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Quantitative Modeling and Analysis of Reliance in Physical Human–Machine Coordination

Smooth and efficient human–machine coordination in joint physical tasks may be realized through greater sensing and prediction of a human partner's intention to apply force to an object. In this paper, we define compliance and reliance in the context of physical human–machine coordination (pHMC) to characterize human responses in a joint object transport task. We apply an optimization framework to explain human intention and behavior. The weighting factor in the optimization problem, lambda (λ), is presented as a person's reliance on the machine in a joint physical task with varying constraints. We demonstrate that with an estimated λ, the intended two-dimensional motion of a person's trajectory can be captured. We also found a relationship between λ and trust while participants performed a familiar task with no distraction. This finding suggests a relationship between the psychological construct of trust and joint physical coordination. The extent to which λ may serve as an online measure of trust and reliance in a physical load sharing task requires further investigation under more complex task scenarios that involve greater degrees of vulnerability and uncertainty. [DOI: 10.1115/1.4044545]

Keywords: trust, dynamics, reliance, physical human–robot interaction, optimization

1 Introduction

Modern theoretical approaches to physical human–machine coordination (pHMC) recognize the importance of sensorimotor exchanges [1]. That is, when a person and a robot engage in joint action, the robot's motor behavior adjusts to the person's motor behavior simultaneously as the person adjusts to the robot's motor behavior. While people are able to smoothly and automatically coordinate their physical actions with one another [2], machine learning algorithms have difficulty reconciling coadaptation [3].

Furthermore, the influence of robot actions on people is difficult to capture as people often have different responses to the same robot actions [4]. We view potential pHMC applications, such as personalized wheelchair assistance [5], robotic dance instruction [6], and collaborative assembly [7], as being embedded within complex human systems in which the degree of reliance on a robot can change, given varying situational constraints.

Prior work on physical human–machine coordination has explored using sensor data to infer human intention and behaviors. For example, electromyography signals of the human arm have been applied to an impedance control framework to improve joint performance in a human-guided collaborative task [8]. Learning methods have also been used on robot motion planning during a human–robot object transport task [9,10], and game theory frameworks have been used to adjust the stiffness of a robot during a co-assembly task [11]. Cognitive systems engineering is a research area that has established several psychological factors to explain human performance in complex systems [12]. Yet, studies examining joint coordination in pHMC typically infer the human partner's intention and behavior through impedance or interaction force [1,13,14], without addressing cognitive factors that can mediate a person's intention and behaviors, such as trust.

Trust has been identified as an important factor that guides human intention and behavior when interacting with automation (including robots and machines), particularly in situations characterized by uncertainty [4]. A person's trust in a machine can be affected by the machine's capability [14], their performance disparity [15], and related factors such as task complexity, multi-tasking requirements [16], system complexity, performance saliency, and decisional freedom [17]. Additionally, cognitive distraction can influence trust in automation because it can cause a person to overlook automation performance, although there is conflicting evidence as to how different distractors influence trust [18,19]. The understanding of human intention and behavior in pHMC may thus be more refined by capturing the variability in levels of trust that people have under various conditions [20]. However, given the difficulty of unobtrusively measuring continuous trust in a physical task environment, we believe that human intention and behavior in physical tasks is best understood through a more measurable concept related to trust—reliance.

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Reliance and the related concept compliance are important indicators of trust with implications for safety [21]. Automation complacency and misuse of machines can emerge as a result of highly reliable or capable machines, leading to delayed or absent human responses when intervention is needed [22]. In contrast, it may be too difficult to observe a machine's status or predict what it may do next, leading to disuse. In the current study, we explore how a machine may measure reliance in real-time pHMC.

1.1 Reliance in Physical Human–Machine Coordination. As originally defined in the context of discrete responses to hazard warning systems, reliance describes inaction when a warning system indicates the system is intact [21]. Reliance is inaction because the operator allows the warning system to provide the capacity of detecting a hazard. In general, reliance is a behavior that allows an agent to provide a capacity for task completion. While definitions of reliance and compliance are conventionally applied to tasks with discrete responses, the concept may be applied to joint work in pHMC involving continuous responses. Because a person's compliance in this situation can be considered independently from reliance actions (e.g., compliance as the act of participating in the joint task, or responding to a robot's request), for scope we will assume compliance and focus on reliance for the remainder of this paper.

A joint object transport task may involve fixed or dynamic allocation of roles, tasks, and capacities which contextualize reliance behaviors. In pHMC, overreliance in the robot's capacity to apply force may mean the operator is less efficient, may lead to disengagement, or may damage the robot. Task disengagement is a concern not just for the quality of work and productivity outcomes, it can also mean a lack of situation awareness needed to notice impending risks and to input the necessary controls in a timely manner. On the other hand, if operators under-rely on the robot, they may take on too much load for themselves, which could lead to injury [23] and less efficient task completion. Appropriate reliance of an operator, as measured by interaction force, would reflect the effort needed to allow the robot to fulfill its intended role in applying force to the object.

In this task, human intention and behavior are modeled as optimizing a cost function that balances the energy cost of the human with the tracking error (distance from the current position to the goal position) [13]. Similar human behavior models have been introduced in previous work that used optimization frameworks to explain human motion based on cost functions [14,24–27]. In this paper, we propose that human intention and behavior in a joint object transport task can be modeled by minimizing the following cost function

$$C(t) \stackrel{\text{def}}{=} e^2(t) + \lambda u^2(t) \tag{1}$$

where $e(t)$ is the task tracking error and $u(t)$ is human effort. This method, in particular, may be useful for robots to acquire general information about a person's intention and behavior based on estimated λ. In Eq. (1), $\lambda \in \mathbb{R}+$ is a weighting factor which represents a person's intention in interacting with the robot. If a person weights task completion more heavily than their own energy consumption, the weighting factor (λ) will be relatively low, compared with people who weight their own effort costs more heavily than task completion during the interaction. Through this method, we posit we could summarize a person's reliance in this specific joint transport task with a single parameter, which can be estimated in real time.

We posit that physical reliance in a joint object transport task translates to applying force in a way that utilizes the partner's capacity to supply force. We model the interaction in a task where a person must guide the robot (thus, we assume compliance) to validate λ's estimation, which can actively reflect the human's intention and behavior in leading the robot, and to establish a baseline for investigating trust and reliance dynamics. This means that, in the current study, reliance is expressed by applying more force to the object so the robot may support activity with its own force.

To establish our understanding of the relationship between trust, reliance, and joint physical motion, we control for role allocation by first considering a situation in which the person is always initiating and leading the robot, who is sharing the load by following and matching the force of the person. Due to the known relationship between trust and reliance, we predict λ will explain a significant amount of variation in trust scores. Therefore, we supplement the model and interaction force measurements with an additional comparison with a validated trust in automation scale [20]. Since λ estimates reliance by sensing physical properties of the interaction in real time, changes in task completion time and force should correspond with changes in λ. Greater trust scores will be associated with lower λ and shorter task completion time. Additionally, we expect variation in the task over time to affect physical measures and λ as participants become more familiar with the robot. Finally, we anticipate there will be performance and trust differences when participants are distracted.

The main research question and hypotheses in this paper are as follows:

RQ: Can reliance on interaction force be represented by λ in an optimization framework during a joint object transport task?

H1: Trust is negatively correlated with λ.

Rationale: If trust is negatively correlated with λ, then λ follows a similar relationship with trust as reliance.

H2: Force, completion time, and λ will be significantly different as participants perform progressively complex tasks.

Rationale: As people engage in more complex tasks, they may plan their motor movements in ways that are more effortful and less efficient than in simple tasks. Changes in these physical measures should be reflected in changes in λ.

H3: Performing the transport task while cognitively distracted will result in slower task completion, less force, greater trust, and greater λ than without distraction.

Rationale: Distracted individuals will divide their attention between physical and cognitive tasks, which may result is less efficient task completion. Dividing attention also means the individual may notice the robot's performance less, and thus have a greater (but potentially miscalibrated) trust [19].

2 Experiment Design

To test our hypotheses, this experiment tested four within-subjects conditions by varying the structure of a joint transport task between a participant and a robotic manipulator arm. That is, the first task (Task 1) was a short-range transport task, the second task (Task 2) was a more challenging long-range transport task, the third task (Task 3) was a short-range transport task with an obstacle, and finally, the fourth task (Task 4) was a short-range transport task that involved two connecting waypoints. Additionally, participants completed one of two between-subjects conditions—a baseline condition and a distraction condition that included a cognitive distraction task.

2.1 Participant. Thirty-eight participants (10 self-reported as female, 27 male, and 1 nonbinary) were recruited from Arizona State University Polytechnic campus through an online course credit management system, posted flyers, or in-person recruitment. All participants reported that they had no prior experience working with manipulator robots, were able to comfortably lift and carry 10 lbs with their right arm, and were comfortable communicating in English. To aid in study recruitment, each participant was entered in a randomized drawing to win one of eight $20 gift cards to a local coffee shop and awarded research credit if applicable.

Five participants were excluded because they displayed extremely high force and λ so as to indicate sensor error, had multiple missing data, or responded as having had prior robot interaction experience in our post-test survey. Thus, analyses were carried out on data for 33 participants (baseline, $n = 17$; distraction, $n = 16$).

2.2 Equipment and Materials. The robot in this experiment was a manipulator arm (UR5, Universal Robots, Denmark). The UR 5 is equipped with a force–torque sensor (FT-300, Robotiq, Quebec, Canada), which provides the measurement of force and torque applied on the end-effector. The manipulator ran the force control mode during the experiment, enabling the robot to follow a participant's action by force guidance. A motion capture system (Optitrack, Natural Point, Corvallis, OR) was also set up to capture the motion behavior of participants. The physical setup of the equipment relative to participants is shown in Fig. 1. Instructions for the task were delivered by researchers using slide presentation software and a script to explain the task and spatial stimuli in the task environment.

The task environment included a table with a starting point labeled on one end, a square 1.92 ft from starting point and a circle 2.36 ft from starting point that represented target waypoints (see Fig. 2). Different shapes were used to differentiate between the different tasks. This visual representation of the task was solely to aid participants in task completion and provided a reference for communicating instructions. A solid wood block was used as the obstacle for task 3. The robot was placed across the table from the participant, clasping another wood block which represented the object being jointly transported. Surrounding the area were motion sensors and a desk with a computer for recording data. For the cognitive distraction task, a randomized list of 20 sentences with basic syntactic structures (10 nonsense and 10 meaningful) were printed on a sheet that contained spaces for the researchers to track errors. Other distractions (e.g., task-irrelevant activity) were minimized by conducting the experiment in a windowless room. Qualtrics was used to record responses to questionnaire data.

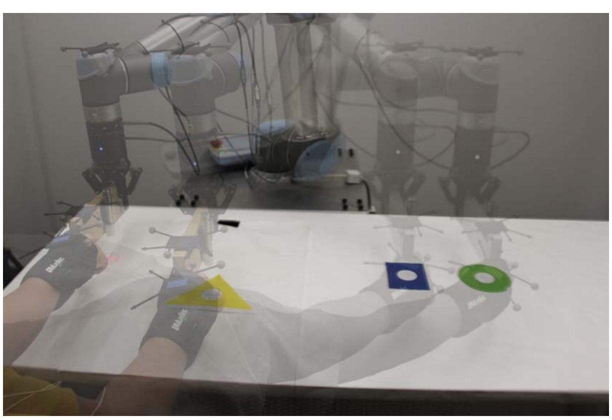

Fig. 1 Experimental setup

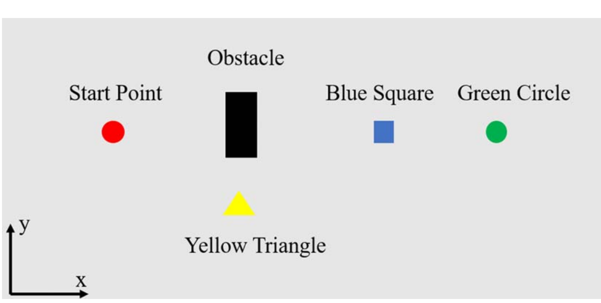

Fig. 2 A graphical view of the task environment with the starting point (left circle), each waypoint (triangle, square, and right circle), and the obstacle (rectangle)

2.3 Procedure. Upon arrival to the study site, and after obtaining written consent, participants were asked to view a series of training slides. Then, the researcher asked the participant if they had any questions and if they were ready to continue. The researcher was able to answer general questions about the task but was not allowed to interpret the instructions for the participants. For participants in the cognitive distraction condition, the researcher would review two example sentences. Then, the researcher would assist the participant in putting the motion capture sensors on the participant's wrist, elbow, and shoulder. All participants were asked to complete each of the four joint transport tasks in one practice trial and four additional trials, once they received a signal from the robot operator. Each task required the participant to remain standing in a designated area while gripping the object with the robot with their right hand. Participants were asked to "help" the robot move from the starting point to four distinct reference points on a table in front of them. Researchers read from a script to help guide participants in each task, e.g., "Move the object from the start point to the blue square" for the short-range transport task (Task 1).

The cognitive distraction involved a secondary task in which participants listened to a simple sentence (including a subject, a noun, and a verb) while performing the tasks [28]. After the sentence was read by the researcher, the participant would respond "yes" or "no." Yes, meaning the sentence made sense, or no, meaning the sentence did not make sense, e.g., "The boy brushed his teeth," (meaningful) or "The ball took a test" (nonsense). Participants would respond to and recall five sentences per task, for each trial. After the tasks were completed, participants completed the trust and demographics questionnaire in a separate room, apart from the researchers and robot. After they completed the questionnaire, they were compensated class credit if applicable, entered into the drawing, and thanked for their participation. The motion data were recorded by the researcher who sat on the left side of the participant throughout the experiment.

2.4 Measures

Physiological and Task Measures. The human's interaction force on the object and computed λ are measured every 10 milliseconds (ms) and averaged in each task, per participant. The process of computing λ will be introduced in Sec. 3. Additionally, participants' completion time for each task were measured. The distraction task is considered an auditory-verbal cognitive distraction. To evaluate the distraction task's effectiveness, the average number of correct responses to the sentences was recorded ($M = 72.9$, $SD = 9.28$).

Trust Questionnaire. An empirically validated scale of trust in automation [20] was used to assess participants' trust in the robot. Twelve questions were asked in total, with five questions referring to a negative or distrusting association (e.g., "The robot is deceptive," "The robot behaves in an underhanded manner"), and the remaining referring to a positive trust association (e.g., "I am confident in the robot"). A response of 1 would indicate, "Not at all," and a response of 7 would indicate "Extremely." The negative trust items were reverse-coded prior to analysis (e.g., 1 is coded as 7). The final responses were summed to create a result ranging from 54 to 84. Table 2 summarizes the trust responses in the baseline and distraction conditions.

Participant Demographics. To address potential confounds in the relationship between trust and physiological measures, demographic measures of age, height, weight, body mass index (BMI), gender, native English speaking, multi-tasking tendency, self-confidence, and handedness (right, left, or ambidextrous) are included in the analysis. A questionnaire item on self-confidence was included as well, using a Likert-like scale from 1 for "Not at all" to 7 "Extremely." Table 1 summarizes descriptive statistics of demographics for baseline and distracted groups.

Table 1 Descriptive statistics of demographics for the baseline ($n = 17$) and distraction ($n = 16$) groups. For continuous and ordinal data, we report the mean and standard deviation, and for categorical data, we report the frequency.

	Baseline		Distracted	
Factor	*M*	*SD*	*M*	*SD*
Age	22.82	3.64	21.69	2.80
Height	69.09	5.88	69.47	4.08
Weight	149.10	24.83	167.27	53.09
BMI	21.71	3.40	23.94	5.34
Self-confidence	5.58	0.87	5.33	0.75
	No	Yes	No	Yes
Native English speaker	4	13	7	9
Multitasker	6	6	6	10
Right-handed	1	16	2	14

2.5 Analysis. A Spearman's correlation test was used to identify the relationships between λ and trust (H1). Then, one-way ANOVAs with task condition as a repeated measure were used to evaluate differences in force, completion time, and λ in the four tasks (H2). Finally, the effects of the baseline and distracted conditions on the force, trust, completion time, and λ were evaluated using one-way ANOVAs (H3). Bonferroni corrections were applied to p-values for hypothesis testing involving multiple comparisons. Additional post hoc tests with Bonferroni corrections were used to interpret results. Effect sizes were reported as partial Eta-squared (η^2) to describe the degree that our independent variables (distraction and task condition variables) influenced dependent variables (trust, force, λ, and completion time). Data were evaluated using the Statistical Package for the Social Sciences (SPSS).

3 Human Reliance Modeling in a Joint Object Transport Task

In this section, a model based on interactive motor control is introduced to provide insight into human intention and behavior during a joint physical task with a robot arm. We first establish the model in a one-dimensional case and discuss possible metrics for cross-participant assessment. Then, our observation of participants' lateral motion to complete the task, which deviates from a direct linear goal tracking motion, suggests that an extended model to two-dimensional cases could be useful. We also present the predicted average trajectory of a person's hand motion in the task to validate the model. By developing an optimal control model, we could summarize reliance as a single number, which we then compare with trust, acquired from the post-test questionnaire.

3.1 Human Reliance Model Based on Interactive Motor Control. The human–robot joint object transport task depicted in this study represents not only a physical connection between a person and machine but also basic haptic sensorimotor control in human activities. The motor behavior of the joint action has been studied and formulated into an optimization framework that assumes people generate their motion based on balancing task performance and energy consumption (i.e., effort) [24]. A human reliance model would describe intention and behavior, connecting predisposition, ability, and perception to observable actions. With the help of the optimization-based motor control model, we can determine the weighting factor (denoted as λ) estimated from our measures of human actions in the joint human–robot task.

In the 1D case, we assume that a person would plan their next step position x^h_{k+1} by optimizing a weighted sum of the goal tracking distance, which is the distance from the goal position to the current human hand position, and the energy consumption term, which is the product of the interaction force and the distance the human hand moves. The following optimization problem is defined to describe the process

$$\min_{x^h_{k+1}} \quad e^2_{k+1} + \lambda^h_{k+1}(\delta_{k+1} f_{k+1})^2 \tag{2a}$$

$$\text{s.t.} \quad e_{k+1} = x_g - x^m_k \tag{2b}$$

$$\delta_{k+1} = x^h_{k+1} - x^h_k \tag{2c}$$

where x^m_k is the observed robot gripper location at time-step k. The person's goal tracking error is e_{k+1}, the action of the person δ_{k+1} is the distance their hand moves within the sample interval, and the interaction force is f_{k+1}. Note that an estimated weighting factor $\hat{\lambda}^h_{k+1}$ is incorporated in the cost function to describe the tradeoff between reaching the goal faster and consuming more energy. In this model, a small λ^h_{k+1} indicates an aggressive goal tracker, because the person emphasizes the completion of the task more than their own energy cost, and vice versa. Based on the observed values of e_{k+1}, δ_{k+1}, and f_{k+1}, we can calculate the $\hat{\lambda}^h_{k+1}$ (the hat notation indicates that it is calculated with observed data) with the following equation

$$\hat{\lambda}^h_{k+1} = \underset{\lambda^h_{k+1} \in \mathbb{R}^+}{\operatorname{argmin}} \quad e^2_{k+1} + \lambda^h_{k+1}(\delta_{k+1} f_{k+1})^2 \tag{3}$$

During the experiment, we recorded observed values and compute λ offline. The data we collected were measured every 10 ms. But the estimation process of λ was solved every 50 ms as the sampling period for human motor control is 30–50 ms [14].

Figure 3 shows the change of λ in a trial versus the time to complete a trial. The upper subfigure of Fig. 3 demonstrates the displacement of human hand, where the human hand starts around 0.15 m and reaches the goal position at 0.75 m.

The value of λ remains relatively small for most of the time in region 1, which indicates the participant aims at reaching the goal quickly. When the participant gets close to the goal, the value of λ increases quickly, which indicates the person tried to slow down and prepare for approaching the final target area precisely. In region 2 of Fig. 3, the value of λ drops suddenly as the participant realizes that the robot stopped quickly and there is still a significant distance to the goal, so the human–robot team accelerates a bit. Another peak of λ shows up again at the beginning of region 3 of Fig. 3 for a similar reason, and finally the person adjusts the force to ensure accurate tracking to the goal, which is a result of the person weighting the accuracy of goal tracking more heavily than energy consumption at the end.

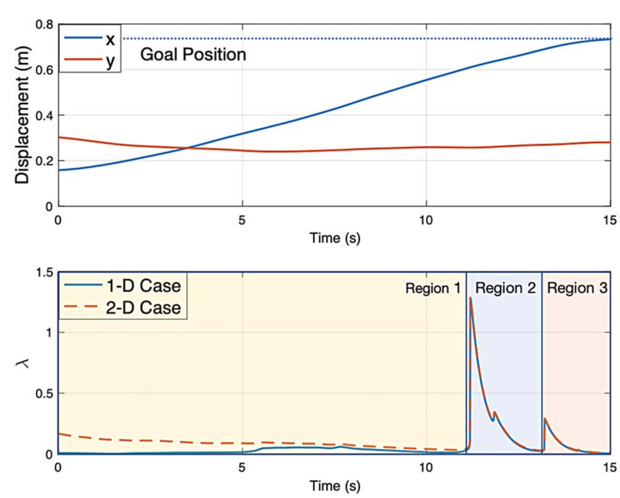

Fig. 3 Human hand motion and the change of λ in a trial in one-dimensional and two-dimensional cases

3.2 Lateral Motion of the Reaching Task. In the prior section, the model is defined in one dimension and is capable of explaining a person's motion toward the goal position. However, as our experiment proceeded, we observed that the motion to transport the object was more sophisticated than expected and often varied from a straight line, even though we set the starting point and the goal as a straight line. In other words, lateral motion in an orthogonal y direction was observed, although this lateral motion did not contribute to the goal tracking parameter.

Figure 4 shows the planar trajectories of five participants from a bird's-eye view. Based on the assumption we made, the optimal solution should be close to participant 5's trajectory, which is represented in the upper set of lines that travel almost directly toward the goal position, while other participants tended to detour from this more direct route. A possible explanation of the detours is due to the kinematic property of the robot, which resulted in different stiffness of moving the robot end-effector from different directions. In other words, as reflected in the weighting parameters, the trajectory of participants might have been a result of moving the object in a direction that was easier, or more comfortable—requiring minimal force—compared with moving the object in a direct path toward the goal.

3.3 Extend Human Decision Model in 2D. Our observations suggest that the model we proposed in Sec. 3.2 is not suitable for explaining lateral motion. The optimization problem is thus extended to a two-dimensional version

$$\min_{x^h_{k+1}} \quad e^T_{k+1}\hat{P}e_{k+1} + (f_{k+1} \circ \delta_{k+1})^T \hat{Q}_{k+1}(f_{k+1} \circ \delta_{k+1}) \tag{4a}$$

$$\text{s.t.} \quad e_{k+1} = x_g - x^m_k \tag{4b}$$

$$\delta_{k+1} = x^h_{k+1} - x^h_k \tag{4c}$$

$$\|f_{k+1\infty}\| \le f_{\max} \tag{4d}$$

where $\hat{P}$ and $\hat{Q}_{k+1}$ are the coefficient matrices. The goal tracking error e_{k+1}, the human action δ_{k+1}, and the interaction force f_{k+1} can be identified based on kinematic and force measurements. $(f_{k+1}{}^\circ\delta_{k+1})$ is the Hadamard product of δ_{k+1} and f_{k+1}, which represents a person's energy consumption during the interaction.

The coefficient matrices $\hat{P}$ and $\hat{Q}_{k+1}$ are symmetric and positive definite. $\hat{P}$ is chosen to be an identity matrix. We observed participants' actions and location, then measured the interaction force between the person and the robot.

During the experiment, the values of e_{k+1}, δ_{k+1}, and f_{k+1} were measured by the motion capture system and force sensor. Then, the coefficient matrix $\hat{Q}_{k+1}$ can be determined as

$$\hat{Q}_{k+1} = \underset{\hat{Q}_{k+1}}{\operatorname{argmin}} \ e^T_{k+1}\hat{P}e_{k+1} + (f_{k+1} \circ \delta_{k+1})^T \hat{Q}_{k+1}(f_{k+1} \circ \delta_{k+1}) \tag{5}$$

In this case, the weighting factor yields a weighting matrix, $\hat{Q}_{k+1}$. Because our eventual goal was to compare a person's behavior and actions in this task with the trust measure, a process that transfers the weighting matrix to a single scalar was needed. For this reason, the two-dimensional version of λ is defined as

$$\hat{\lambda}^h_{k+1} = \|\hat{Q}_{k+1}\| \tag{6}$$

The $\|.\|$ is the matrix norm operator which calculates the maximum singular value of the matrix, which yields the maximum eigenvalue of $\hat{Q}_{k+1}$ as the symmetrical property. Thus, our two-dimensional model result was similar to our 1D model results in Fig. 3, which indicates that this norm operation still captures behavior and intention as well as in the one-dimensional case. The behaviors in the three phases mentioned in the 1D case were also identified in 2D; the lateral motion of the "detours" resulted in an increase of λ in region 1 of Fig. 3; which suggests that lateral motion behavior could be captured by the two-dimensional version of λ.

4 Results

Table 2 contains the overall trust scores in the baseline condition ($n = 18$) and the distraction condition ($n = 17$). In the baseline condition, the overall average trust score was 61.29 ($SD = 9.6$). In the distraction condition, the overall average trust score was 62.25 ($SD = 6.05$).

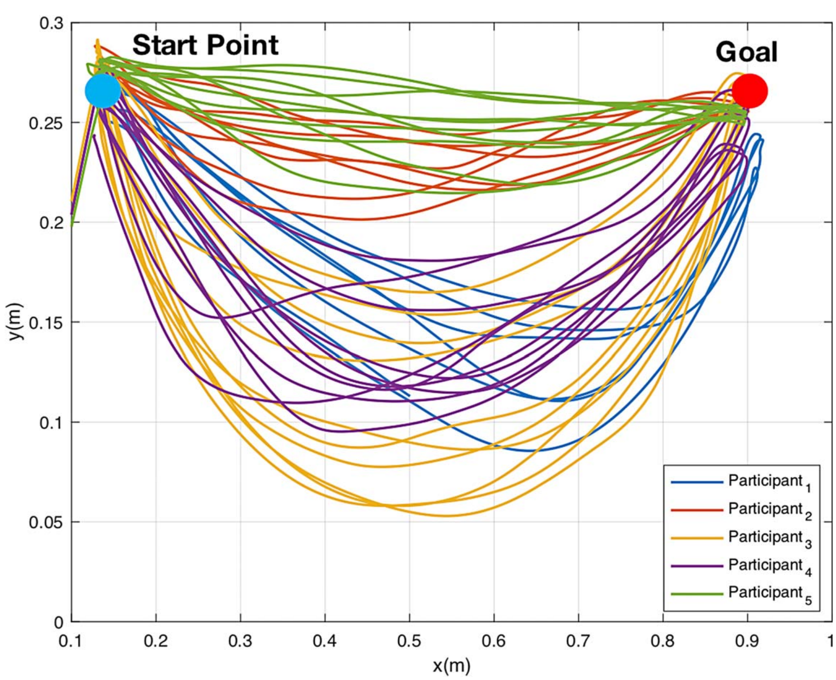

Fig. 4 A sample of planar trajectories in the object transport task for five different participants in task 2, baseline condition

Table 2 Mean and standard deviation of responses to a posttreatment trust in automation scale [20] for baseline ($n = 17$) and distraction ($n = 16$) condition

Question	Baseline *M*	Baseline *SD*	Distracted *M*	Distracted *SD*
1. The robot is deceptive[a]	6.00	0.98	5.88	1.28
2. The robot behaves in an underhanded manner[a]	5.41	1.83	5.19	1.48
3. I am suspicious of the robot's intent or action[a]	5.94	1.22	6.00	1.28
4. I am wary of the robot[a]	5.47	1.39	5.56	1.13
5. The robot's action will have a harmful or injurious outcome[a]	6.29	0.96	6.06	0.97
6. I am confident in the robot	4.59	1.43	4.75	1.21
7. The robot provides security	4.18	1.39	4.62	1.46
8. The robot has integrity	3.82	1.87	4.62	1.51
9. The robot is dependable	4.82	1.35	4.94	1.04
10. The robot is reliable	5.00	1.34	5.19	0.81
11. I can trust the robot	5.29	0.83	5.31	0.92
12. The robot feels familiar	4.47	1.59	4.12	1.59
Overall score	61.29	9.6	62.25	6.05

[a]Denotes that the question has been reverse scored.

4.1 Correlation Analysis. There was a significant negative correlation between trust ($M = 61.294$, $SD = 9.822$) and the optimization parameter λ. As shown in Fig. 5, the average λ ($M = 0.381$, $SD = 0.296$) in Task 2 was negatively correlated with trust ($r = -0.416$, $p < 0.05$). These results are consistent with our expectation that trust can be explained by λ rather than interaction force on its own, or by other measured factors. However, we only observed significant results in Task 2. This means that the resulting λ values corresponded to trust only in the long-range task, while in the short-range, obstacle, and waypoint tasks they did not. Thus, our first hypothesis is only partly supported by the results.

We also predicted that greater trust would correspond with faster task completion time, and lower trust will reflect with a slower task completion time. As expected, there was a significant negative correlation ($r = -0.347$, $p < 0.001$) between force and completion time. This result indicates that as force increased, participants completed each task faster. However, there was no significant correlation between completion time or force with trust and λ.

4.2 ANOVA Analysis

Task Conditions. Results from the ANOVAs are summarized in Figs. 6 and 7. Mauchly's test for sphericity was violated ($\epsilon = 0.713$). Therefore, results with repeated measures are reported with the Greenhouse–Geisser correction. There was a significant effect of task condition on force, ($F(2.140, 12.873) = 8.034$, $p < 0.001$, $\eta^2 = 0.217$). Interaction force in the short-range task (Task 1; $M = 2.982$, $SD = 0.893$) and the long-range task (Task 2; $M = 3.138$, $SD = 1.128$) was less than the interaction force in the connecting waypoints task (Task 4; $M = 4.265$, $SD = 1.106$). There was no significant effect of task on λ or completion time. Overall, this shows that while interaction force generally increased over successive trials, λ and completion time did not.

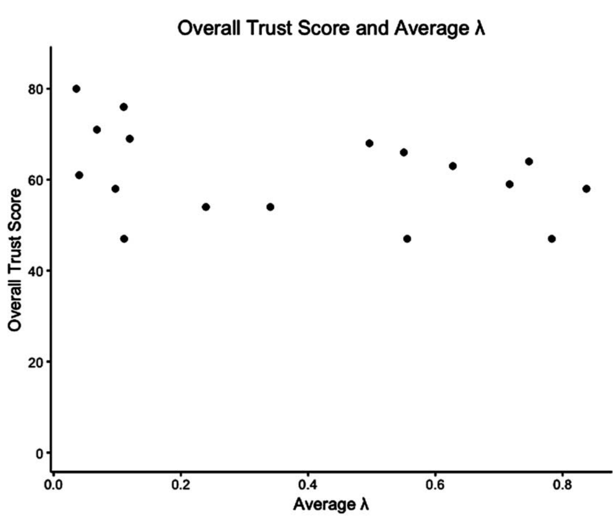

Fig. 5 Trust scores compared with average λ for task 2 with no distraction

Distraction Conditions. Condition had a significant effect on average force ($F(2, 31) = 16.932$, $p < 0.001$, $\eta^2 = 0.353$). Interaction force was higher without distraction ($M = 4.014$, $SD = .786$) than with distraction ($M = 2.971$, $SD = 0.659$). Additionally, completion time was significantly different between conditions ($F(2, 31) = 8.972$, $\eta^2 = 0.224$. Participants took more time to complete the task when they were distracted ($M = 17.5$, $SD = 9.646$) than when they were not ($M = 9.559$, $SD = 5.002$). There was no significant between-group effect for λ or trust, nor was there any significant interaction. This means that task completion time and interaction force varied when participants were distracted, but trust and λ did not.

In addition to the findings we pursued in light of our hypotheses, we also observed some interesting behaviors such as a learning process and the effects of a robot malfunction on our optimization framework. In this section, we present these results and discuss related future work.

4.3 Model Application in Different Scenarios

Learning Process of the Participants. Because participants without prior experience working with robots were recruited for this study, it was expected that they were not familiar with the specific kinematic properties of the robot. So, intuitively, participants would have an initial period when they learned and adapted to the robot and environment.

Some participants, e.g., participants 3 and 4, differed largely in their time to complete a trial. As this was the first interaction with the robot for all participants, some of them may have been cautious in the earlier trials, which resulted in longer completion time as participants adjusted their interaction force and trajectory to the goal. In contrast, the difference in completion time for participants 4 and 5 was relatively small, which suggests they did not change their way of interacting with the robot over the course of the experiment. It was interesting to observe that all five participants' times fell into a 5–10-s interval in the final trials of task 1, even though their initial trial times were very different. By assessing time to

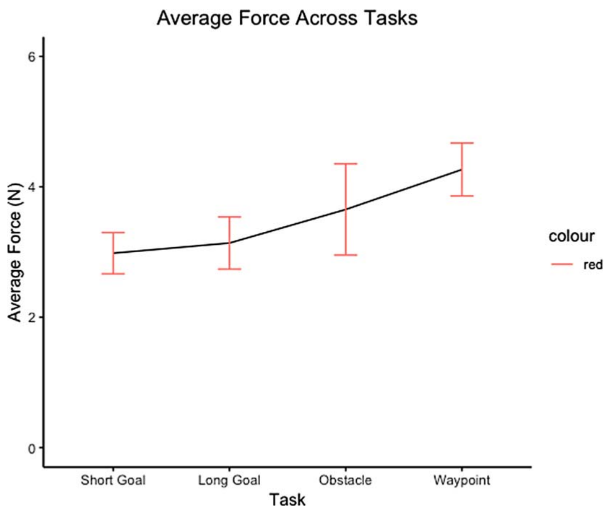

Fig. 6 Estimated mean interaction force with 95% confidence intervals for participants across tasks and trials in each condition

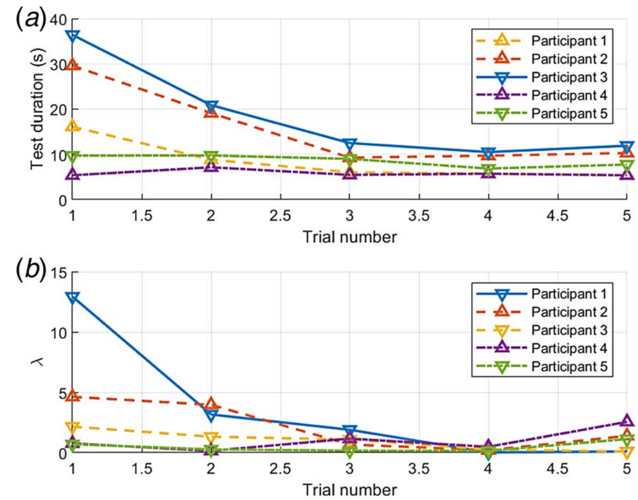

Fig. 8 (*a*) Time of task completion in task 1, across the practice and experimental trials, for five different participants in the baseline condition. (*b*) λ for five different participants in task 1, baseline condition.

completion of these sequential trials, we can infer that participants got familiarized with the robot and tasks over time.

Figure 8 shows the average of a normalized λ, by trial number, for five broadly representative participants in Task 1. The normalization of λ in the two-dimensional case is helpful to visualize the data. As Fig. 8(*a*) shows, participants who showed a strong learning process in Fig. 8(*b*) also had a relatively stronger decaying λ, which might be explained by an increase of trust in the robot as the experiment proceeded.

Effects of Malfunction of the Robot. In Fig. 9, the general trend of λ for the participant decreased across trials, except for an irregular spike in the fourth trial, which indicates at that trial, the subject was more concerned about the interaction force during the task. From researcher's observations, as well as confirmation from reviewing an experiment video, an emergency stop of the robot (by the researcher operating the robot) occurred at the end of the third trial, which was caused by a limit violation of the robot kinematics. We have excluded this participant's data from our statistical analysis, but we find it is an interesting observation to report separately.

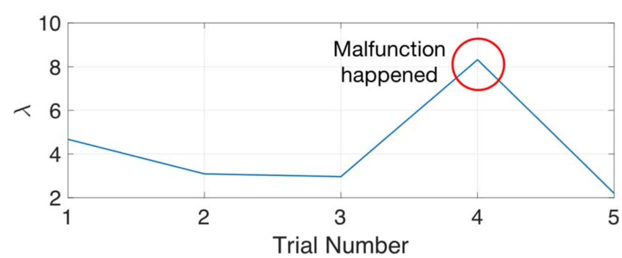

Fig. 9 Malfunction effects on λ

Figure 9 highlights the sudden increase of λ in the fourth trial following the robot malfunction, indicating that the participant changed to a cautious state. After the fourth trial, the subject might have realized the malfunction was an accident, so the λ decreased again. This observation encourages us to pursue future work studying the effects of a malfunction during physical human–robot interaction.

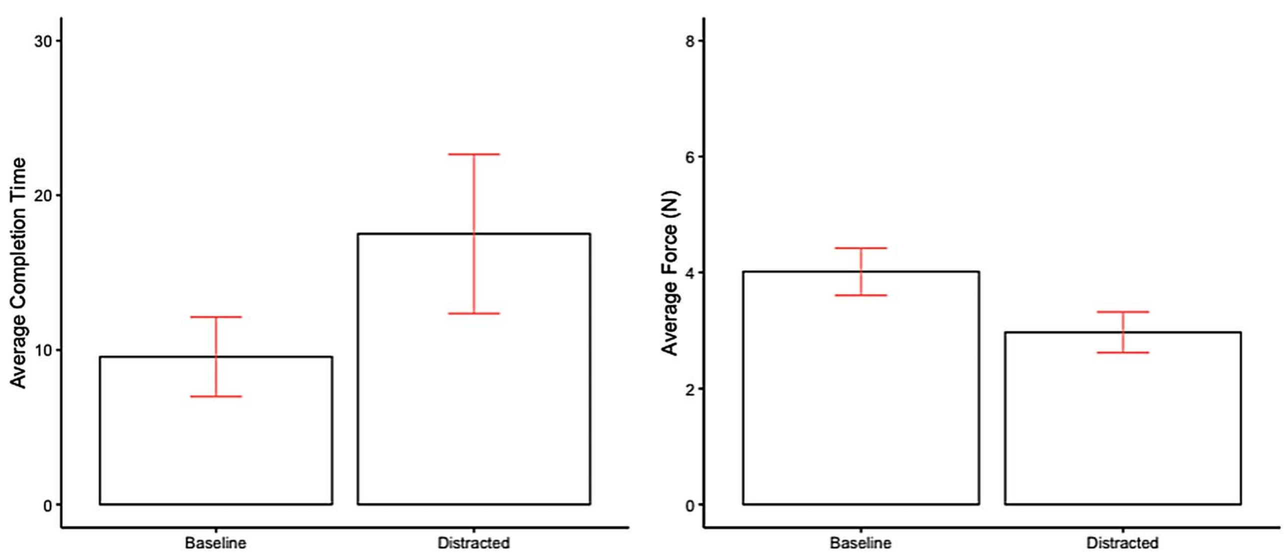

Fig. 7 Average completion time and average force with 95% confidence intervals for participants in each condition

5 Discussion

5.1 Research Question and Hypotheses. In this study, we applied an optimization framework to explain a person's interaction force reliance during a human–robot joint object transport task. The weighting factor λ is presented as a parameter to capture human behavior and intent to share in the effort of the task.

We gleaned three major findings from testing our hypotheses. First, we observed a significant negative correlation between the estimated λ values in task 2 and the trust post-test scores for the baseline group, but no similar effects were observed in other tasks. Although we did not find significance in other tasks, we anticipated this result given that λ does not account for changes in behavior as a consequence of the human's familiarity in the task (task 1, short-goal), or situational constraints beyond the target (tasks 3, with an obstacle, and 4, with waypoints). Furthermore, the distraction condition imposed an attentional constraint on participants, which added further noise to λ's estimation.

Second, we found in a multivariate analysis that participants' average interaction forces in tasks 3 and 4 were higher than in task 1, but completion time and λ were not significant. This may be due to the participants familiarizing themselves with the task over time. Alternatively, the complexity of tasks 3 and 4 may have required greater force to reach the goal in a relatively similar time as the other tasks. In either case, these changes did not reflect in significant changes of λ across trials, which also may be evidence that it is not sensitive to task complexity or familiarity changes.

Finally, there was significantly less interaction force and longer completion times in the distracted condition compared with the baseline condition, with no significant difference between groups for λ or trust. For distracted participants, having to balance multiple tasks seemed to have affected their performance in the joint object transport task. Interestingly, there were no significant differences in the post-test trust results between groups, possibly indicating a lack of sensitivity of subjective post-task measures, compared with an online measure of behavior and intent. Future work may address this gap through experimentation with different distractors (e.g., visual-spatial), in different joint physical tasks, or possibly by alternative subjective measures for trust in physical human–machine collaboration.

Our research question concerned whether or not interaction force reliance could be abstracted using λ. Overall, our results showed that λ was related to the participant's trust in simple joint object transport tasks. This partially confirms our research question. Since λ models effort intention using physical parameters alone, the combination of parameters such as measures of attention or environmental complexity may be needed to accurately predict reliance in complex systems. In essence, λ may describe interaction force reliance to the extent that factors other than the physical interaction affect effort tradeoffs.

5.2 Limitations. We acknowledge there are considerable limitations to the generalizability of these findings in real-world pHMC. Our sample was not able to represent the broader population since it mainly consisted of college students who are relatively well-educated and exposed to technology compared with many other parts of the world. Additionally, in joint physical activity, the value of the object and the risk to carry objects would likely greatly affect trust and reliance. In this study, a 10-g block of wood was used as the object to transport. However, real-world applications would likely involve objects that are much heavier and that could injure the person. Such risks would likely be taken into account in completing the task, which is not considered in this study. To evaluate the contribution of our study in real-world situations, experimentation with λ in a variety of situations will be necessary. The current quadratic form cost function is not efficient enough to capture the human motor behavior comprehensively. A more sophisticated model is suggested to model human behavior under more complicated tasks rather than moving on a plane. Relevant situations to explore in this context include those characterized by uncertainty and vulnerability (i.e., a trusting situation) such as pHMC involving a highly valuable payload or highly interdependent tasks that involve dynamic planning.

Additionally, the sample sizes in the baseline and distracted conditions were slightly imbalanced by one participant. While the addition of one more participant would completely balance the design and potentially improve the statistical validity of our results, we do not anticipate that this would significantly affect the results or interpretation reported.

5.3 Applications. Interactive robots for physical tasks are widely needed in myriad work-life situations, from industrial manufacturing to mobility assistance. It is important to distinguish between the context we used to test λ from other possible applications, such as dynamic role allocation [14]. On one hand, for a scenario in which a person is always leading the robot, applying less force means that the robot will respond with less force. In this case, the person is in complete control of the pace of the interaction as the leader. Thus, the overall efficiency in reaching goal completion depends primarily on the person's physical effort. In more dynamic role allocation, a robot would be able to adjust its force continuously and maintain the dyad's efficiency to the goal. Consequently, the human's response to the alternative motor control policy may depart from patterns of compliance and reliance observed in our task. Future work may also consider more dynamic role allocation using λ as a weighting factor, to enable more cooperative interaction (i.e., role switching).

6 Conclusions

Overall, we were able to show that λ is a potential online measure of interaction force reliance, albeit in simplistic advisory control interactions. A more diverse and data-driven profile of trust and reliance dynamics may advance the study of pHMC, toward more realistic representations of real-world human–robot interactions, as well as advance the development of robot control algorithms for smooth reliance adaptation policies. However, as our study and findings suggest, much work needs to be done before adaptive control may be realized outside of steady-state interactions. For instance, machine malfunction may have different effects on trust [17] that were not investigated here. In this direction, simulating typical as well as atypical situational constraints may reveal opportunities for developing control algorithms that enable sustained stability, adaptation, and appropriate reliance even in unprecedented conditions. Identifying how human dyads overcome challenges in joint coordination may be another useful approach to advancing improved interactions. However, we expect there to be differences in reliance as task interdependency changes.

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