Estimation of Energy Absorption Capability of Arm Using Force Myography for Stable Human-Machine Interaction

Andres Ramos and Keyvan Hashtrudi-Zaad

***Abstract*— Human-robot interactions help in various industries and enhance the user experience in different ways. However, constant safety monitoring is needed in environments where human users are at risk, such as rehabilitation therapy, space exploration, or mining. One way to improve safety and performance in robotic tasks is to include biological information of the user in the control system. This can help regulate the energy that is delivered to the user. In this work, we estimate the energy absorbing capabilities of the human arm, using the metric Excess of Passivity (EOP). EOP data from healthy subjects were obtained based on Forcemyography of the subjects' arm, to expand the sources of biological information and improve estimations.**

***Clinical relevance*— This protocol can help determine the ability of rehabilitation patients to withstand robotic stimulation with high amplitudes of therapeutic forces, as needed in assistive therapy.**

***Index terms*— Arm impedance, control systems, excess of passivity, human-robot interaction, rehabilitation robotics, robot control, stability, upper-limb, variability.**

I. INTRODUCTION

Robotic systems are becoming increasingly reliable, making them suitable for various applications, but human-machine interaction is still an area in which functionality and safety must be ensured. Human-robot interactions can be found in scenarios like assembly lines, space exploration, and even medical diagnosis and treatment. The most challenging areas to improve this human-robot connection are those where the safety of the human is at risk, such as in robotic rehabilitation therapy. Therefore, our work focuses on this major problem, and the principles discussed in this work can be applied to other areas of robotics with human participation.

The need for rehabilitation therapy has been significantly increasing for the last decades [1], demanding more therapy related resources to treat a wide variety of motor impairments [2]. The cost of therapy is high, and health care facilities do not have enough physical and human resources to cover all the variety of patients' needs [3]. One way to address this problem is to deliver therapy, either on-site or remotely, using robotic systems. This can help therapists reduce their physical effort and increase their availability [4], which improves the recovery of patients.

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Robotic rehabilitation systems are now being used for precise tasks, such as assessments of motor impairments [5]. They can also generate therapeutic stimulation and display objective metrics using purpose-made sensors [6][7]. However, when actuation is required, the use of robotic devices needs to be safe and easy to perform by humans. Therefore, proper control systems are needed to guarantee safety, stability and performance in any scenario.

Human-robot interactions can be performed in a stable fashion under certain conditions, which depend on the characteristics of both the robotic systems and human users [8]. The stability of the robot relies on mechanical parts, control systems, and communications delays [9], while the human part depends on the physiological properties of the tissues and the biomechanical characteristics of the extremities, such as muscle contraction, joint flexion and extension, and neuromotor control [10].

The human arm has a natural ability to stabilize robotic systems [11]. This is achieved by absorbing the destabilizing energy generated by the robot, through the modulation of the arm dynamics [12]. As a result, the passivity of the dynamics projected to the human can be relaxed to increase performance, and only the amount of energy that can be absorbed by the human arm is transferred to the user [13].

There are various methods to reduce the amount of energy that flows to the user. Among these methods are damping, to flush the excess of energy [7], and scaling or capping of the interaction forces to limit the energy flow [13]. The efficiency of these methods depends on how accurately the arm's energy absorption capability is estimated.

Atashzar et al. [12] introduced the notion of excess of passivity (EOP) as a measure of energy absorption capability, which depends on the interaction velocity and the non-voluntary force of the user's arm. The authors argue that the EOP is a function of the grasp force. Therefore, they propose to linearly interpolate between pre-calculated EOP values, obtained at two specific levels of grasp pressure, as the human user changes her/his grasp force.

In this work, we aim to obtain more accurate EOP estimations using full arm force myography (FMG). This physiological knowledge will allow us to design controllers that closely compensate for the amount of energy that has the potential to induce instability, providing a better trade-off between stability and performance. We explain our work within the context of robotic rehabilitation as this is one of the most challenging applications to study, and the results of this work can be applied to other areas of human-robot interaction.

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II. ESTIMATING EXCESS OF PASSIVITY

According to Passivity Theory, humans are considered energy sources or sinks, depending on their arm's physiological properties [14]. This makes measuring passivity an important process to detect boundaries for energy transfers and maintain stable interactions. In this section, we present the work of Atashzar et al. [13] in estimating Excess of Passivity and lay the groundwork for our proposed methods to acquire more accurate estimates of EOP.

The human arm and robot can be modelled as mechanical systems, according to how they exchange energy with each other. The interaction forces are of interest; thus, the dynamics of this type of interaction is represented by the linearised model

$$z(t) * v_h(t) = u_c(t) + f_h(t), \tag{1}$$

where t is the time, $*$ is the convolution operator, $z(t)$ is the impulse response of the robot dynamics, $u_c(t)$ is the control input for the robot, $v_h(t)$ is the arm's velocity, and $f_h(t)$ is the force applied by the human to the robot [13]. The human's force can be decomposed into voluntary $f_h^*(t)$ and reactive $f_{react}(v_h, t)$ components so that

$$f_h(t) = f_h^*(t) - f_{react}(v_h, t). \tag{2}$$

As the metric EOP represents the energy absorbed by the arm, it is defined as a function of the reactive force, that is

$$EOP = \frac{\int_0^{T_s} f_{react}(t)^T \cdot v_h(t)dt}{\int_0^{T_s} v_h(t)^T \cdot v_h(t)dt}. \tag{3}$$

where T is the transpose of the indicated vector, and T_s is the duration of the estimation procedure [13]. The reactive force cannot be measured directly. In fact, it is measured through the interaction of the arm with a force sensor, that is $f_{react}(v_h, t) = f_h$, only when the voluntary forces are negligible, that is $f_h^*(t) = 0$. In addition, the arm dynamics, and as such its energy absorption capability, varies with the level of muscle contraction. As a result, the EOP estimation protocol involves a few measurements where the subject's arm is stimulated through a robotic device while he/she applies a specific amount of grasp pressure to the handle of the robotic device. The applied hand forces and the perturbation velocity are used to compute EOP at each of the grasp pressure levels.

We think there is one flaw in this approach as only the muscles involved in grasping participate in conventional EOP estimations. These muscles are mostly located in the hand and forearm, so no upper arm contribution is being measured.

Two approaches are studied in this work to compare the effects of using grasp force against the sum of grasp force and upper arm FMG, as reference signals to perform EOP estimations. We believe our new approach will allow us to better estimate EOP as more muscles are involved in the estimation process. Therefore, more energy absorption capabilities are being measured, improving the accuracy of EOP values. Differences in EOP estimations for the two FMG references are described in the analysis of results.

III. EXPERIMENTAL SETUP

We conducted our experiments on the QARM, a one degree-of-freedom (1-DOF) manipulator developed by the Biorobotics Laboratory at Queen's University for research purposes. The setup consists a 400 watt Maxon EC-60 brushless motor equipped with a resolver. A position signal is obtained through the motor driver AMC model DPRALTR-020B080. An ATI Gamma force /torque sensor is used at the base of the handle to measure the interaction forces. Four Tekscan Flexiforce A502 pressure sensors are used for measuring FMG at the handle, and upper arm, as shown in Fig. 1. It is worth mentioning that no sensors were placed on the forearm as the grasp forces measured at the handle are product of hand and forearm muscles extensions and contractions. All components are commercially available. Three bipolar sensors are positioned on biceps, triceps and flexor carpi radialis for EMG, which helps monitor muscle activation. However, no EMG data is presented in this article.

All sensors were calibrated at the start of each experimental session. The force sensor is calibrated using a calibration matrix and following instructions provided by the supplier. Pressure sensors are calibrated by applying pressure on sensors within their entire sensing range for 5 minutes.

MATLAB Simulink R2018 and QUARC 2018 are used for real-time control of the QARM. Velocity estimates are derived from position signals using discrete differentiation. Force and velocity are not filtered for EOP estimations. Grasp pressure signals were filtered with a 3 hertz low-pass FIR filter for smoothing. All signals were recorded at 1000 hertz.

IV. EXPERIMENTAL PROCEDURE

A total of 10 healthy subjects with no motor impairments participated in this series of experiments. At the time of the experiments, they were aged 23 to 39 (mean value: 28.8, standard deviation: 4.62), being 8 right-handed and 2 left-handed. All subjects used their right arm during all trials. A

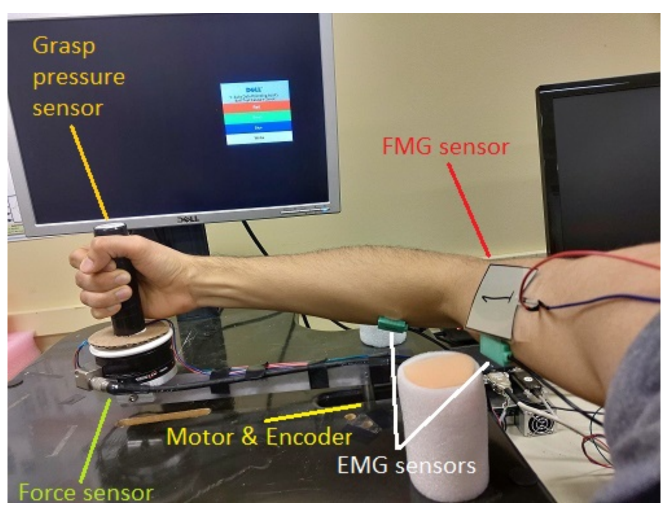

Fig. 1. Human arm interacting with the QARM robotic system for estimation of Excess of Passivity. FMG sensors are not covered by the usual bands for visualization purposes.

letter of information and consent approved by the Research Ethics Board was signed by all subjects at the start of their first experimental session. All EOP estimations were performed over 2 sessions for each of the subjects. Estimations were performed in real-time for monitoring purposes and off-line for processing, and analysis. An example of an online EOP estimation signal is shown in Fig. 2. As it can be seen, EOP converges to a maximum value after a few repetitions of the stimulus, for each estimation. This online estimation performs a simpler method of integration that allows the computation in real time and lacks some accuracy, thus, an off-line estimation algorithm is used for data processing and analysis.

Subjects were positioned next to the QARM robotic system, holding the end effector with their right hand and starting with a 90-degree flexion of the elbow over the horizontal plane of the robot's workspace. No gravitational support was added to the subjects' arms and no contact with the robot was allowed except for the handle. Therefore, motion of the arm was mainly in respect to the elbow joint, but it could shoulder motion, as each individual reacts differently to the stimulus. A 20 second stimulus was applied to the subjects through the QARM. The stimulus was a sum of 10 sinusoidal waves in the frequency range of 0 to 2 Hz, producing a maximum displacement of 9 cm. This frequency range is based on natural human motion [13] and typical rehabilitation tasks[1]. A PD position controller with feedback was implemented to generate motion and stimulate the subjects' hands.

Each experimental session consisted of 5 EOP estimations per level, with a total of 25 randomly performed measurements per session and subject. The levels were set at 5%, 20%, 40%, 60%, and 80% of the maximum grasp force for the first trials, or combined maximum grasp force and upper arm FMG, which the authors refer to as full arm FMG, for the second trials. The first 5 seconds of each signal were discarded due to sensor calibration, signal conditioning as well to give time to subjects to hold the handle after calibration. Subjects were provided with visual feedback to monitor their own signal and attempt to maintain it at a pre-set constant level based on their maximum value. Fig. 3 shows an example of this visual feedback including an actual grasp force signal and the 5 levels to track during estimations. To measure maximum values, subjects were asked to hold the handle applying their maximum effort using their grasping strength. For maximum values of FMG at biceps and triceps, subjects were asked to flex and extend their elbows respectively with maximum effort while holding the handle, which was locked in position to maintain a 90 degree flexion of the elbow.

Data resulted in 500 sets of signals from two sessions and ten subjects. The first 250 trials correspond to EOP estimations based on grasp force only, and the second 250 trials relate to EOP estimations based on full arm FMG. Fig. 4 shows the mean values of EOP estimations at the five levels, representing grasp force and full arm FMG sets of data.

It is worth noticing that the use of mean values from EOP estimations of the same level reduces the effect of natural variability within a subject's arm dynamics[15]. Therefore, it is expected that estimates computed from a linear interpolation between the EOP values obtained at 5% and 80% may result in overestimation. This overestimation allows a larger amount of therapist's active energy to be passed on to the patient, who may not be able to absorb and dissipate the excess of energy. As a result, the patient can experience constant instability, which translates to pain and possible injuries. Therefore, an EOP estimation process that includes more than two levels could help increase safety in controllers for human-robot interactions, with the cost of slightly longer calibration protocols before performing an actual therapeutic procedure.

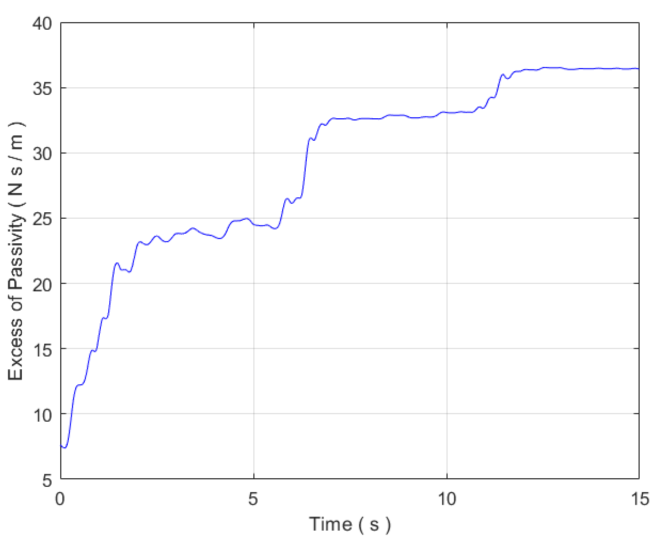

Fig. 2. Time-profile of online-estimated EOP values for subject S6 at 80% of maximum full arm FMG.

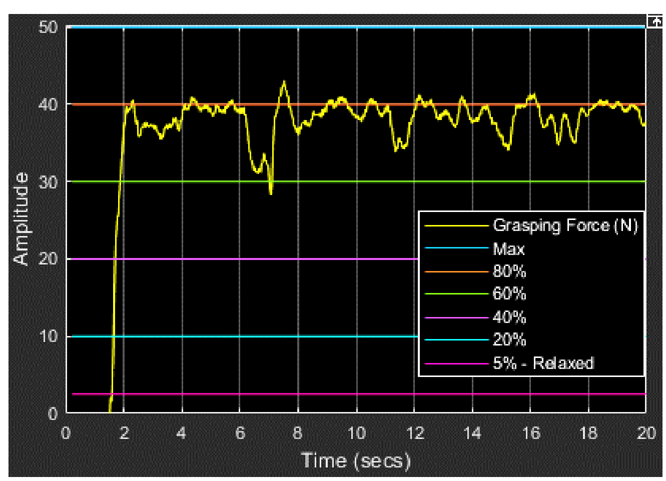

Fig. 3. Visual feedback of grasp force. Subjects follow one profile during each EOP estimation. This image has been adjusted for illustration purposes. Only one reference level was displayed at a time during experiments.

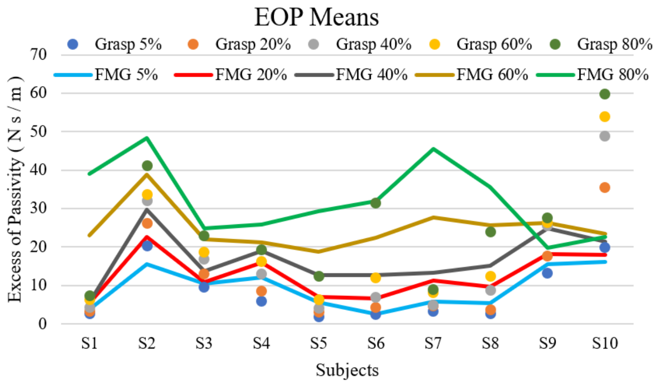

Fig. 4. Excess of Passivity mean values at five levels of grasp pressure and full arm FMG for 10 subjects. Each mean value consists of five estimations.

V. ANALYSIS OF RESULTS

Series of two-factor ANOVA tests with replication were performed to find differences in EOP estimations between grasp force and full arm FMG based protocols, according to the level of grasp force and full arm FMG. An alpha factor of 0.05 was chosen for all statistical analyses. Differences among subjects were not included in the analyses as these are not of interest. However, all subjects' EOP values were lumped together as series of 5 repeated measurements.

Significant differences were found for estimations at the five levels of grasp force compared to those of full arm FMG. EOP estimations at 5% were significantly higher for full arm FMG (mean = 10.23 Ns/m) compared to grasp force (mean = 8.22 Ns/m), with a p value of 0.00966. EOP estimations at 20% were significantly higher for full arm FMG (mean = 13.96 Ns/m) compared to grasp force (mean = 11.99 Ns/m), with a p value of 0.00831. EOP estimations at 40% were significantly higher for full arm FMG (mean = 21.1 Ns/m) compared to grasp force (mean = 16.52 Ns/m), with a p value of 0.0001.EOP estimations at 60% were significantly higher for full arm FMG (mean = 33.0 Ns/m) compared to grasp force (mean = 19.38 Ns/m), with a p value of 8.77 E^{-19}. Similarly, EOP estimations at 80% were significantly higher for full arm FMG (mean = 43.9 Ns/m) compared to grasp force (mean = 25.5 Ns/m), with a p value of 2.83 E^{-31}.

VI. DISCUSSION AND CONCLUSIONS

The measurement of energy absorption capabilities of the human arm can be improved by extending the number of biological signals involved in the EOP estimation process. The use of FMG on the entire arm makes EOP estimations more accurate as muscles from the hand, forearm and upper arm contribute to the value of this metric. Therefore, we recommend using at least three points of muscle activity detection, such as hand, biceps and triceps, to obtain EOP estimations based on more realistic arm dynamics.

We found out that using FMG sensors is a very inexpensive and easy way to detect muscle activity of the arm. The implementation of these type of sensing technique only costs a few hundred dollars, requires minimum circuitry, does not need any skin preparation, and are less sensitive to electromagnetic interference. Therefore, the authors claim that they are a reliable substitute of EMG sensors in human-robot interactions.

For future work, we hope to combine and compare FMG and EMG data to better estimate EOP, as well as to use interpolation methods such as a radial basis artificial neural network. This method may allow us to connect the five levels of estimation without requiring all measurements and perform real time calculations, which is essential when a robot tries to deliver the exact amount of energy needed by a potential patient during therapeutic interactions.

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