01 Jan 2022

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Recommended Citation

Holmes, G. L., Bonnett, K. M., Costa, A., Burns, D. M., & Song, Y. S. (2022). Guiding a Human Follower with Interaction Forces: Implications on Physical Human-Robot Interaction. *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics* Institute of Electrical and Electronics Engineers.
The definitive version is available at https://doi.org/10.1109/BioRob52689.2022.9925337

2022 9th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob) | 978-1-6654-5849-8/22/$31.00 ©2022 IEEE | DOI: 10.1109/BIOROB52689.2022.9925337

Guiding a Human Follower with Interaction Forces: Implications on Physical Human-Robot Interaction

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***Abstract*— This work challenges the common assumption in physical human-robot interaction (pHRI) that the movement intention of a human user can be simply modeled with dynamic equations relating forces to movements, regardless of the user. Studies in physical human-human interaction (pHHI) suggest that interaction forces carry sophisticated information that reveals motor skills and roles in the partnership and even promotes adaptation and motor learning. In this view, simple force-displacement equations often used in pHRI studies may not be sufficient. To test this, this work measured and analyzed the interaction forces (*F*) between two humans as the leader guided the blindfolded follower on a randomly chosen path. The actual trajectory of the follower was transformed to the velocity commands (*V*) that would allow a hypothetical robot follower to track the same trajectory. Then, possible analytical relationships between *F* and *V* were obtained using neural network training. Results suggest that while *F* helps predict *V*, the relationship is not straightforward, that seemingly irrelevant components of *F* may be important, that force-velocity relationships are unique to each human follower, and that human neural control of movement may affect the prediction of the movement intent. It is suggested that user-specific, stereotype-free controllers may more accurately decode human intent in pHRI.**

***Index Terms* — Human-robot interaction, intention detection, interaction forces, neural network**

I. Introduction

In the near future, robots are expected to seamlessly interact with humans through physical coupling. Such applications include patient rehabilitation in physical medicine [1–6], surgeon-robot interaction [7], [8], or Wearable robots [9–11]. In these physical human-robot interaction (pHRI) tasks, the key is for the robot to understand the human partner's movement intention through non-verbal, physical communications. A reasonable starting point of interpreting the human intent would be through analyzing the interaction forces [12]. For example, a push on the robot would be the sign of the human operator wanting the robot to move away from him, whereas a pull would be the sign of the opposite movement [13]. The assumption is that the movement intention of a human user can be simply modeled with dynamic equations relating forces to movements. Details of the human intent, such as the velocity of the movement or the precise direction, are inferred using the forces and the time-invariant, delay-free, and general (i.e., not user-specific) equations of motions of the human-robot pair. This approach has been successfully applied in several pHRI studies, particularly in partnered dancing [12–14] or during walking [15], [16] with a robot.

On the other hand, evidence from studies in physical human-human interaction (pHHI) implies that motor communication through interaction forces may be much more sophisticated. Between two human partners, physical interaction with forces can lead to the distinction of the skill levels of the partner [17], leader-follower role assignments [18], improved performance without explicitly shared motor goals [19], [20], or even motor adaptation between the partners [21], [22]. Admitting that humans are much better than robots in physical collaboration, cooperation, and assistance with another human [23], pHRI robots have the potential to be smarter like in pHHI, in which the motor communication is more sophisticated and intelligent beyond what physics-based dynamic equations allow.

To this end, the aim of this study is to capture the movement intention embedded in the interaction forces in pHHI using empirical modeling and to investigate whether such interpretation could be general enough to be practical in future pHRI applications for guiding a robot [24], [25]. We present a pHHI experiment in which the follower needs to understand the leader's intention as the leader guides the blindfolded follower in one of four randomly chosen paths. Assuming that the interaction forces correctly conveyed the information for the follower to stay on the path, the measured force profile is mapped onto the speculated movement commands issued by the leader using artificial neural

Manuscript submitted on January 24, 2022. This work was supported in part by the National Science Foundation under Grant #1843892.

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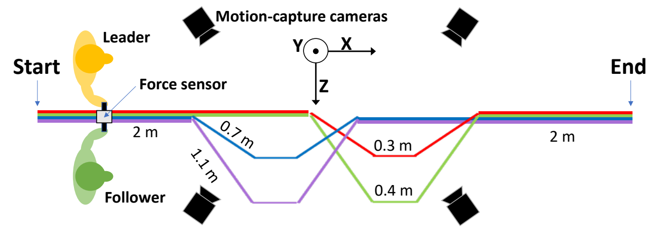

Fig. 1. Top view of the pHHI experiment. At each trial, the follower is led through one of the four (red, blue, green, or purple) trajectories known only to the leader. The actual trajectory of the follower is measured using a 3D motion-capture system.

networks (NN). The characteristics of the resulting force-command relationship are then discussed focusing on the generalizability and human-specific features.

II. Methods

A. Technical Framework and Approach

This work is built upon a specific and practical scenario of pHHI in which a helper (or the leader) helps a vision-deprived person (the follower) to walk on an unknown path (Fig. 1). There is no verbal communication; all information and intent exchange is done through the physical coupling of hands. As the pair move across the room, there will be a constant negotiation of non-verbal cues of how each person is expecting the other to move. This is measured by a force sensor (Mini 45, ATI Industrial Automation, MA, USA) on a handle connecting the pair. For simplicity, it is assumed that the interaction forces convey the intent of the leader only and that the follower simply 'listens' to it. This assumption is based on the experimental setup that 1) the follower, who is blindfolded, is explicitly instructed to follow the guidance of the leader, 2) the leader is explicitly instructed to guide the follower on a specific path at a relatively constant speed, and 3) only the leader, and not the follower, knows the exact path. Then, if the follower was successful in following the path despite being vision-deprived, the interaction forces generated by the leader must have conveyed the necessary information that the follower can interpret as movement commands.

To decode the interaction forces ($\boldsymbol{F}$), it is necessary to first obtain the movement command. The movement command is extracted from the follower's movement trajectory measured by a 3D motion-capture system (Flex 3, Optitrack, OR, USA) as follows: It is first assumed that the same interaction force profile from the leader is provided to a hypothetical robot follower, which is expected to reproduce the human follower's trajectory. In this work, the follower is a differential-drive wheeled robot (dr12, Cubictek co. ltd.) with a kinematic controller [26–28]. This robot platform has kinematic and dynamic constraints that must be adhered to, to ensure safety and stability. Guided by the extensive prior work on differential drive robot modeling [26], [28], [29] and control [30], [31], the movement trajectory can be turned into the velocity commands for the robot through a dynamics simulator (Virtual Robotics Experimentation Platform, VREP) with the kinematic controller gains of k1 = 2, k2 = 2, and k3 = 1 [32], [33]. The resulting linear and angular velocity profile ($\boldsymbol{V}$) is regarded to be the movement intent embedded in the interaction forces from the human leader. More details can be found in [34].

TABLE I
NEURAL NETWORK TRAINING PARAMETERS

Parameter	Value
Test fraction	20%
Neurons per layer	100
Epochs	3500
Learning rate	0.001
Hidden layers	3
NN inputs	6 inputs, $[F_x, F_y, F_z, T_x, T_y, T_z]$
NN outputs	2 outputs, $[v, w]$
Validation split	0.2
Activation function	Sigmoid

Then, multiple considerations are made in order to find the mapping from the interaction forces to the movement command of a follower ($\boldsymbol{F} \rightarrow \boldsymbol{V}$). Currently, there are no algorithms that relate human interaction forces to robot velocities. Also, the force data contains components that are fundamentally different from one another (forces in [N] and torques in [Nm]). As a result, the scale of the data varies considerably. Further, the mapping algorithm would need to take into consideration large amounts of multidimensional datasets. This work addresses this problem by using a multilayer perceptron artificial Neural Network to capture the mapping. If there exists a mapping between the interaction forces and the movement command (which there clearly should be because the blindfolded follower was successful in interpreting the leader's intent), the NN will be able to capture it [35]. In addition to the ability to process a dataset with mixed data types, the biomimetic nature of the NN which is inherently designed to loosely mimic the function of the human nervous system makes a NN a reasonable choice for research involving human motor control processes.

B. Experiment Protocol

The human participants were recruited under the rules and regulations set forth by the CITI Program Human Subjects Research protocol, and the entire experimentation process was approved by the Institutional Review Board of Missouri University of Science and Technology. A designated research personnel served as a human leader while a naïve, recruited participant was the follower. Together, their task is to jointly move on a predefined trajectory that is known only to the leader (Fig. 1). The leader's goal was to guide the trajectory of the force handle to be above a chosen trajectory, whereas the blindfolded follower was instructed to simply follow the guidance provided by the leader. Verbal communication was not allowed between the participants. At the start of a trial, the human pair held the force handle between them and stood at the starting point of the trajectory. Then, from the four possible trajectories, only the leader is notified of the specific trajectory to guide the follower. These trajectories were traversed by the human pair at a moderately slow, constant walking speed (approximately 1 m/s). There were no stops,

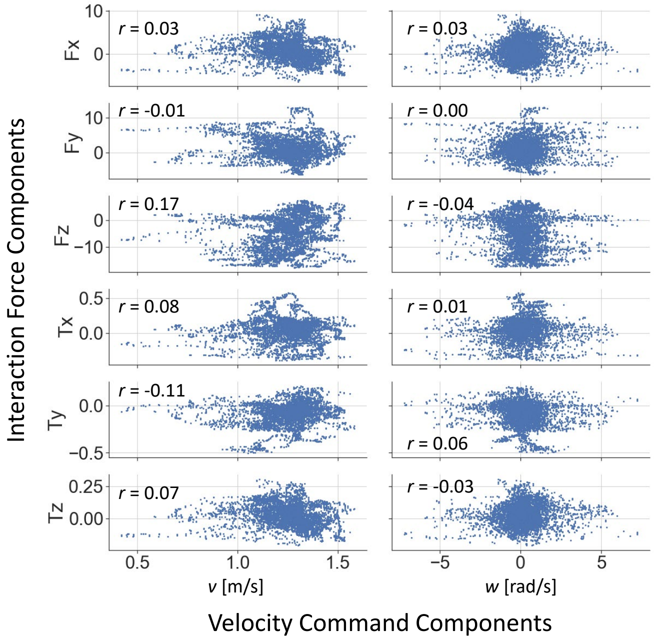

Fig. 2. Marginal distribution plot with Pearson Correlation Coefficient (r) of the interaction force and velocity command components from participant 1's data.

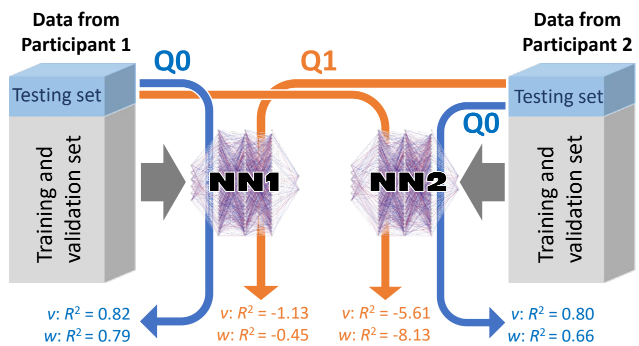

Fig. 3. Schematic of the NN training and testing. Q0: testing of the predictability of the velocity commands of each NN trained from the same participant's data. Q1: cross-testing of the velocity command predictability of each NN given another participant's testing data set.

and the motion was generally smooth in the forward direction. A total of 24 trials per participant were collected, consisting of a random ordering of 6 repetitions of each of the four trajectories in Fig. 1. In each trial, the data collected included the movement trajectory of the handle and the interaction forces and torques between the human pair. There was a total of two follower participants in this experiment (2 males, average 21.5 years old).

C. Data Correlation and Neural Network Training

To investigate if any of the 6 force elements ($\boldsymbol{F} = [F_x, F_y, F_z, T_x, T_y, T_z]$) relate directly to the velocity commands ($\boldsymbol{V} = [v, w]$, where v and w are linear and angular velocities, respectively), and also to provide an initial qualitative and quantitative assessment of the data for the training of the NN, marginal distribution plots and Pearson's product-moment correlation coefficient (r) were obtained between $\boldsymbol{F}$ and $\boldsymbol{V}$ (Fig. 2). However, because no apparent direct correlation between any force element to any velocity element was found (see Results), a NN mapping was then investigated (Fig. 3). The input $\boldsymbol{F}$ with mixed data types ([N] and [Nm]) was normalized using the Z-score normalization. Then, the parameters in Table I were used with a multilayer perceptron trained using backpropagation, whose initial weights were randomly assigned. These parameter values were selected initially by examining the marginal distribution plots (e.g., Fig. 2), Pearson's correlation coefficient, and raw data statistics. The values were refined by experimentation, observing the training performance, and tuning values accordingly. For a given participant, 80% of the experimental data were used as the training set (64% of the total data) and the validation set (16% of the total data). The remaining 20% of the data were set aside as the testing set, with which the performance of the training was addressed. The predicted velocity commands ($\boldsymbol{V}_p$) from the testing set was then compared to the actual velocity command ($\boldsymbol{V}$) to address the performance of the NN training.

D. Research Questions and Analysis

With the above scenario and technical framework, four questions were identified which this research seeks to answer.

Q0: Are there signatures in the human-human interaction force data to infer the appropriate robot velocities - that is, is $\boldsymbol{V}$ strongly correlated with $\boldsymbol{F}$? This question is addressed by directly comparing the elements of $\boldsymbol{F}$ to the elements of $\boldsymbol{V}$ using Pearson's product-moment correlation coefficient (r) as well as qualitatively using marginal distribution plots. This analysis is aimed at revealing any direct, intuitive coding of human intent in $\boldsymbol{F}$. In addition, after training the NN for each participant, the predicted ($\boldsymbol{V}_p$) and actual ($\boldsymbol{V}$) commands are compared using the coefficient of determination (R^2), where $R^2 = 1$ means perfect prediction and $R^2 < 0$ implies that a simple average of the data provides a better fit than the NN prediction. We considered the coefficient of determination above 0.5 to be good. This second analysis is aimed at revealing an indirect coding of human intent in $\boldsymbol{F}$ that was not apparent in direct comparison.

Q0-1: A sub-question to Q0 is the following: Do forces and moments in certain directions contain most of the human-robot interaction signature information, such that training the neural network with this data alone gives good performance? If there are signatures within the six forces/torques to infer the velocity command (Q0), perhaps only a subset of the force data needs to be used to understand the mapping appropriately. Indeed, since the movement trajectory is 2D, it is not unreasonable to assume that only forces and moments on this 2D plane would contain the movement intention. If this hypothesis is supported, it provides the mapping algorithm a variety of benefits related to efficiency. The analysis method for Q0-1 is identical to the method for Q0.

Q1: Does the neural network generalize across different participants? If a mapping is found to exist between $\boldsymbol{F}$ and $\boldsymbol{V}$ for a given participant, how well does that mapping work for another participant(s)? This is a way of testing the universality of the force-velocity mapping. First, each participant's data are used to obtain the individual participant's NN (NN1 and

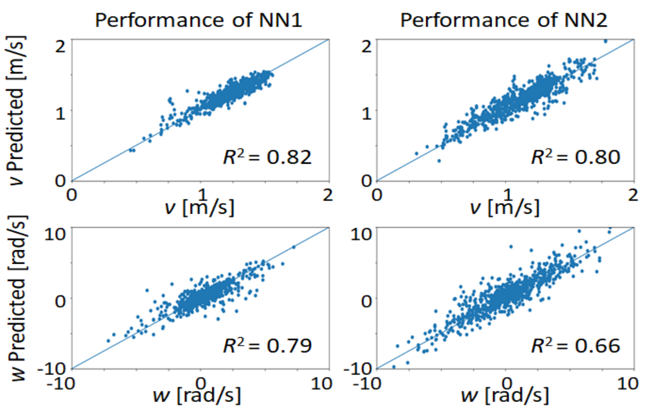

Fig. 4. The actual velocity commands versus the NN-predicted velocities. Left column: Participant 1. Right column: Participant 2. Top row: linear velocity (v). Bottom row: angular velocity (w).

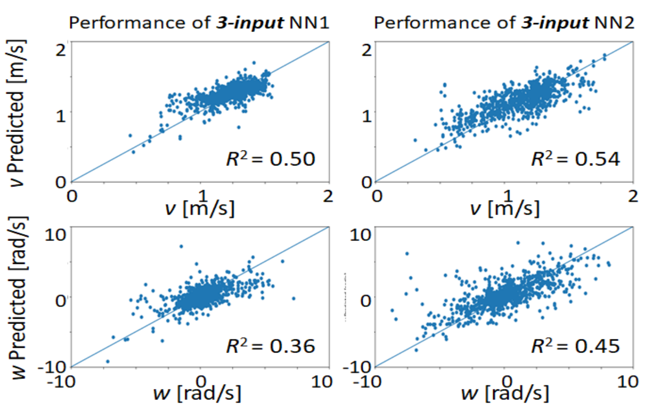

Fig. 5. The predictability of the NN after training with only three inputs, F_x, F_z and T_y. Left column: Participant 1. Right column: Participant 2. Top row: linear velocity (v). Bottom row: angular velocity (w).

NN2, respectively). Then, the testing set of participant 2 is provided to NN1. The performance of NN1 in decoding $\boldsymbol{F}$ from participant 2 is evaluated using R^2. The same is repeated for the testing set of participant 1 and NN2.

Q2: Does $\boldsymbol{F}$ from a near-past better predict the current $\boldsymbol{V}$ than the current $\boldsymbol{F}$ does? It is well known that human motor control comes with signal delays and processing time from the human nervous system in the order of 100 ms [36]. Then, it is reasonable to assume that there would be a similar delay between the input forces to the output motion during human-human interaction, and that current velocities may be better inferred by past forces. For both of the participants' data, the following time delays were applied: 50, 100, 150, 200, 300 ms, shifting force inputs early. For each of the five cases, individual neural networks were trained for both participants, using six-direction force inputs. Then, the performances of these NN from time-shifted data were compared to the performance of the trained with original data with no time offset. This is a way of testing the effect of the nature of the human biosystem to the force-velocity mapping.

III. Results

A. Raw force statistics and the Controller Performance

The interaction forces between humans were in the range of -24.54-13.18 N (linear forces) and -0.5-0.58 Nm (torque).

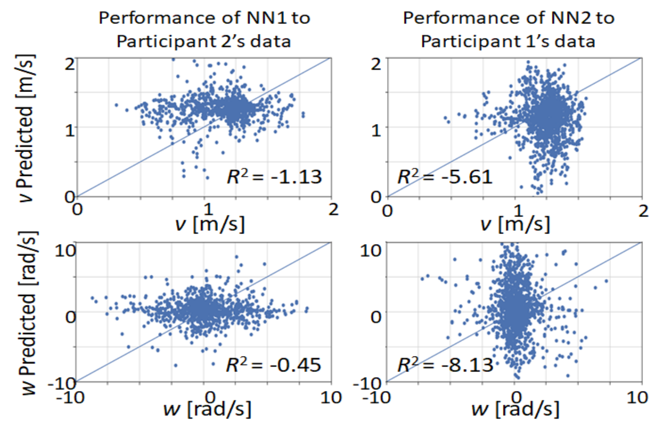

Fig. 6. Performance of the individual participant's neural network (NN) when used to estimate the velocity commands from another participant's data. Left column: Participant 1's NN given Participant 2's data. Right column: Participant 2's NN given Participant 1's data. Top row: linear velocity (v). Bottom row: angular velocity (w).

TABLE II
Effect of Time Shift to NN Performance

Time shift (ms)	Participant 1		Participant 2	
	R^2 of v	R^2 of w	R^2 of v	R^2 of w
0 (baseline)	0.82	0.79	0.80	0.66
50	0.69	0.64	0.73	0.67
100	0.74	0.64	0.80	0.66
150	0.78	0.71	0.75	0.63
200	0.85	0.76	0.80	0.75
300	0.83	0.75	0.81	0.76

*Gray cells indicate better prediction than baseline.

These values are comparable with the force values in another pHHI study [17]. Also, the kinematic controller was successful in tracking the movement trajectory of the follower. In VREP simulation, the dr12 robot with the velocity command ($\boldsymbol{V}$) was able to track the measured trajectory of the human follower with a mean squared error of only 0.074 m. As expected, the trajectory error decreases through the course of each trial as the simulated robot followed the velocity command – a known feature of the kinematic controller. The linear velocity converged to approximately 1.4 m/s which is similar to the average human walking speed. Hence, we can regard the velocity commands ($\boldsymbol{V}$) generated by the kinematic controller to reflect the human leader's intention to guide the follower, whether it is a human or the dr12 robot.

B. Interaction Force-to-Velocity Command Mapping

The marginal distribution plot with Pearson Correlation Coefficient, r (Fig. 2), did not show a notable direct relationship between an element in $\boldsymbol{F} = [F_x, F_y, F_z, T_x, T_y, T_z]$ and an element in the velocity commands, $\boldsymbol{V} = [v, w]$. The highest correlation coefficient observed was 0.26 between T_y and v of participant 2. On the other hand, NN training with all 6 forces and torques as the inputs showed the coefficient of determination (R^2) between 0.66-0.82 (Fig. 4).

While this result indicates that there exists some useful mapping from forces to velocities, it is possible that not all six force/torque inputs may be necessary to obtain a good enough prediction of the follower's velocity. For example, because the follower's trajectory is on the x-z plane, forces and torques on this plane (F_x, F_z, and T_y) may possess most of the velocity information. However, our NN training with only these three inputs showed a much poorer prediction of the velocity commands (Fig. 5) with R^2 between 0.36-0.54.

C. Generalizability of the Force-Velocity Mapping

We tested whether the NN1 trained from the training set data of participant 1 could predict the velocity commands of the testing set data of participant 2, and vice versa (Fig. 3). In contrast to how each NN performed well in estimating the velocity commands from each participant's data, they were not able to estimate the velocity commands in another participant's data. For example, NN1 showed a very low coefficient of determination ($R^2 < 0$, Fig. 6) given the testing set of participant 2. Similarly, NN2 did not predict the velocity commands from the testing set of participant 1. This is significant given that both participants were interacting with the same leader following the same paths and speed.

D. Effect of Time Shift

It was found that when the force data preceded the velocity data by 200~300 ms, the trained NN performed similar or better than the baseline scenario when no time-shift was presented (Table II). In particular, in participant 2, the angular velocity was better predicted using time-shifted data than the baseline. In contrast, time shifts of 50, 100, or 150 ms tended to reduce the fit values.

IV. Discussion

The crucial consideration in this work is to identify the correct velocity commands themselves. Given a measured 2D trajectory, one may derive the linear and angular velocities by a simple differentiation in time. However, this velocity input does not guarantee specific wheeled robot hardware to follow the original trajectory. The dynamics of the robot, which is affected by many design factors, may steer it off the desired path. Hence, instead of simple differentiation of a trajectory, it is more logical to derive the velocity command for a specific robot that is proven to generate the desired trajectory for that robot - in this case, through the kinematic controller and VREP simulation.

The results imply that, while there is not a direct relationship between the elements of $\boldsymbol{F}$ and those of $\boldsymbol{V}$, the interaction forces as a whole encode the leader's movement intent (Q0 in section II.D). The low r in direct comparison (Fig. 2) suggests that there is no simple and obvious relationship exists between a force in a specific direction and the velocities, contrary to intuition. For example, forward force (F_x) was not correlated with the forward movement (v). Similarly, turning torque (T_y) was not correlated with the turning movement (w). The seemingly obvious kinematic relationships between $\boldsymbol{F}$ and $\boldsymbol{V}$ did not hold. However, this relationship was, in fact, deeply embedded within the interaction forces, such that it was revealed only after the NN training. With interaction forces as inputs, the NN was able to predict the velocity commands reasonably well ($R^2 > 0.66$).

The result in Fig. 5 implies that the seemingly irrelevant F_y, T_x, and T_z are necessary to predict the leader's intent well (Q0-1 in section II.D). It is thus suggested that all six forces and torques be used as the inputs for the trajectory control of a future mobile robot without prematurely assuming that some force or torque components do not matter.

The generalizability result in Fig. 6 implies that the trained NNs are specific to the participant of the dataset it is trained with, further implying that each participant may be unique in how they interpret the interaction forces to determine their movement (Q1 in section II.D). Even though both participants had a common leader as well as the fact that their movement trajectories were similar, the force-velocity relationship may be highly individualized. From the perspective of developing a robot to guide a human follower through force, the guidance strategy should be user-specific and may not be generalized. The robot must be informed of the change of users if it occurs and should be able to adapt to that by switching to the user-specific guidance strategy.

the results in Table II may be interpreted as a possible opportunity to improve the NN prediction of velocities (Q2 in section II.D). Despite that 1) the length of the time-shifted data was shorter than the length of the data for baseline NN training, and 2) the NN parameters in Table I were tailored for the no-shift data and not the time-shifted data, the performance of the NN trained with 200~300 ms shifted data were at least comparable with the performance of the NN in Fig. 4 in predicting $\boldsymbol{V}$ (Table II). While the presented result is only from two participants, it is consistent with the widely known characteristics of human-in-the-loop control. It further suggests that it may be beneficial for the robot to consider the inevitable delay in human neuro-mechanics while interpreting the interaction forces imposed by humans.

It is noted that the analyses and interpretations in this work assume that the interaction force profiles are determined by the leader. While this assumption may be reasonable in this work as mentioned earlier, it is also important to note that in general, the effect from the follower's reaction cannot be fully neglected. For example, the mechanical impedance of the arms of both the leader and the follower affect the force profile. This may be the reason behind the non-generalizability of the NN mapping in different follower participants. For this reason, future robots for pHRI may benefit from human-like dynamic characteristics, such as a robot arm that matches the low human arm stiffness for sensing small interaction forces [37].

In this experiment, it was entirely up to the leader to ensure that the follower was on the correct trajectory. The blindfolded followers could not receive any visual feedback on how 'good' their trajectory was, neither during nor after a trial. However, in future pHRI applications where the follower could also adapt, the individual differences may not become as relevant. Indeed, in [17], pairs of expert dancers adapted to their partners as the experiment progressed. While this work did not analyze the existence of learning, future experiments may investigate the possible convergence of the guidance strategies (such as NN1 and NN2) when both the leader and the follower are allowed to learn and adapt.

V. Summary and Conclusion

This work was motivated by the ability of humans to effectively interact with another human through physical coupling that is beyond what simple kinematics or dynamic equations can explain. By studying how humans interact with one another in an overground physical human-human interaction task, notable implications were found regarding using interaction forces to design future interactive robots to follow a human's lead. These include the need to interpret the interaction forces in an integrated manner (for example, by using a NN and including all directions of forces without stereotype), the need for a personalized decoder, and the possible improvement in interpreting human intent using near-past interaction forces. Together, these results suggest important features to incorporate in designing physical medicine robots that have human-like interaction.

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