Real-time Estimation of the Strength Capacity of the Upper Limb for Physical Human-Robot Collaboration

Stefano Aldini, Yujun Lai, Marc G. Carmichael, Gavin Paul and Dikai Liu

***Abstract*— In physical Human-Robot Collaboration (pHRC), having an estimate of the operator's strength capacity can help implement control strategies. Currently, the trend is to integrate devices that can measure physiological signals. This is not always a viable option, especially for highly dynamic tasks. For pHRC tasks, the physical interaction point usually occurs at the operator's hand. Therefore, a musculo-skeletal model was used to have a real-time estimation of the strength capacity of the operator's upper limb. First, the model has been simplified to reduce the complexity of the problem. The model was used to obtain offline estimations of the strength capacity, that were then curve-fitted to enable real-time estimation. An experiment was carried out to compare the results of the approximated model with human data. Results suggest that this method for estimating the strength capacity of the upper limb is a viable solution for real-time applications.**

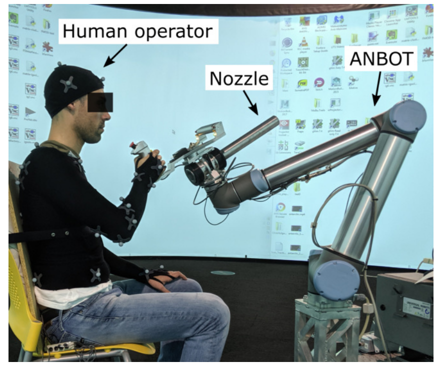

Fig. 1. A human operator physically interacting with a collaborative robot called ANBOT [1].

I. INTRODUCTION

Physical Human-Robot Collaboration (pHRC) happens when a human and a robot are in physical contact and willingly exchange forces to complete a common task. An example is shown in Fig. 1, with a human physically interacting with a robot for pHRC, the ANBOT [1]. Given the close proximity between human and robot during pHRC, any information obtained on the human operator can provide metrics for improving safety, efficacy and efficiency.

For physically-demanding applications, the strength capacity of the human co-worker represents useful information. Attempts to understand the underlying mechanisms of the human body resulted in the creation of musculo-skeletal models based on live and cadaveric data [2]. Recent literature has worked towards the integration of musculo-skeletal models with exoskeleton control [3]. This includes reducing the dimensionality of muscles in the human body to provide quasi-one-to-one correspondence for controlling an exoskeleton [4]. Further works have shown the feasibility of targeted muscle force estimation [5], with physiological criteria in their model based on Surface Electromyography (sEMG) to control an assistive exoskeleton [6].

Early works looked at Artificial Neural Networks to estimate endpoint force under different conditions [7]. With the aim of estimating and managing muscle fatigue in pHRC, Peternel et al. [8] used a complex bio-mechanical model offline to train a Gaussian Progress Regression (GPR) that could map joint configurations and end-point forces (on the hand) to muscle forces. The online system would then use the obtained GPR-based model. This system still requires the human joint configuration and the interaction forces with the robot. More recently, the estimation of strength capacity has been framed as a transfer learning and deep learning problem, using sEMG to train the deep neural networks [9].

The placement of sEMG electrodes is difficult and signals present a high noise-to-signal ratio and numerous artifacts [10]. If the collaborative task is highly dynamic, the sEMG sensors are likely to move with respect to the muscles they are recording from. Human musculo-skeletal models are usually complex high dimensional models that require long computational times to be solved. This is the main reason behind the lack of systems that use such models in the control system of collaborative robots.

Due to the limitations of sEMG and the challenges associated with bio-mechanical models, a simplification of a musculo-skeletal model of the upper limb [11] is proposed for online estimation of the operator's strength capacity. The model of the upper limb is chosen with the understanding that many physically demanding jobs apply a load to that limb, such as drilling, jack-hammering, abrasive blasting, and heavy manual handling. Peternel et al. [12] used the GPR model with a similar purpose, but to estimate the muscle fatigue, which still requires the configuration of the upper limb joints. Individual physiological differences between people have a big impact on their strength capacity. Model parameters are set to represent the average human's physiology based on demographic surveys. The magnitude of the estimated strength capacity is not regarded as the most valuable outcome of this work. This work aims to find an estimate of the strength capacity trend with respect to the pose of the upper limb. The model is simplified, to reduce its complexity, during the offline estimation of the

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strength capacity around the limb workspace, as described in Section II-A. The data is fitted to a curve for real-time estimation, and validated through an experiment performed with a collaborative robot, as presented in Section II-B.

II. METHODOLOGY

A. Estimation of the Strength Capacity

A musculo-skeletal model [2] is used to estimate the strength of a human arm, with a previously developed optimisation procedure [13], [14]. OpenSim [15] was used as a platform for the bio-mechanical the model. The dynamic equation of the upper limb can be formulated as follows:

$$\boldsymbol{H}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}}) + \boldsymbol{\tau}_G(\boldsymbol{q}) = \boldsymbol{\tau} + \boldsymbol{J}^T \boldsymbol{u} \cdot F_E \tag{1}$$

The elements of (1) are defined as: $\boldsymbol{H}$ is the inertia matrix, $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$, $\ddot{\boldsymbol{q}}$ and $\boldsymbol{\tau}_G$ are the vectors of the joint positions, velocities, accelerations and gravitational torques, respectively, $\boldsymbol{C}$ is the matrix describing the Coriolis and centrifugal effects, $\boldsymbol{\tau}$ is the vector of the musculo-tendon unit torques, $\boldsymbol{J}$ is the Jacobian matrix mapping velocities from the skeletal joints to the hand and F_E is the magnitude of the external force multiplied by the unity vector $\boldsymbol{u}$, direction of the force.

For slow motions, static conditions can be assumed, and inertial, centrifugal, and Coriolis effects can be approximated to zero. A Hill-type model is used for musculo-tendon units, as a combination of active and passive elements:

$$\boldsymbol{\tau}_G = \boldsymbol{K}_\tau \boldsymbol{a} - \boldsymbol{\tau}_P + \boldsymbol{r} \cdot F_E \tag{2}$$

In (2), $\boldsymbol{r}$ is the vector used to transform the external load into joint torques. The torques generated by the passive element of the musculo-tendon units are represented as $\boldsymbol{\tau}_P$. The active force of the musculo-tendon units is given by $\boldsymbol{K}_\tau \boldsymbol{a}$, where $\boldsymbol{K}_\tau$ is a matrix whose elements are coefficients of the torques generated by the active elements of muscles transformed to the joint space. $\boldsymbol{a}$ is the muscle activation vector which is constrained by $0 \leq a_i \leq 1$. Excluding the external force and its direction, all the parameters in (2) are calculated from the aforementioned musculo-skeletal model [2]. To find the maximal load sustainable by the human arm, the solution suggested by [13] is used:

$$S = max[F_E] = \left[\frac{\tau_{Gi} - \tau_{Pi}}{r_i}\right] - min\left[\frac{\boldsymbol{K}_{\tau i}}{r_i}\boldsymbol{a}\right] \tag{3}$$

The objective function in (3) is obtained with i being the element corresponding to the arguments where $|\boldsymbol{r}|$ is at its maximum. The optimisation problem is constrained by:

$$\left[\boldsymbol{K}_\tau - \frac{\boldsymbol{r}}{r_i}\boldsymbol{K}_{\tau i}\right]\boldsymbol{a} = \boldsymbol{\tau}_G - \boldsymbol{\tau}_P + \boldsymbol{r} \cdot \left[\frac{\tau_{Pi} - \tau_{Gi}}{r_i}\right] \tag{4}$$

To solve the optimisation problem, a primal-dual interior-point optimisation method ([16]) is used.

The calculation of the strength capacity is a computationally demanding process. To simplify the process, the external force is considered unidirectional. In many tasks, the load that a person has to sustain has a main direction. The direction $\boldsymbol{u}$ of the external force was assumed to be from the capitate bone in the hand to the centre of the thorax. This assumption was given by the application used to validate this method. The human arm can be approximated as a 7-degrees-of-freedom (DoFs) kinematic chain: three DoFs in the shoulder, one in the elbow and three in the wrist. In this work, precision tasks are not considered, hence the wrist joint can be neglected, leaving a 4-DoFs kinematic chain. To obtain an estimate of the strength capacity, the pose of the upper limb is required. The redundancy of the human arm is resolved by optimising the elbow swivel angle [17], using a primal-dual interior-point optimisation method [16]. These simplifications allow the estimation of the strength capacity to occur with the position of the hand relative to the thorax as the only input into the model.

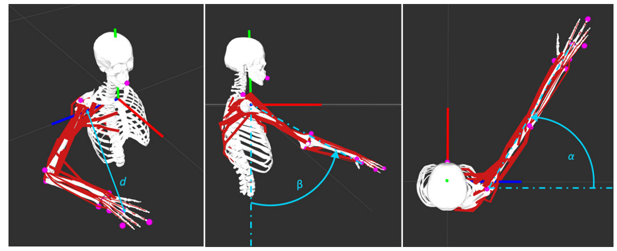

Fig. 2. Three dimensions used to discretise the human operational workspace.

Even with these simplifications, the computational times are not sufficiently short for real-time applications. To overcome this, the strength capacity was estimated offline for 910 hand positions. The upper limb workspace was discretised using three variables shown in Fig. 2. The angles α and β identify the line connecting shoulder and hand, on the horizontal and vertical plane respectively, while d is the distance between shoulder and hand, with$45^o \leq \alpha \leq 135^o$, $30^o \leq \beta \leq 150^o$ and $0.25m \leq d \leq 0.55m$. In order to have a set of points that is dense enough, the resolution along α and β is 10^o, while for d it is $0.05m$.

Strength capacity values that are not positive or with swivel angles not between $-0.1rad$ and $0.1rad$ were excluded. Also values with a distance from the median value that are greater than three scaled median absolute deviations (MAD) were excluded. Out of the 910 points examined, 636 were considered valid. A 3D curve-fitting of the strength capacity throughout the upper limb workspace was then performed with the following non-linear model:

$$\begin{aligned} S = a_0 + a_1 x^3 + a_2 x^2 + a_3 x + a_4 y^3 \\ + a_5 y^2 + a_6 y + a_7 z^3 + a_8 z^2 + a_9 z \end{aligned} \tag{5}$$

where x, y and z are the coordinates of the hand position with respect to the centre of the thorax, and a_i are the coefficients resulting from the fitting problem.

B. Validation

To validate the strength capacity estimation, six healthy adults performed an experiment to measure their strength capacity in ten hand positions. The participants (4 males and

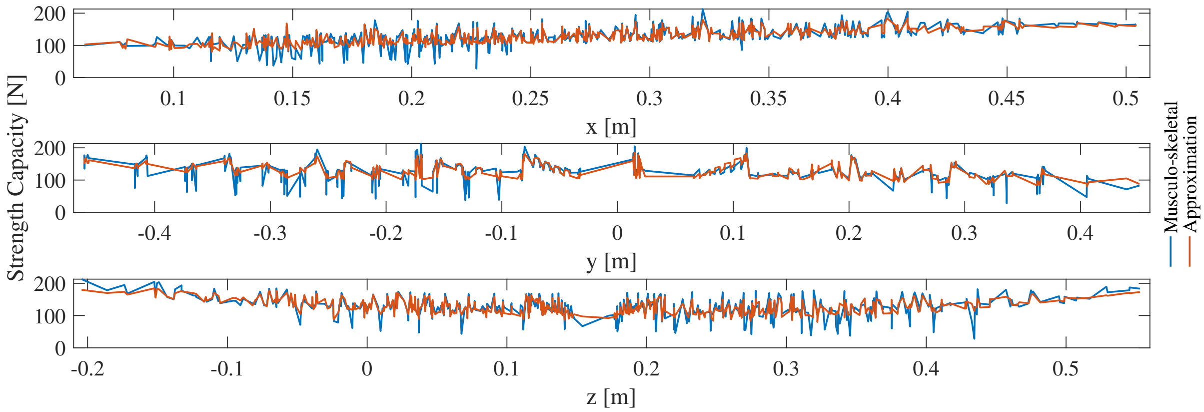

Fig. 3. Strength capacity [N] estimated with the musculo-skeletal model (in blue) and with the approximated model (in orange) with respect to the distance [m] from the centre of the thorax.

2 females) gave informed consent to participate in the experiment approved by the ethics committee at UTS (Sydney, Australia), with approval number ETH18-3029.

Interaction forces were measured from participants using the ANBOT, pictured in Fig. 1 and presented in [1]. It consists of a UR10 robot (6-DoFs manipulator), with a 6-axis force-torque sensor mounted between the end-effector and the back handle to measure the interaction forces.

The participants were constrained on a chair so that the location of their torso would be known with respect to the robot. The hand is in contact with the back handle, so the hand position is also known through the robot kinematics. The robot end-effector leads the participant's hand to ten positions in the shared workspace. The nozzle on the end-effector has been programmed to aim in the direction defined by the line connecting the centre of the thorax to the hand. Starting from those positions, participants were asked to exert as much force as possible in the direction of the nozzle. The robot features a hybrid control system, with an admittance control implemented only for the direction defined by the nozzle and a proportional position control for the other directions. Only the component of the interaction force that lies on the nozzle direction is converted to motion. The admittance gain is set to provide high resistance to the participant's motion. This approach does not prevent participants from exerting forces in undesired directions, but converting the interaction forces to motion gives the participant feedback about the direction of the exerted force and engages them to push with maximal strength.

As the participants were asked to push as hard as possible, the trend of the measured forces should be comparable to the trend of the estimated strength capacity. The interaction forces collected were compared to the estimated model.

III. RESULTS AND DISCUSSION

The musculo-skeletal model was used to estimate the strength capacity for the given 910 hand positions in the upper limb workspace. Some results were then excluded using the aforementioned criteria. The remaining 636 points are plotted in Fig. 4.

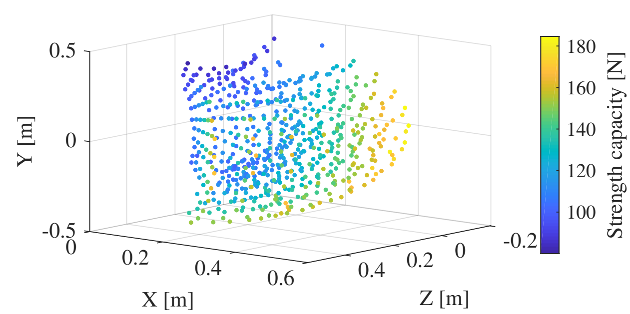

Fig. 4. Strength capacity (N) with respect to the distance (m) from the centre of the thorax.

The curve-fitting procedure resulted in the following equation, with $\hat{S}$ the approximated strength capacity and x, y and z being the coordinates of the hands with respect to the thorax:

$$\begin{aligned}\hat{S} = 121.49 - 818.44x^3 + 997.67x^2 - 185.40x - 456.02y^3 \\ + 45.53y^2 + 9.74y + 161.79z^3 + 275.03z^2 - 146.08z\end{aligned} \tag{6}$$

The strength capacity obtained with this equation and the one obtained by the bio-mechanical model are both shown in Fig. 3, with respect to the hand coordinates. The orange curve represents the strength capacity approximated by (6), while the blue one depicts the strength capacity estimated with the musculo-skeletal model. The dynamics of the curves are comparable and look similar. The strength capacity obtained by the approximated model presents an average root mean square error (RMSE) of 16.80N when compared to the results of the bio-mechanical model. Most of the samples have an error in the range of ± 20N, with some outliers having an error up to 90N in magnitude.

With the experiment described in Section II-B, the maximum force generated by the six participants was measured for ten different hand positions. The measured forces were compared with the results of the approximated model. The residuals are shown in Fig. 5. Positions 10 and 7 present the greater standard deviation (blue bar) and mean resid-

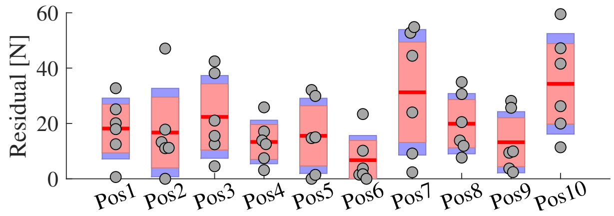

Fig. 5. Absolute value of residuals [N] between the measured maximum force and the strength capacity calculated with the approximated model for the 10 positions tested. Plot obtained with [18].

ual (red line), with the same participant generating the largest residuals, which are equal to 59.5N and 54.8N respectively. Those positions are located just in front of the torso, where a pushing action engages larger muscles like the pectoralis, which widely vary in dimensions depending on gender and physical condition. In the other positions the difference between the approximated strength and the measured forces is significantly lower. The RMSE for the six participants is on average 24.16N $\pm$ 4.02N.

The proposed online model for the estimation of the strength capacity has already been used in a real-world application with a collaborative robot. In fact, an online model-based AAN strategy was implemented to dynamically assist the operator during abrasive tasks with the ANBOT. Details about the implemented AAN strategy can be found in [1]. While residuals for specific users might be relatively high, the trend of the strength capacity remains consistent with the model. Therefore, this AAN strategy scales the strength capacity for a specific position to the maximum strength capacity of the shared workspace, to provide the user with appropriate assistance.

IV. CONCLUSIONS

A musculo-skeletal model was simplified and used to estimate the strength capacity of the upper limb, given the position of the hand relative to the thorax. The model is high-dimensional and involves multiple optimisation steps, causing long computation times. To obtain a model capable of delivering real-time estimates of the strength capacity, results from the bio-mechanical model were used to create an approximated model. This model was obtained through a curve-fitting procedure and validated with an experiment where participants were asked to exert maximum strength in specific poses. Results suggest that the accuracy of the model depends on the arm configuration.

In the field of pHRC, in which humans and robots work so closely together, a more comprehensive flow of information allows the implementation of more targeted and dynamic control strategies.

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