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# Adaptive Task-Space Force Control for Humanoid-to-Human Assistance

Anastasia Bolotnikova<sup>1,2</sup>, Sébastien Courtois<sup>1</sup>, Abderrahmane Kheddar<sup>2</sup>

**Abstract**— We envision a humanoid robot to serve as a source of an additional force in motion assistance for frail persons. We present a control strategy for a humanoid to adaptively regulate its assistive force contribution. First, we identify a human model torque control strategy for an optimal execution of a priori known motion task from sample recordings of this task performed by a healthy individual. We utilize the identified model in the proposed position discrepancy based observer of the human torque contribution, the unknown and unmeasurable variable. We propose an experience-based human contribution model learning strategy that allows improving the human contribution estimate from trial-to-trial. The target assistive torque contribution is then calculated as the difference between the optimal torque required for the motion task and the estimated human contribution. The target assistive torque is integrated into a multi-robot quadratic programming task-space controller to compute the desired interaction force required for the robot to supply the necessary assistive torque for the human model. We use the non-optimal recordings of the human motion task to simulate human model frailty and apply our proposed adaptive force control strategy to demonstrate the results of a humanoid successfully assisting the simulated human model to restore the optimal motion task performance.

## I. INTRODUCTION

A promising area of the humanoid robots application is daily assistance for frail and elderly, e.g. [1], [2], [3]. Such robotic platforms are specifically designed to be user-friendly, multi-functional and safe [4]. These properties allow us to envision a humanoid robot providing companionship through social assistance [5] and helping people in need to perform daily chores. Being a platform capable of physical interaction, one of the useful functionalities for humanoids would be to assist frail people with motion tasks that typically require assistance from a human caregiver. Enabling a humanoid to provide such assistance safely and efficiently can help to increase frail person autonomy.

During the assistance, two sources of force contribute to the human motion: forces that can be generated by the human and the assistive forces supplied by the robot (Fig. 1). The challenge for a robot control in such a scenario is the fact that human force contribution is not known and cannot be directly measured. The exact intended human motion is not known either. Only if robot force contribution to the human motion task is adaptively regulated to account for the presence of another (unknown and unmeasurable) source of force, the motion can be performed correctly. Lower than

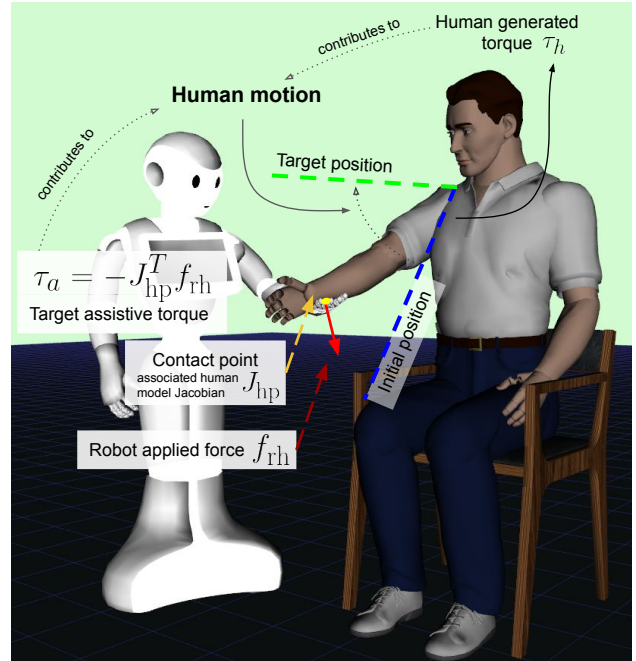


Fig. 1: Humanoid-to-human physical assistance in motion.

required wouldn't provide the necessary assistance; more than required could engender fear, stress or deviate the motion greatly from the way it should be correctly executed, causing discomfort and potentially harm to the human.

We propose a control scheme for a humanoid to assist with a priori known human motion while accounting for human force contribution. Using a human model and sample recordings of the motion performed by a healthy individual, a model of a human torque control that results in correct execution of the motion is identified (Sec. III-A). This model is used in the proposed position discrepancy based human torque contribution observer (Sec. III-B). An experience-based prediction strategy allows to improve human contribution estimate from trial-to-trial (Sec. III-C). The assistive torque required to restore desirable motion task performance is then defined as a difference between the torque required for the correct motion execution and the estimate of the human contribution. Finally, the target assistive torque is integrated into a Multi-robot Quadratic Programming (MQP) controller to compute the desired force for the robot to apply that will result in providing required assistive torque (Sec. III-D). We use sample recordings of non-optimal human movement to simulate human frailty and demonstrate how the proposed method enables humanoid to assist the human model to restore the desired motion task performance (Sec. IV).

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## II. PROBLEM STATEMENT

For a common and well defined human motion task (e.g. reaching motion, sit-to-stand transfer, physical exercise) a sample recording of the motion executed correctly unassisted by a healthy individual can be obtained using motion capture system. Such recording can be used to define the desired motion task performance. This includes the position that human joints must reach  $q_h^{\text{task}}$ , as well as the speed  $\dot{q}_h^{\text{task}}$  and acceleration  $\ddot{q}_h^{\text{task}}$  of the correctly performed exercise. The torque  $\tau^{\text{task}}$  required to perform the motion correctly is computed using a sample personalized model of a human body with dynamic link properties [6], [7] (eq. 1).

$$\tau^{\text{task}} = M_h(q_h^{\text{task}})\ddot{q}_h^{\text{task}} + C_h(q_h^{\text{task}}, \dot{q}_h^{\text{task}}) \quad (1)$$

where  $M_h$  is a human model inertia matrix and vector  $C_h$  incorporates Coriolis, centrifugal and gravity terms.

As mentioned in the introduction, in the physical assistance process, the total torque required to perform a motion task correctly is composed of two elements: human possible generated torque  $\tau_h$  and the assistive torque  $\tau_a$  provided by the robot through physical interaction, i.e. by applying a force from robot to human  $f_{\text{rh}}$  at a point  $p$  on a link of the human model (eq. 2).

$$\tau^{\text{task}} = \tau_h + \tau_a = \tau_h + J_{\text{hp}}^T f_{\text{hr}} \quad (2)$$

where  $J_{\text{hp}}$  is a human body model Jacobian that maps the forces ( $f_{\text{hr}} = -f_{\text{rh}}$ ) applied at point  $p$  into human model joint torques.

For a frail human  $\tau_h < \tau^{\text{task}}$ , i.e. human muscular strength is not sufficient for achieving the motion task correctly. The goal of the robotic assistance is to apply the contact forces that supplement the human generated torques to achieve desired motion task performance, i.e. such that it resembles as closely as possible the correctly executed motion. Thus, roughly saying, the amount of the required assistive torque is a difference between the total torque required for a given human model to perform the motion task correctly and the human generated torque (eq. 3).

$$\tau_a = \tau^{\text{task}} - \tau_h \quad (3)$$

The human muscle generated torque cannot be known a priori and cannot be directly measured. The main challenge in the assistance process is the adaptation of the robot force contribution to the unknown and unmeasurable variable  $\tau_h$ . In this letter, we suggest that the robot contribution adaptation can be achieved by observing the discrepancies between expected and measured human motion.

In the next section, we describe how the total torque required for the correct motion task execution,  $\tau^{\text{task}}$ , is computed and used to identify a model of a human torque control strategy. Then, we present the position discrepancy based human torque contribution observer coupled with an experience based prediction model of  $\tau_h$ . Finally, we present details of integration of the target assistive torque into the MQP task-space whole-body controller for steering assistive humanoid robot behaviour.

## III. PROPOSED METHOD

### A. Identifying reference task torque control model

In our proposed method, first, we identify a torque control strategy for a personalized human model from a sample motion recordings of a correctly executed motion task to compute the total motion task torque,  $\tau^{\text{task}}$ . In this section, we describe the construction of a training dataset and a torque control strategy model identification.

The recording of a correctly executed motion task contains a time series of the human joint angles  $q_h^{\text{task}}(t)$ ,  $t = 0, \dots, T$ , where  $T$  is the time when the target joint position  $q_h^*$  for the given motion task is reached. We derivate this data to obtain respective joint velocity  $\dot{q}_h^{\text{task}}(t)$  and acceleration  $\ddot{q}_h^{\text{task}}(t)$  time series. For every acceleration time series element, the torque required for a human model to achieve this acceleration is computed via inverse dynamics (ID, eq. 4).

$$\tau^{\text{task}}(t) = M_h(q_h^{\text{task}}(t))\ddot{q}_h^{\text{task}}(t) + C_h(q_h^{\text{task}}(t), \dot{q}_h^{\text{task}}(t)) \quad (4)$$

In parallel, the task error  $e = q_h^*(t) - q_h(t)^{\text{task}}$  is recorded along with its integral  $\int e$  and derivative  $\dot{e}$ .

With this dataset, the relation between task error evolution data and the total torque required for the motion task to be performed correctly can be identified.

In this study, we use a neural network (NN) model for identifying this relation (eq. 5).

$$\tau^{\text{task}} = \text{NN}(e, \int e, \dot{e}) \quad (5)$$

Given the current motion task error state ( $e, \int e, \dot{e}$ ), this model predicts what would be the total torque if a given human subject (represented by a personalized human model) would execute the motion task correctly un-assisted ( $\tau_a = 0$ ). Network structure in our study comprises 3 neurons in the input layer, 12 neurons in a single hidden layer and a single neuron in the output layer. Based on our experimentations with the model fitting, such structure proved to be an optimal compromise between the model complexity and accuracy of the prediction.

In the next subsection, we show what role  $\tau^{\text{task}}$  plays in the estimation of the human contribution to the motion task  $\tau_h$  and subsequent computation of the target assistive torque  $\tau_a$  required to compensate for possible human frailty. In the Sec. IV, we demonstrate the use of eq. 5 for  $\tau^{\text{task}}$  computation in the proposed control framework (Fig. 2).

### B. Human torque contribution observer

We derive a position discrepancy based observer for estimation of the human torque contribution  $\tau_h$  to the motion task. At the very start of the interaction, we use an initial guess of the human torque contribution estimate,  $\hat{\tau}_h^{\text{init}}$ , to compute the target assistive torque  $\tau_a^* = \tau^{\text{task}} - \hat{\tau}_h^{\text{init}}$ .

As shown on Fig. 2, the target assistive torque is passed to the multi-robot QP controller (MQP) [8]. In the latter paper, extension of the MQP to consider a human as an additional robot model was left as future work that we partly address in this letter. Indeed, the MQP computes the desired robot motion, and the force for the robot to apply at a contact

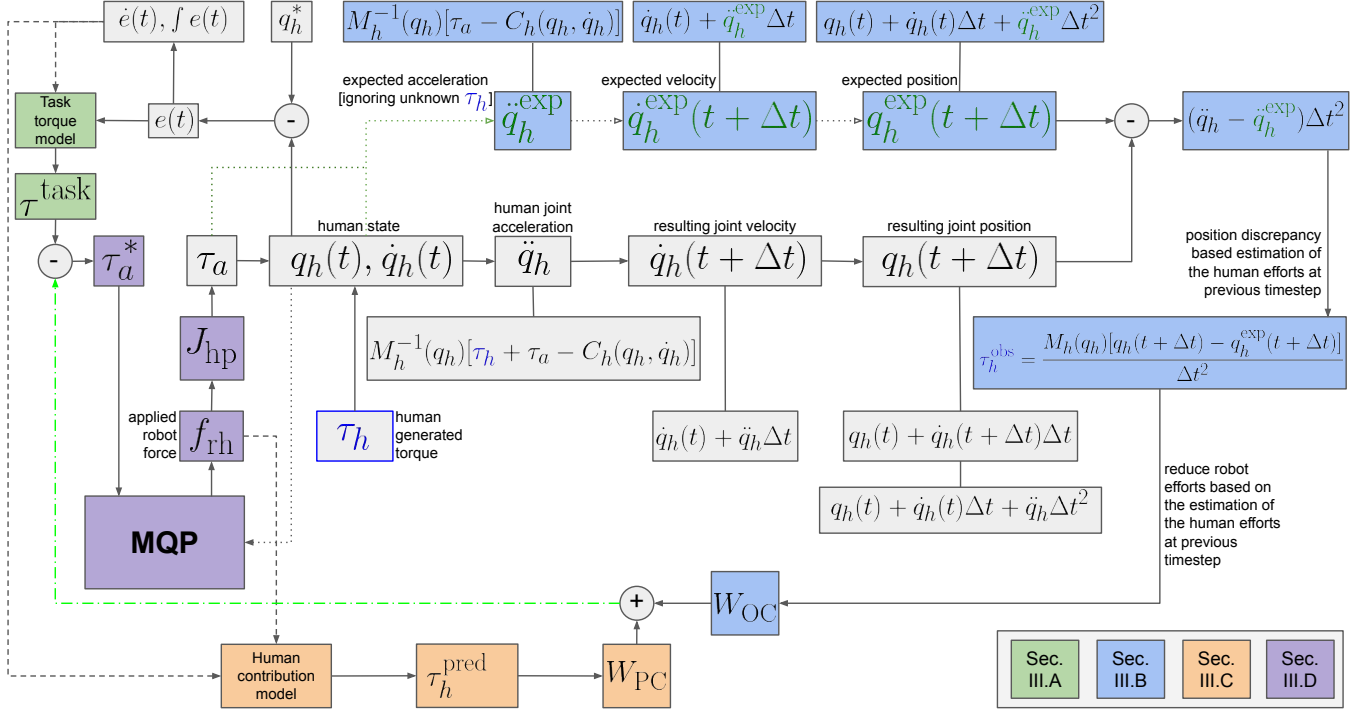


Fig. 2: The proposed control scheme for adaptive humanoid-to-human assistance with a motion task.

point with the human model to generate  $\tau_a^*$ . More details on the MQP controller are provided in Sec. III-D. Such MQP based control of the humanoid robot results in  $f_{rh}$  force being applied on the human link. This force is mapped to the human joint torques via contact Jacobian  $J_{hp}$  (eq. 2). The result is the assistive torque  $\tau_a$  provided by a humanoid to the human model joints for the motion task, in addition to all other humanoid current tasks and constraints.

In order to observe yet unknown human contribution to the task  $\tau_h$ , we assume  $\tau_a$  to be the only joint torque acting on the human model. With this assumption in mind, we compute an *expected acceleration* of the human model joints via forward dynamics (FD, eq. 6).

$$\ddot{q}_h^{exp} = M_h^{-1}(q_h)[\tau_a - C_h(q_h, \dot{q}_h)] \quad (6)$$

Then, we compute respective *expected velocity and position* for the following time step  $t + \Delta t$  (eq. 7-8)

$$\dot{q}_h^{exp}(t + \Delta t) = \dot{q}_h(t) + M_h^{-1}(q_h)[\tau_a - C_h(q_h, \dot{q}_h)]\Delta t \quad (7)$$

$$\begin{aligned} q_h^{exp}(t + \Delta t) &= q_h(t) + \dot{q}_h^{exp}(t + \Delta t)\Delta t = \\ &= q_h(t) + \dot{q}_h(t)\Delta t + M_h^{-1}(q_h)[\tau_a - C_h(q_h, \dot{q}_h)]\Delta t^2 \end{aligned} \quad (8)$$

After  $\tau_h$  and  $\tau_a$  are applied to the human model at time  $t$ , the resulting human joint position  $q_h(t + \Delta t)$  is measured (e.g. via motion tracking). This measured quantity can be expressed through integration of forward dynamics, this time taking both sources of torque,  $\tau_a$  and  $\tau_h$ , into account (eq. 9)

$$\begin{aligned} q_h(t + \Delta t) &= q_h(t) + \dot{q}_h(t)\Delta t + \\ &+ M_h^{-1}(q_h)[\tau_h + \tau_a - C_h(q_h, \dot{q}_h)]\Delta t^2 \end{aligned} \quad (9)$$

Now, the difference between the *expected* and measured human model joints position is computed (eq. 10).

$$\begin{aligned} q_h(t + \Delta t) - q_h^{exp}(t + \Delta t) &= q_h(t) + \dot{q}_h(t)\Delta t + \\ &+ M_h^{-1}(q_h)[\tau_a - C_h(q_h, \dot{q}_h)]\Delta t^2 - q_h(t) - \\ &- \dot{q}_h(t)\Delta t - M_h^{-1}(q_h)[\tau_h + \tau_a - C_h(q_h, \dot{q}_h)]\Delta t^2 \end{aligned} \quad (10)$$

Simplifying this equation results in (eq. 11)

$$q_h(t + \Delta t) - q_h^{exp}(t + \Delta t) = M_h^{-1}(q_h)\tau_h\Delta t^2 \quad (11)$$

which allows us to write an expression for position discrepancy based observer of human contribution to the motion task  $\tau_h$  (eq. 12)

$$\tau_h^{obs} = \frac{M_h(q_h)[q_h(t + \Delta t) - q_h^{exp}(t + \Delta t)]}{\Delta t^2} \quad (12)$$

The computations involved in the  $\tau_h$  observer are presented schematically in the Fig. 2.

### C. Experience based human contribution prediction

The position discrepancy based observer for human contribution estimation presented in Sec. III-B only produces the estimate  $\tau_h^{obs}$  after the motion is observed, i.e. after the human has actually applied its contribution  $\tau_h$ . This results in a delayed one time-step behind estimation. Assuming that between two consecutive timesteps human contribution does not change significantly, i.e.  $|\tau_h(t) - \tau_h(t-1)| < \delta$  for some small  $\delta$ , this approach for human contribution estimation is likely to result in an overall good assistance performance of the proposed control scheme, regardless of the estimation of  $\tau_h$  being delayed.

As a strategy to compensate for being one step behind in  $\tau_h$  observation, we propose to combine the observer with an *experience based* human contribution prediction. The idea is based on trial-to-trial learning of the human contribution. During the very first assistance trial, as there is no data to learn from yet, we fully rely on the  $\tau_h^{\text{obs}}$  for computing  $\tau_a^*$ . After the first trial, the experience gained –namely the observed human contribution and the task error evolution data computed during the assistance trial, can be used to learn the model for predicting human contribution. We suggest the task error evolution and assistive robot force contribution to be the features for learning such a model (eq. 13)

$$\tau_h^{\text{pred}} = f(e, \int e, \dot{e}, \tau_a) \quad (13)$$

Thus, the training dataset is of the following structure: feature vector  $(e(t), \int e(t) dt, \dot{e}(t), \tau_a(t))$ ; label  $(\tau_h^{\text{obs}}(t + \Delta t))$ .

During the next assistance trial (with the same human subject and for the same motion task), besides relying only on the observed human contribution  $\tau_h^{\text{obs}}$ , we can also make use of the ability to predict  $\tau_h^{\text{pred}}$  and anticipate what the human contribution is likely to be at the upcoming time step based on the model learned from previous assistance experiences.

The final  $\tau_h$  estimate is then computed as a weighted sum of two terms: one from observer and one from prediction (eq. 14)

$$\hat{\tau}_h^{\text{fin}} = W_{\text{oc}}\tau_h^{\text{obs}} + W_{\text{pc}}\tau_h^{\text{pred}} \quad (14)$$

where  $W_{\text{oc}}$  is the diagonal matrix of observer confidence weights and  $W_{\text{pc}}$  is that of the prediction confidence weights that satisfy (eq. 15)

$$W_{\text{oc}} = \mathbf{1} - W_{\text{pc}} \quad (15)$$

$\mathbf{1}$  is the identity matrix. The prediction confidence weight  $W_{\text{pc}}$  is updated online based on the evaluation of the human contribution prediction model test error. After each time-step, the difference between predicted human contribution and the one observed will inform the system how accurate the experience based prediction model is (eq. 16).

$$E_{\text{test}} = |\tau_h^{\text{pred}}(t) - \tau_h^{\text{obs}}(t + \Delta t)| \quad (16)$$

If the test error  $E_{\text{test}}$  is big, it is a sign that actual human contribution is significantly different from what was learned from previous experiences (e.g. the human is recovering and thus can contribute more than in the previous trials). In this case, the  $W_{\text{pc}}$  is decreased. If the prediction matches closely the observed  $\tau_h^{\text{obs}}$ , the  $W_{\text{pc}}$  is increased.

After every assistance trial, the data gathered during the process can be added to the training set and used to retrain and improve the experience base human contribution prediction model. If human performance does not improve or degrade significantly from one trial to another, with every new assistance trial such a model becomes an increasingly more reliable source of human contribution estimation.

A supplementary benefit of iteratively and continuously training an experience based human contribution prediction model, is the ability to evaluate the human performance

during the assistance trial and report the progress compared to the previous assistance experience. If human performance does improve or degrade significantly, this change in human performance can be detected by monitoring the magnitude and sign of the prediction error  $E_{\text{test}}$  recorded during the assistance process. For instance, if the observed human contribution is systematically higher than predicted one, it can be detected using the proposed system and subsequently reported that the human is recovering from frailty.

#### D. Force control for human assistance via MQP

In the previous sections, we explained the strategies for computing  $\tau^{\text{task}}$  and estimating  $\tau_h$ . With these quantities, we can compute the target amount of *assistive torque* (eq. 17).

$$\text{if } |\hat{\tau}_h^{\text{fin}}| < |\tau_{\text{task}}|: \tau_a^* = \tau^{\text{task}} - \hat{\tau}_h^{\text{fin}}; \text{ else: } \tau_a^* = 0 \quad (17)$$

In this section, we explain how this value is used in the MQP to compute the amount of required interaction contact force for humanoid-to-human physical assistance.

Both humanoid and personalized human models are included in the MQP formulation with all related typical MQP constraints and objectives (eq. 18)

$$\min_{\hat{q}, \mathbf{f}} \mathcal{P}_r + \mathcal{O}_r + \mathcal{M}_r + \mathcal{C}_r + \mathcal{P}_h \quad (18a)$$

$$\text{s. t.} \begin{cases} \text{joint position/velocity/torque limits} & (18b) \\ \text{(self-)collision avoidance} & (18c) \\ \text{fixed environment contacts} & (18d) \\ \text{friction cone limits} & (18e) \end{cases}$$

where  $\mathcal{P}_r$  and  $\mathcal{P}_h$  are robot and human model posture tasks respectively,  $\mathcal{O}_r$  is robot head orientation task,  $\mathcal{M}_r$  is robot mobile base position task,  $\mathcal{C}_r$  is robot CoM task,  $\hat{q}$  and  $\mathbf{f}$  are MQP decision variables accelerations of the joints of the models and interaction contact forces. A set of contact constraints between two models is defined. The contact point locations can be planned in advance [3].

The feasibility of the physical interaction is ensured by including a combined robot-human equation of motion as a dynamics constraint in MQP, where robot-human interaction forces  $F_{\text{th}}$  are part of the QP decision variables  $\mathbf{f}$  (eq. 19)

$$\begin{aligned} & \begin{pmatrix} M_h(q_h) & 0 \\ 0 & M_r(q_r) \end{pmatrix} \ddot{q} + \begin{pmatrix} C_h(q_h, \dot{q}_h) & 0 \\ 0 & C_r(q_r, \dot{q}_r) \end{pmatrix} = \\ & = S\tau + \begin{pmatrix} J_{\text{eh}}^T & 0 \\ 0 & J_{\text{er}}^T \end{pmatrix} F_e + \begin{pmatrix} J_{\text{th}}^T & 0 \\ 0 & -J_{\text{hr}}^T \end{pmatrix} F_{\text{th}} \end{aligned} \quad (19)$$

Here  $q = (q_h, q_r)$ ,  $\tau = (\tau_h, \tau_r)$ ,  $F_e = (F_{\text{eh}}, F_{\text{er}})$ , and  $F_{\text{eh}}, F_{\text{th}}, F_{\text{er}}$  are stacked vectors of environment-human, robot-human and environment-robot exerted forces respectively. For instance, for  $K$  environment-human contacts  $F_{\text{eh}} \in \mathbb{R}^{6K}$ , with corresponding Jacobians stacked into  $J_{\text{eh}} \in \mathbb{R}^{6K \times d_h}$ , where  $d_h$  is number of DoF in the human body model. Selection matrix  $S$  indicates actuated DoFs.

For the presentation clarity, consider here a single contact between humanoid and human  $p$  (e.g. as in Fig. 1) where

robot applies a force  $f_{rh}$ , which is represented by a geometric contact constraint in MQP (eq. 20)

$$J_{rp}\dot{q}_r = J_{hp}\dot{q}_h \quad (20)$$

where  $J_{rp}$  in a robot model link body Jacobian at the contact point  $p$  and  $J_{hp}$  is a corresponding body Jacobian at a contact point on a human model. For more details on MQP implementation please refer to [9], [8].

With  $\tau_a^*$  computed, we know what is the human model torque that the robot needs to generate through  $F_{rh}$  application. Therefore, we can incorporate this assistance requirement into MQP as a constraint (eq. 21).

$$\tau_a = -J_{hp}^T f_{rh} \quad (21)$$

However, considering many other constraints (such as robot joint position or torque limits), it might be unfeasible for a robot to satisfy (eq. 21) as a strict constraint. Alternatively, the target assistive torque can be incorporated into MPQ objective function (eq. 22).

$$\|\tau_a + J_{hp}^T f_{rh}\| \quad (22)$$

The amount of assistive force will be computed by the MQP solver along with desired robot motion that satisfy all MQP constraints.

In order for a position controlled robot to realize the desired assistive force  $f_{rh}$ , the admittance task is additionally included in the MQP. This task takes the difference between desired force and force sensor readings and outputs the desired end-effector velocity to minimize this difference, see [8] for more details.

In the following section, we present and discuss the simulation experimental results of the proposed force control method in a sample assistive scenario in a rehabilitation exercise use case.

## IV. EXPERIMENTAL RESULTS

### A. Data description

In this study, we use a rehabilitation exercise as a sample human motion task that requires robotic assistance. We use the data set of human body movements for physical rehabilitation exercises [10] [11] that contains recordings of both correct or optimal task execution as well as non-optimal movement examples that we use to simulate human frailty and study how our proposed method compensates for it.

We validate the performance of our proposed control scheme in simulation using the human motion recordings of the shoulder scaption rehabilitation exercise<sup>1</sup>. The goal of this exercise is for a human subject to raise one arm in front of the chest until reaching the shoulders height, while other joints remain static (the parts of such human motion assisted by the robot are illustrated in Figs. 1 and 4).

For the study of the humanoid-to-human assistance process we use the motion recordings of a correctly executed

rehabilitation exercise as a reference motion (optimal/desired performance of the motion task). The non-optimal movement recordings, available in the same data set [10], are used to simulate human model frailty.

From the whole-body motion recordings, we extract the right shoulder joint position around the Y axis (indicated by the green axis arrow in Fig. 4); it is the primary joint involved in the exercise. The other joint of the human model are kept at a fixed position in our study and only assistance supplied to the shoulder Y joint is focused on. The human model is configured to be in the sitting position to enable the Pepper robot to reach the right forearm human model surface and maintain the contact as the human arm is moving upwards during the shoulder scaption exercise.

Using the sample human model, we compute the torques required to follow the recorded motion using ID (eq. 1). Fig. 3 shows the sample motion recording data used for validation of our proposed approach.

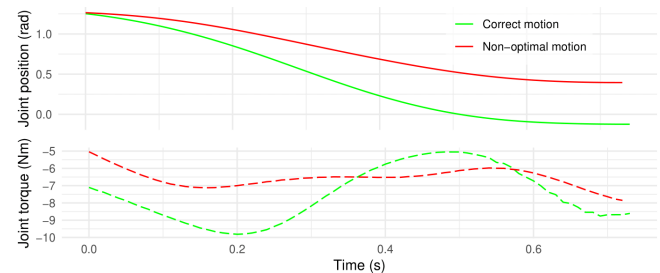


Fig. 3: The correctly performed shoulder scaption (green), non-optimal performance of the same exercise (red). Position and torque plots for the right shoulder joint around Y axis.

The top plot of the above figure demonstrates that, compared to the correctly performed exercise, during the non-optimal motion recording the human subject failed to reach the shoulders height level. The bottom plot shows that the range of torques for the non-optimal motion recording is indeed narrower compared to the correct motion. Therefore, this sample data of the non-optimal motion is suitable for our goal of simulating the lack of human joint torque (frailty) to achieve the desired performance of the motion exercise.

### B. Computing torques required for the task

We use a single sample correctly executed exercise motion recording, to identify the task torque control model as described in Sec. III-A. Fig. 5 shows the performance of the NN model in computing task torque from the information of the task error evolution.

Using the NN model, it is possible to compute a task torque that matches closely the reference torque computed from the correct motion recording sample and a personalized human model.

### C. Estimated human contribution

Now that the model to compute the  $\tau^{\text{task}}$  is obtained, we study the performance of the proposed human contribution observer  $\tau_h^{\text{obs}}$ . At this point, we consider that no previous

<sup>1</sup>Due to the ongoing COVID-19 pandemic situation, it was not possible to realize the real experiments and new data set collection. We hope to be able to resume initially envisioned experimental activities as soon as sanitary conditions allow it.



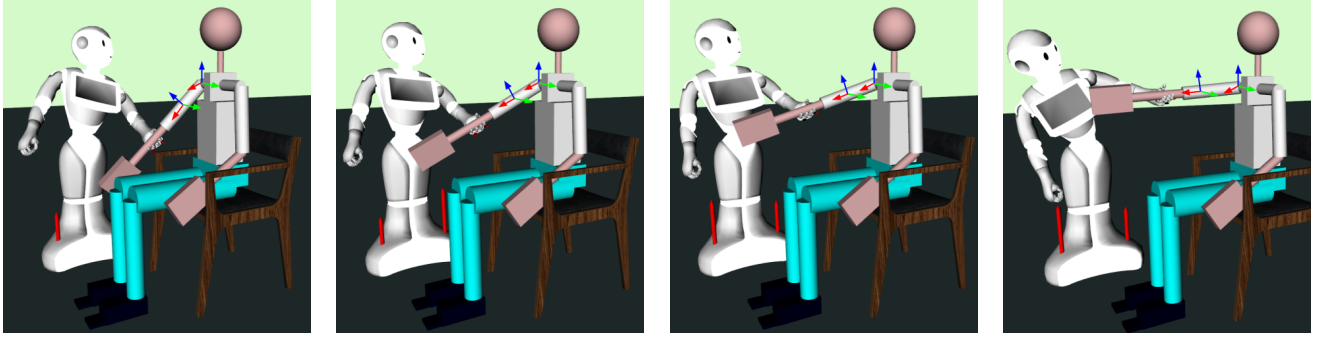


Fig. 4: MQP controller scenes of the interaction wrench and robot motion computation for assistance under pHRI constraints.

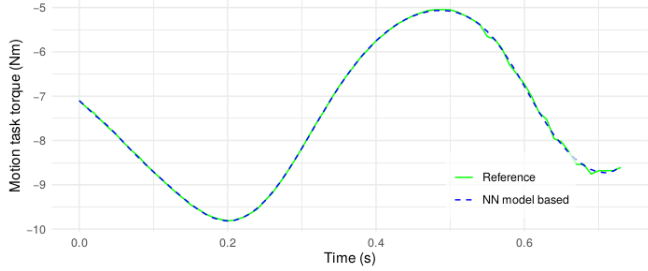


Fig. 5: Identified model of the task torque.

assistance trials took place, therefore no human contribution models yet exists. That means:  $\tau_h^{\text{pred}} = \text{NA}$ ;  $W_{\text{pc}} = \mathbf{0}$ ;  $W_{\text{oc}} = \mathbf{1}$ ;  $\tau_h^{\text{fin}} = \tau_h^{\text{obs}}$ ). Fig. 6 shows the observed and true value (unknown to controller) of the human torque contribution.

Assuming that the position and velocity of the human model joints ( $q_h(0), \dot{q}_h(0)$ ) are measured before the start of the assistance process, the model based value is used as the initial guess of human contribution estimate (eq. 23).

$$\hat{\tau}_h^{\text{init}} = C_h(q_h(0), \dot{q}_h(0)) \quad (23)$$

The observed human contribution data, collected in the previous (first) assistance trial, excluding the initial guess, is used to train the experience based human contribution prediction model as explained in Sec. III-C. Starting from the second assistance trial, this model is used in combination with the observer to improve the final human torque contribution estimate. Fig. 6 shows that the initial guess of the human contribution is improved significantly using the experience based prediction model. This plot also shows that the human torque contribution magnitude starts to exceed the task torque magnitude after about 0.44 s of the assistance process. After this point, according to eq. 17, the human contribution to the task alone is considered to be sufficient to achieve the desired performance, the robot is thus moving along with the human, but is not required to generate an assistive wrench.

#### D. Assisted motion

With  $\tau^{\text{task}}$  and  $\tau_h^{\text{fin}}$  computed, the assistive torque  $\tau_a$  can be computed (eq. 3). As described in Sec. III-D, the

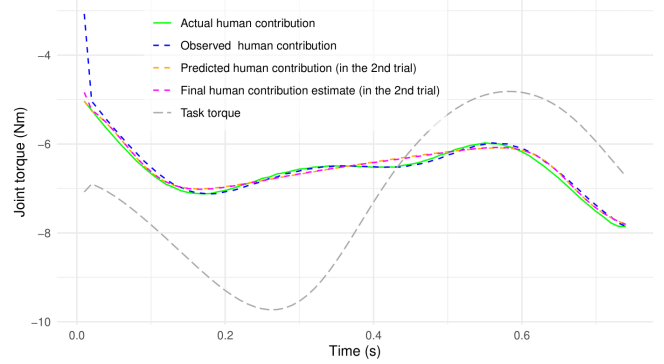


Fig. 6: Estimated human contribution.

human model state and the required amount of the assistive torque are integrated into the MQP controller (eq. 21). The latter computes the interaction wrenches and robot motion that are necessary to perform the assistance process while satisfying the human model-, robot- and contact constraints and minimizing the MQP objective function (eq. 18).

The MQP computed assistive robot-human wrench for the first assistance trial (with no prediction of the human contribution) is shown in Fig. 7. The same computation results for the second assistance trial (with prediction of the human contribution) are shown in Fig. 8. The MQP controller scenes during the wrench computation process at different times of the rehabilitation exercise are shown in Fig. 4. In Fig. 6, it is shown how the use of the predictive model helps to significantly improve the initial guess of the human contribution. This in turn results in lower  $\tau_a$  being computed at the very start of the interaction, and consequently lower interaction forces being computed by MQP (Fig. 8). This results in lower (and closer to the reference motion) human joint acceleration at the start of the assistance process (Fig. 10).

The MQP computed wrench is applied to the human model forearm link in *pybullet* [12] simulation along with the simulated insufficient human torque contribution, the result is the improved motion performance shown in Figs. 9 and 10. These plots demonstrate that, supplied assistive wrench helps to achieve motion performance that is closer to the reference

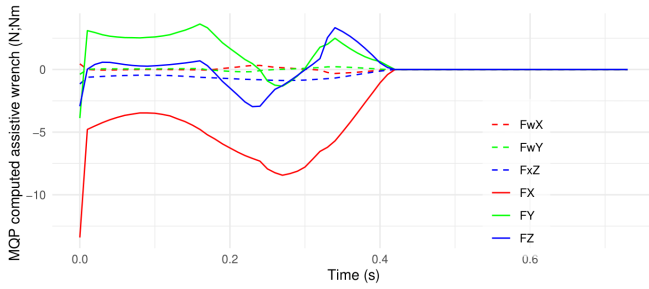


Fig. 7: MQP computed assistive wrench.

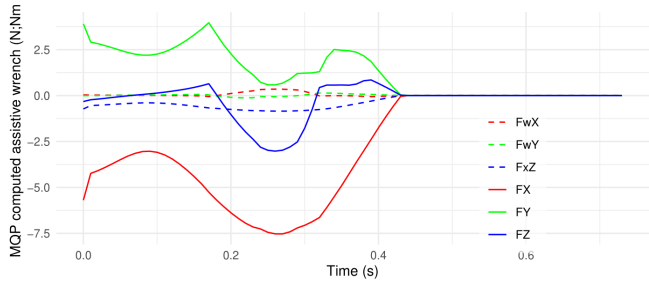


Fig. 8: MQP assistive wrench with experience based human contribution prediction.

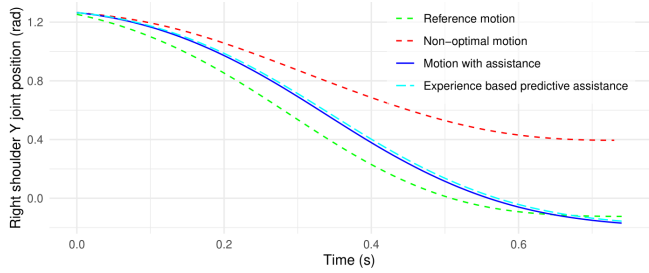


Fig. 9: Joint position during correct motion, non-assisted non-optimal motion and non-optimal assisted motion.

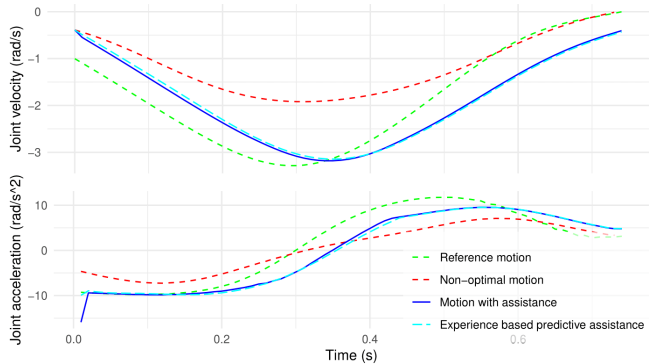


Fig. 10: Joint velocity and acceleration during correct motion, non-assisted non-optimal motion and non-optimal assisted motion.

motion of a correctly executed rehabilitation exercise.

### E. Discussion, limitations, related and future work

The proposed humanoid-to-human physical assistance method and the presented simulation results assume perfect knowledge of the human model links dynamic parameters. The human state, namely position and velocity, is also assumed to be measurable at every time-step. Finally, in the presentation of the simulation results, it is assumed that the assisting robot can instantly apply the desired assistive wrench  $f_{th}$ , as computed by the MQP, to generate the required assistive torque  $\tau_a$  at the human model joint.

In reality, however, the dynamic link properties of a human model can only be approximately known via appropriate estimation [13], [7]. As the human torque contribution observer and the MQP parts of the proposed method heavily rely on the human model knowledge, their performance will degrade if the human model knowledge is highly inaccurate. External interaction forces of the human are computed from the MQP, being a decision variable. However, they can be better guided from the knowledge of the human dynamic parameters estimation [13] and the knowledge of joint accelerations obtained from external sensors as in [14] that can be replaced by the human tracking from vision as in [15]

A study of the effects that the human model inaccuracies have on the performance of the overall proposed assistive pHRI system in terms of quality of the motion task performance recovery can be done using the tools developed in this work<sup>2</sup>. The proposed framework can then be enhanced with robust mechanisms to better deal with human model uncertainties. The same applies for the future study of the influence of the human state measurement noise and potential errors on the performance of the proposed method for humanoid-to-human physical assistance with a known motion task.

One promising method to investigate for making the proposed framework more robust could be the domain randomization technique [16], [17]. The proposed method could be extended with an iterative reinforcement learning of the optimal assistive strategy while different variations of the human model are being tested against the method to help with better transfer of the efficient assistive strategy from simulation to real experiments.

In order for the position controlled Pepper robot to realize the assistive wrench, a closed-loop admittance task based system needs to be implemented as part of the interaction MQP controller. This would require a real-time wrench sensing solution to be implemented on the robot, either as an additional sensor, or more preferably as a proprioceptive sensor-based estimator [18], [19]. A study of the effect of wrench application delays can be done as a future work to make the proposed system robust against such effect.

Last, but not least, once the method is safely transferred from studies in simulation to the real experiments, the user studies must be conducted to evaluate how the proposed robotic assistance is perceived by the real human user and

<sup>2</sup>The developed software tools to be made publicly available upon final publication submission



answer such important questions as: (i) does the interaction process feel safe and intuitive?, (ii) does the assistance provided by the robot feel useful? etc. Additionally, the benefits of using a humanoid robot technology in such physical assistance context can be investigated in such user studies. The simpler robots specifically designed for the task of human assistance during rehabilitation might be used in such context more straightforwardly [20], [21]. Nevertheless, the use of the humanoid technology can allow the developers to provide a more user-friendly pHRI experience through the use of additional Pepper humanoid features, such as verbal, visual and body language communication [22]. Besides providing just the physical assistance, a more interactive robot with a humanoid form can also provide encouragement for better exercise performance via communication channels familiar to the human users [23], [24].

## V. CONCLUSION

In this letter, we studied humanoid-to-human physical assistance with a known motion task. An adaptive force control framework has been proposed for a humanoid robot to supply the required assistance. The proposed method consists of several interacting components, explained in detail. First component is the model for computing total human joint torque required to achieve desired motion task performance, trained on a sample data of the motion being performed by a healthy individual. Second component, is the observer of the actual and potentially insufficient human contribution to the task. The third component is the experience based human task contribution model training. The final component is the multi-robot whole-body humanoid control framework that computes the robot motion and the amount of assistive wrench to apply on the human model to generate the required amount of the assistive torque. We exemplify and discuss the performance of the proposed method on a sample humanoid-to-human assistance with a rehabilitation exercise, using the data of a human subject performing the exercise in a non-optimal way. Discussion of the proposed method, its limitations and future axes of research and development for the proposed method amelioration were discussed.

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