking error across 'alone trials' in individuals who interacted with a human or our robot, and compared it with 10 additional solo subjects who practised the same target-tracking task alone for the same duration. All subjects who occasionally interacted with a human or robot partner, and those who practised solo, displayed a large initial tracking error that exponentially converged after 10 trials (see Supplementary Fig. 2). First, the tracking error e from individual subjects was fitted with an exponential function of the form $e(T) = e_L + a\exp(-\lambda T)$, where a is a constant, λ is a learning rate and T represents the trial number. We then compared the error after learning, e_L, across the subjects in the three conditions of: individuals interacting with a human partner, with our robot partner, and practising solo. The fit was done only for the 'alone trials' without haptic interacting forces (see Methods). A one-way ANOVA of e_L with condition as a factor revealed a significant effect of the condition on the error after learning ($F(2,29) = 13.23$, $P < 10^{-4}$). Post-hoc Tukey–Kramer tests revealed that the error after learning was significantly lower for subjects who had haptically interacted with a human ($P < 0.005$) and with our robot partner ($P < 10^{-4}$), in comparison to the solo subjects. Furthermore, our robot partner improved motor learning as a human partner did, as the errors after learning were similar between the two conditions ($P > 0.6$).

Our robot partner's ability to boost motor performance during, and to improve motor learning after haptic interaction with it, supports our hypothesis that physically interacting humans are able to acquire information about the target's motion from the partner. This haptic information from the partner can be combined with one's own visual information of the target for improved target estimation. Previous studies have shown that information across vision and haptics are weighted optimally by an individual subject[7,8], but our computational model demonstrates an equivalent situation occurring across partners. Such sharing of complete task information was not observed in verbally communicating partners during a joint decision-making task[17], highlighting the fact that physical interaction may provide complementary possibilities to verbal interaction for sharing sensory information across partners.

Although haptic forces do provide information about where a partner's hand is, they do not provide direct information about where the partner wants their hand to go — that is, the partner's target. During physical interaction, one must infer the partner's target from their motion. The process of extracting the intention or goal of a visually observed action is described as action understanding in social neuroscience[18]. Our model, which proposes that humans extract a partner's target or goal through the haptically estimated partner's motion, suggests a form of haptically mediated action understanding[18] during physical interaction. Previous studies have suggested specialized inference[19], hierarchical predictive coding[20] and partner models[21–24] as possible mechanisms for visual action understanding. Our model implementation simulates the partner's target through one's own forward model of the task and corresponds to modelling of a partner[21–24]. However, further studies are necessary

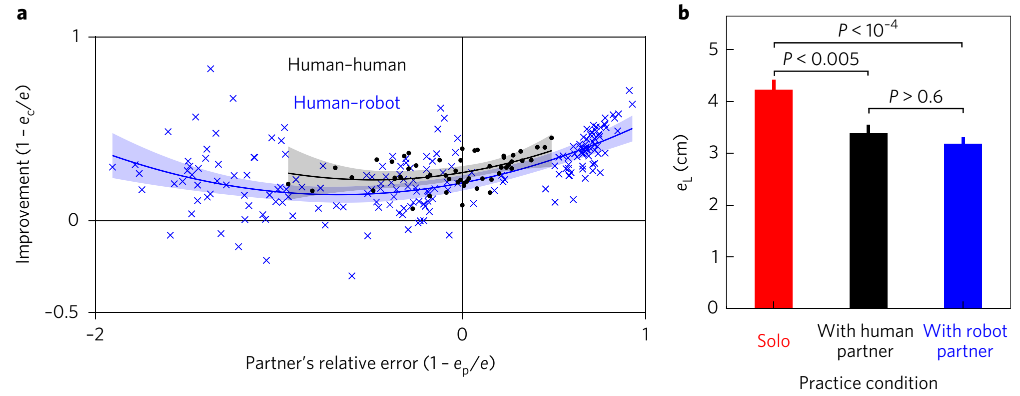

Figure 3 | A robot partner embodying the 'interpersonal goal integration' model physically assists human users as human partners do. a, Performance improvement as a function of the partner's relative performance (shaded region shows the 95% confidence interval). The same setup as Fig. 1b was used, but each partner interacted with a robot partner. The robot was programmed with a superior, similar and inferior performance (tracking error 2 cm lower, same and 3.5 cm higher than average human performance respectively). Humans interacting with the robot (blue trace) improved with all robot partners, exhibiting similar improvements to haptic interaction between humans (black trace). **b**, Error after learning, e_L, from individual exponential fits of subjects (mean ± s.e.m.) who practised solo (red bar, $N = 10$), and from 'alone trials' of subjects who practised with a human partner (black bar, $N = 18$) or a robot partner (blue bar, $N = 12$). Initially, subjects in all three conditions began with similar performance (see Methods).

to clarify specifically how the partner is modelled by the central nervous system to estimate their movement goal.

Irrespective of the neural mechanism used by haptically interacting individuals to estimate the partner's target, our study clarifies how the sharing of movement goals can improve the motor performance of both interacting partners, and yields a robot behaviour for human assistance. A fundamental issue with collaborative robots that work in contact with humans is to define robot behaviours that benefit the human user but do not interfere unnecessarily with the user's movement[25]. The robot control algorithm that we propose continuously improves the performance of superior human partners and corrects the movement of an inferior one. Furthermore, humans who practised with our robot learned the tracking task better than those training alone for the same duration. These results promise collaborative robots that can provide human-like assistance for humans in manufacturing tasks[25], in functional augmentation[26] and in rehabilitation[27,28].

Methods

Dynamics of the tracking task. A model is developed to understand and simulate how two individuals connected by an elastic band plan their movement to track a randomly moving target. Here, we describe the dynamics of the task in one dimension.

To track a randomly moving target with position t, its trajectory must be estimated, then a motor command u must be generated to move the hand's position h to the target. The motor command has the form

$$u = -[L_p, L_v, L_a]\begin{bmatrix} h-t \\ \dot h - \dot t \\ \ddot h - \ddot t \end{bmatrix} \tag{1}$$

which is the control law to move the hand towards the target, and $\mathbf{L} \equiv [L_p, L_v, L_a]$ is the vector of control gains for position, velocity and acceleration.

The target is assumed to be buffeted by Gaussian noise in its jerk, $\dddot t \equiv \mu$, yielding the second-order system

$$\dot{\mathbf{t}} = \mathbf{A}\mathbf{t} + \mathbf{B}\mu, \quad \mathbf{A} \equiv \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \quad \mathbf{B} \equiv \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \ \mu \in \mathrm{G}(0, \mathbf{M}) \tag{2}$$

where $\mathbf{t} \equiv [t, \dot t, \ddot t]^T$ and $\mathbf{M} \equiv E[\mathbf{t}\mathbf{t}^T]$ is the covariance matrix. The hand is modelled as a point-mass m with dynamics

$$m\ddot h = u + F \tag{3}$$

where F is the interaction force from the elastic band, with stiffness K and damping D, that couples one's own hand to a partner's hand with position $\tilde h$, thus

$$F = K(\tilde h - h) + D(\dot{\tilde h} - \dot h) \tag{4}$$

In 'alone trials', when the subjects are not connected, the interaction force $F = 0$. The dynamics of the hand $\mathbf{h} \equiv [h, \dot h, \ddot h]^T$ are described, following equation (3), as

$$\dot{\mathbf{h}} = \mathbf{A}\mathbf{h} + \mathbf{B}(\dot u / m + \dot F / m) \tag{5}$$

Therefore, the control of the hand to track the target, described in equations (2) and (5), can be summarized by combining these two equations in the state equation

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}(\dot u / m + \dot F / m + \mu) \tag{6}$$

where $\mathbf{x} = \mathbf{h} - \mathbf{t}$ is the difference vector between the hand and the target.

Motion planning. Here, we describe the motion planning strategy of one individual tracking the target alone. To generate the motor command according to equation (1), the state of $\mathbf{x}$ must be estimated. The state $\mathbf{x}$ is observed through

$$z = h - t + \nu, \quad \nu \in \mathrm{G}(0, \sigma_\nu), \quad \sigma_\nu \equiv E[(z - E[z])^2] \tag{7}$$

In general, with a state equation of the form of equation (6) and an observation $\mathbf{z}$ with noise

$$\boldsymbol{\nu} \in \mathbf{G}(\mathbf{0}, \mathbf{N}), \quad \mathbf{N} \equiv E[\mathbf{z}\,\mathbf{z}^T] \tag{8}$$

the state $\hat{\mathbf{x}}$ is estimated using the measurement with $\hat{\mathbf{z}}$ through minimization of the prediction error

$$E[||\mathbf{z} - \hat{\mathbf{z}}^2||] \tag{9}$$

under the constraints of equation (6). This linear quadratic estimation can be computed in discrete time using an iterative Kalman filter algorithm[29]. Sensory delay in vision and proprioception can be compensated by integrating equation (6).

Interaction model. Which mechanism could be used to track the randomly moving target whilst being physically coupled to a partner? In the 'no computation' model, the target is tracked as in 'alone trials' while under the influence of the interaction force, yielding

$$\mathbf{z} = h - t + \nu \tag{10}$$

The observed behaviours would be the by-product of the mechanical connection between two individuals performing their own task independently.

The 'follow the better' model suggests that the partner's hand is tracked if it is nearer to the target than one's own hand; otherwise, the target is tracked. We assume that the state of the partner's hand is known to an individual from the interaction force in equation (4). The observation is dependent on

$$\mathbf{z} = \begin{cases} h - t & \text{if } |h - t| \le |\tilde h - t| \\ h - \tilde h & \text{otherwise} \end{cases} \tag{11}$$

'Multi-sensory integration' proposes to track the statistically optimal combination of the partner's position and one's own visual estimate of the target

$$\mathbf{z} = \begin{bmatrix} h - t \\ h - \tilde{h} \end{bmatrix} \tag{12}$$

where the partner's hand position $\tilde{h}$ is known through the interaction force in equation (4).

Finally, the 'interpersonal goal integration' model proposes that the partner's target is optimally combined with one's own visual estimate, such that

$$\mathbf{z} = \begin{bmatrix} h - t \\ h - \tilde{t} \end{bmatrix} \tag{13}$$

How is the partner's target $\tilde{t}$ estimated? Individuals could use an abstract representation of the partner, who tracks the same target in a similar manner to oneself. An individual would consider that the partner carries out a tracking task similar to equation (6), and sends a motor command

$$\tilde{u} = -[\tilde{L}_{\mathrm{p}},\ \tilde{L}_{\mathrm{v}},\ \tilde{L}_{\mathrm{a}}] \begin{bmatrix} \tilde{h} - \tilde{t} \\ \dot{\tilde{h}} - \dot{\tilde{t}} \\ \ddot{\tilde{h}} - \ddot{\tilde{t}} \end{bmatrix} \equiv -\tilde{\mathbf{L}}\tilde{\mathbf{x}} \tag{14}$$

to move their hand's position $\tilde{h}$ to their target position $\tilde{t}$.

The partner's state is estimated through the interaction force and the state of the individual's hand. To estimate the partner's target $\tilde{\mathbf{t}} \equiv [\tilde{t}, \dot{\tilde{t}}, \ddot{\tilde{t}}]^T$, their control law $\tilde{\mathbf{L}}$ must be identified. As $\tilde{\mathbf{L}}$ is unknown, it is assumed to evolve according to noise through

$$\dot{\tilde{\mathbf{L}}} \equiv \boldsymbol{\lambda},\ \ \boldsymbol{\lambda} \in \mathbf{G}(\mathbf{0},\ E[\dot{\tilde{\mathbf{L}}}^T \dot{\tilde{\mathbf{L}}}]) \tag{15}$$

Thus, the abstract representation of the partner's task $\mathbf{x}$ would include the states of his/her target, hand, control law, one's own hand and the interaction force, yielding

$$\bar{\mathbf{x}} \equiv (\tilde{\mathbf{t}},\ \tilde{\mathbf{h}},\ \tilde{\mathbf{L}},\ \mathbf{h},\ F) \tag{16}$$

This abstract state evolves nonlinearly in time with $\dot{\bar{\mathbf{x}}} \equiv f(\bar{\mathbf{x}})$, which is approximated by linearizing this function at every time instance and then used for linear quadratic estimation[30].

To identify the partner's control, the abstract state is approximated by assuming that the partner tracks the same target $\mathbf{t}$. Specifically, the sensory information $\mathbf{z} \equiv (t, h, F)$ of one's own target and hand positions and the interaction force is used; a linearization of $f(\bar{\mathbf{x}})$ and the minimization of the squared estimation error $E[||\mathbf{z} - \hat{\mathbf{z}}^2||]$ provides an estimate for $\bar{\mathbf{x}} \equiv (\mathbf{t},\ \tilde{\mathbf{h}},\ \tilde{\mathbf{L}},\ \mathbf{h},\ F)$. After identifying the partner's control $\tilde{\mathbf{L}}$, the observation $\mathbf{z} \equiv (\tilde{\mathbf{L}},\ h,\ F)$ is used to estimate $\bar{\mathbf{x}} \equiv (\tilde{\mathbf{t}},\ \tilde{\mathbf{h}},\ \tilde{\mathbf{L}},\ \mathbf{h},\ F)$, yielding $\tilde{t}$.

Simulations. For each proposed model, we conducted a sensitivity analysis to compare the predictive power of each model of interaction over a parameter space. Two free parameters of the model were adjusted: σ_μ^2, a multiplier for the Gaussian noise μ in the jerk in equation (2), and $q > 0$, a multiplier for the state cost $\mathbf{Q}$ in the controller. $\mathbf{L}$ will minimize

$$\int_0^\infty \mathbf{x}^T(q\mathbf{Q})\mathbf{x} + u^T R u \ \mathrm{d}t \tag{17}$$

where the state cost $q\mathbf{Q}$ is positive semi-definite and control cost $R > 0$.

The parameter σ_μ^2 determines the frequency content of the simulated trajectory, and q modulates the strength of the partner's controllers. σ_μ^2 was bound within a range that matched the spectrum of the trajectories in the data, and q was varied within the limits of human strength (see Supplementary Information for more details).

The squared distance from each model to the data was used as a metric for predictive power. Over the whole parameter space, the 'interpersonal sensorimotor integration' model had the most predictive power (Supplementary Fig. 1a).

Experiments. All 40 subjects described in the main paper gave informed consent for their participation in the experiments, which were conducted according to the principles in the Declaration of Helsinki and approved by the ethics committee at the Advanced Telecommunication Research Institute (www.atr.jp). The subjects tracked a moving target on the visual screen in consecutive 60-s trials. Details of the target function can be found in the previous study[3]. In the solo experiment, 10 subjects completed 10 consecutive 'alone trials'. In the interaction experiment, 18 subjects completed 10 trials, of which half were 'alone trials' and half were 'connected trials'. The order of 'alone trials' (A) and 'connected trials' (C) followed one of two sequences: either ACACAACCAC or CACACCAACA. During 'connected trials', the hands of the dyad were connected by a virtual compliant elastic band of stiffness $K = 120\,\mathrm{N\,m^{-1}}$ and a small damping $D = 7\,\mathrm{N\,s\,m^{-1}}$.

The human–robot experiment consisted of three sessions, each alternating 'connected' and 'alone trials' for a total of 10 trials per session with a fixed sequence of CACACACACA. The robot's performance was kept constant within each session, and 12 subjects experienced the sessions in the order of superior, similar and inferior robot performances (tracking error 2 cm lower than, same as, and 3.5 cm higher than average human performance, respectively). The human-like robot control consisted of equations (6), (8) and (13) and was implemented in discrete time using a step size of $\mathrm{d}t = 0.005\,s$ and with the parameters $K = 120\,\mathrm{N\,m^{-1}}$, $D = 7\,\mathrm{N\,s\,m^{-1}}$ and $m = 1\,\mathrm{kg}$. The sensory delay was set to 150 ms and was compensated by iterating the forward model of equation (6) in time.

Statistical significance for the better and worse partners in the interaction experiment and when interacting with superior, similar and inferior robot partners was tested using a one-sample t-test, of which all passed the Jarque–Bera normality test at the 5% significance level.

Statistical significance of the improvement in the experimental condition was tested using a one-sample t-test of the mean improvement of each subject. Data from the human–human and human–robot experiments were fitted using a linear mixed-effects model with improvement $I = 1 - e/e_{\mathrm{c}}$ as the dependent variable, and with the partner's relative error $E = 1 - e_{\mathrm{p}}/e$ and E^2 as predictors in the form

$$I = \beta_{0i} + \beta_1 E + \beta_2 E^2 + \varepsilon_i \tag{18}$$

where β_{0i} is the intercept, β_1 the slope and ε_i the unexplained variance of the improvement for each dyad i. We compared the difference in improvement between the human–human and human–robot by adding the condition factor C, labelling each datum as coming from the human–human or human–robot experiment, in the model

$$I = \beta_{0i} + \beta_1 E + \beta_2 E^2 + \beta_3 C + \beta_4 (EC) + \beta_5 (E^2 C) + \varepsilon_i \tag{19}$$

and compared the two models from equations (18) and (19) using a likelihood ratio test.

Motor learning was estimated by an exponential fit ($e(T) = e_{\mathrm{L}} + ae^{(-\lambda T)}$ where e_{L} is error after learning and T is trial number) of the trials (only the ones without haptic forces) from all subjects. The error fit at $T = 0$ was estimated as the error in the first 5 s of the first trial, as subjects exhibited rapid motor learning in the first 60 s of the tracking experiment. We conducted one-way analysis of variance on the baseline error ($e(0) = e_{\mathrm{L}} + a$) with condition as a factor, and found an insignificant difference in the baseline error of subjects in the solo, human–human and human–robot conditions ($F(2,29) = 0.71$, $P > 0.5$). A one-way analysis of variance on e_{L} with condition as the factor showed a significant effect ($F(2,29) = 13.23$, $P < 10^{-4}$); a multiple comparisons Tukey–Kramer test revealed significant differences between the solo and human–human ($P < 0.005$) and solo and human–robot conditions ($P < 10^{-4}$), whereas the human–human and human–robot error after learning was similar ($P > 0.6$).

Data availability. The data that support the findings of this study are available from the corresponding authors upon request.

Code availability. The code used for the simulations in this study is available from the corresponding authors upon request.

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Author contributions
A.T., G.G., M.K. and E.B developed the computational model. G.G. and T.Y. conducted the empirical experiments with human pairs, and A.T. and T.Y. tested human users with the robot assistant. A.T. and G.G. analysed the data and simulated the models. A.T., G.G., M.K. and E.B. wrote and edited the manuscript.

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Competing interests
The authors declare no competing interests.