Estimating the Effect of Robotic Intervention on Elbow Joint Motion

Keya Ghonasgi, Ana C. de Oliveira, Anna Shafer, Chad G. Rose, and Ashish D. Deshpande

***Abstract*— Much effort has been placed into the development of robotic devices to support, rehabilitate, and interact with humans. Despite these advances, reliably modeling the neuromuscular changes in human motion resulting from a robotic intervention remains difficult. This paper proposes a method to uncover the relationship between robotic intervention and human response by combining surface electromyography (sEMG), the musculoskeletal modeling platform OpenSim, and artificial neural networks (ANNs). To demonstrate the method, a one degree of freedom (DOF) elbow flexion-extension motion is performed and analyzed. Preliminary results show that while the robot provides assistance to the subject, it also appears to produce other unexpected responses in the movement. Further investigation using the new method reveals the neuromuscular effect of an unintended resistance to the subject's motion applied by the robot as it enforces a speed slower than the subject selects. The characterization of the differences in expected and actual interaction is enabled by the method presented in this paper. Thus, the method uncovers previously obscured aspects of human robot interaction, and creates possibilities for new training modalities.**

I. INTRODUCTION

Robots for physical rehabilitation are designed to work closely with humans, and are in fact meant to affect deliberate and controlled change in the movement produced by the subject. Harmony, a bimanual upper-limb exoskeleton robot (Fig. 1) is one such device [1]. Since Harmony is attached directly to the limbs of the subject, control of the robot and safety during movement is of utmost importance. A combination of careful mechanical design and impedance control affords the robot a level of compliance which can be varied for individualized movements or rehabilitation protocols.

Several robotic interventions have been developed towards the goal of individualized therapy. Typically, interventions vary along a spectrum going from active high impedance assistance, through no intervention, to high impedance resistance [2, 3] as conceptualized in Fig. 2. The levels of assistance and resistance provided to the subject are both zero at the neutral mode and increase as the axis moves off to the left or right of this mode respectively. Ideally, impedance control can be used to smoothly vary the robotic intervention applied to the subject along this axis. A common method used to analyze the effects of such training is to measure muscle activations through surface Electromyography (sEMG). Unfortunately, the use of impedance control results in loss of information regarding the 'true motion' that the subject is being trained for. This refers to the hypothetical motion that the subject would perform with the same muscle activations in the absence of active robotic intervention. This information is vital toward understanding the effects of intervention, and could aid in the design of more effective training protocols.

De Oliveira et al. [4] present a way to modulate Harmony's impedance to alter the human effort required to perform a motion. They show that it is indeed difficult to separate the dynamics of human movement and that of the robotic intervention. The authors propose a method to exploit the relationship between effort and measured muscle activation to fill this information gap. However, they find low correlations between the estimated voluntary effort and the measured sEMG data in cases where the robot applied assistance to the subject. This is accompanied by unexpected performance of the sEMG data. Specifically, even when Harmony assists the motion, the muscle activations are found to be higher than when the robot is passive. These results motivate an in-depth analysis of the relationship between the applied robotic intervention, the measured sEMG, and the kinematics of the motion.

Models relating measured kinematics and sEMG data have been suggested in the literature [5–9]. However, complex relationships exist between the muscle force, the musculotendon architecture and joint geometry which makes it difficult for sEMG to capture the true neural activations which produce the given motion [10]. Further, the results from these methods are often convoluted by the noise introduced by skin artifacts [11]. Thus, there is a need to use a more reliable structure that exploits the information provided by sEMG data while also adhering to the underlying dynamics of the musculoskeletal system. Pang et al. [12] proposed a method that came close to solving the problem, but relied on complex mathematical models that require prior knowledge about muscle parameters such as contraction velocity and muscle length, making it difficult to reproduce. Inspired by a

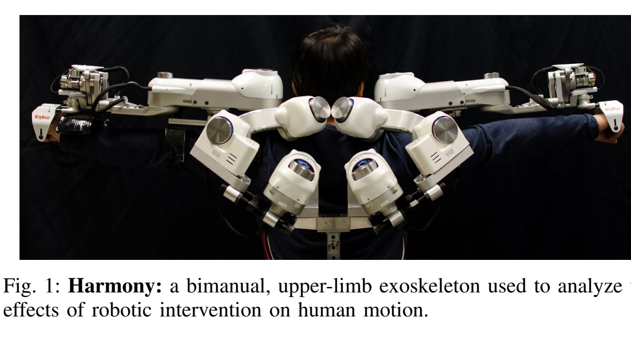

Fig. 1: **Harmony:** a bimanual, upper-limb exoskeleton used to analyze the effects of robotic intervention on human motion.

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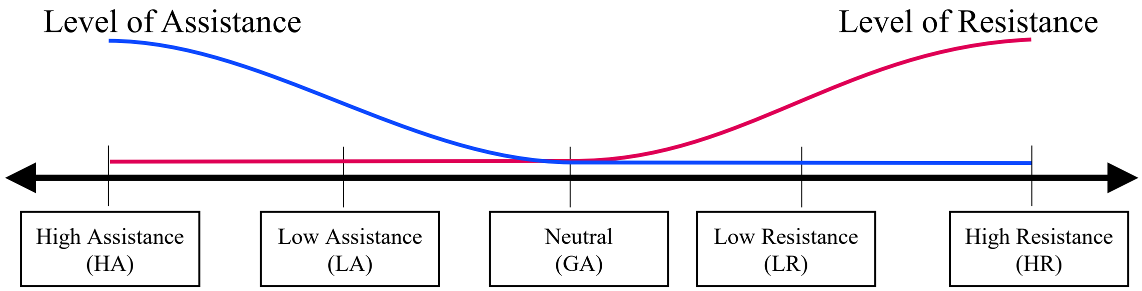


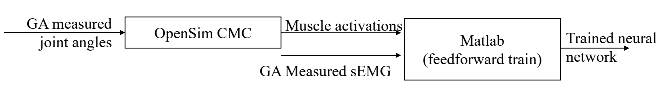
Fig. 2: **Conceptualization of the Intervention axis:** The level of assistance provided by the robot (in blue) and the level of resistance (in red). At the left end, the level of assistance is high and it reduces to zero as it reaches the neutral mode. To the right of this mode, the assistance remains zero while the level of resistance applied increases from zero to the maximum. High impedance: $K = 1$; $D = 0.25$; low impedance: $K = 0.1$; $D = 0.01$.

structure suggested by Sartori et al. [7], this paper proposes a method to tackle all of these issues. Experimental sEMG data is used in conjunction with computational modeling using OpenSim, which allows for a more comprehensive analysis of neural activations and the corresponding 'true motion'.

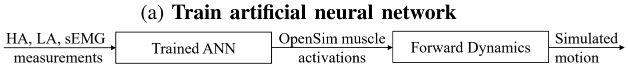
Motivated by the anomalous results shown by De Oliveira et al [4], the main aim of the current study is to analyze the effect of robotic interventions on muscle activations and the intended motion of the subject. Specifically, the study aims to answer the questions, *what is the true effect of the intervention applied by the robot,* and more importantly, *does the impedance controller result in unintended effects on the subject's motion?* These questions are answered using the method depicted in Fig. 3.

II. Method

The method used in this study can be split into two parts (Fig. 3). First, the experimental mode where the robot remains passive is considered to be the baseline. The position data collected during this mode is used to generate the muscle activations predicted by OpenSim's Computed Muscle Control tool. Assuming these are the true muscle activations, a neural network is trained to fit the relationship between these activations and the measured sEMG data. The second half of the method uses this neural network to estimate the OpenSim muscle activations using the measured sEMG data from the remaining robot intervention modes. These activations are then used to simulate the 'true motion' hypothetically performed by the subject, thus closing the information gap. The data processing and artificial neural network training are done using Matlab R2018a (MathWorks Co. USA). OpenSim version 3.3 is used for the muscle activation estimation and forward dynamics simulation. All of the analysis presented is carried out on a Laptop computer (core i5, 2.3 GHz Quad core processor, 8GB RAM).



(a) **Train artificial neural network**



(b) **Simulate motion**

Fig. 3: **Flow chart representing the method:** Fig. 3a shows the steps taken to generate the ANNs. Fig. 3b shows the next steps taken to simulate the motion in OpenSim.

A. Experimental Protocol

A one DOF elbow flexion-extension movement is designed to analyze the effect of varying the impedance controller used with Harmony. The movement is repeated nine times for five distinct levels of robot intervention. The five levels are High impedance robot Assistance (HA), Low impedance robot Assistance (LA), Gravity Assistance only (GA), Low impedance robot Resistance (LR), and High impedance robot Resistance (HR). The GA mode allows the subject to move freely without the weight of the robot and the remaining robot interventions are layered over this mode. The five levels of assistance and resistance, and the corresponding high and low impedance values are described on the conceptual intervention axis in Fig. 2. In all trials the subject is instructed to complete the motion and a metronome is used along with visual cues to control movement speed. The trajectory of the arm is predefined for the robot in the active intervention modes. This is identical to the protocol implemented by De Oliveira et al. [4].

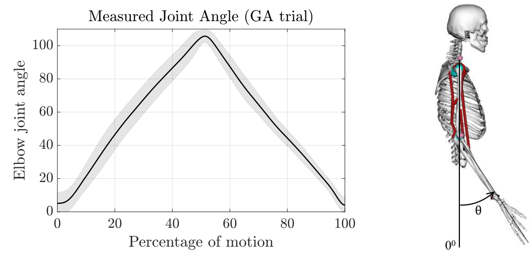
Data has been collected for one healthy individual performing the motion with the right arm only. An sEMG data acquisition system (Delsys Inc., Trigno Wireless EMG) is used to measure muscle activity in the biceps brachii and in the long and lateral heads of triceps brachii. Fig. 4 illustrates the experimental setup. The sEMG signals have been filtered by a fifth-order low-pass Butterworth filter at 5 Hz and normalized by the maximal voluntary contraction. Position and torque data from the robot have been sampled at 100 Hz and smoothed using a fifth-order moving median filter. Synchronization between the robot data and the sEMG data is ensured in the post-processing by matching a spike signal generated by an abrupt elbow flexion at the start of each trial. The time matched movement is further averaged over the repetitions to generate the average movement of the subject during each robot intervention trial. This movement is then scaled, beginning at full extension of the elbow (0% of the motion) running till full flexion (at about 50% of the motion), and then returning to full extension (100% of the motion). This can be visualized in terms of the elbow angle in Fig. 5.

B. The OpenSim Model

The single joint elbow flexion-extension movement performed by the subject requires the use of two main muscle groups, namely, the Biceps and the Triceps. The simplified

(a) **Sensor placement** (b) **Arm configuration**

Fig. 4: **Experimental setup:** The subject performed the elbow flexion motion with the right arm only. The sEMG sensor placement is shown in 4a for the biceps brachii, and the triceps brachii long head and short head. The placement of the subject's arm in the robot is shown in 4b.



(a) **Elbow joint angle (GA)** (b) **OpenSim model**

Fig. 5: **Measurements and Model:** Fig. 5a shows the average elbow joint angle trajectory (standard deviation shaded) for the GA condition. Fig. 5b shows the Arm26 model. θ is the elbow joint angle. 0° refers to the fully extended position.

upper-extremity OpenSim model Arm26 [17] is ideal to analyze the movement as it models these same muscle groups, which were also measured experimentally using sEMG sensors. Since the model (shown in Fig. 5b) only includes 6 muscles it is computationally inexpensive. The 6 muscles are the Triceps Long Head (TLH), Triceps Lateral (TLa), Triceps Medial Head (TMH), Biceps Long Head (BLH), Biceps Short Head (BSH), and the Brachialis (BRA). The plots presented in this paper are representative of the BLH data, but the same analysis has been repeated for all 6 muscles. Prior to performing the analysis, the model is scaled to the upper arm and forearm lengths of the subject.

C. Computed Muscle Control

OpenSim's Computed Muscle Control (CMC) tool derives the generalized coordinates (in this case, muscle activations) of a dynamic musculoskeletal model for a desired kinematic trajectory. This is done using a combination of proportional-derivative control and static optimization [18, 19]. The GA robot intervention data is treated as the baseline for the motions performed by the subject while wearing Harmony as the other interventions are layered over this mode of robot operation. The averaged position data collected during this trial is used to generate a motion file to animate the Arm26 model in OpenSim. This motion is then used with the CMC tool to generate the muscle activations required to perform the prescribed motion. The resulting six muscle activations are set up as the target outputs for two neural networks.

D. Artificial Neural Network Design

Two curve fitting Artificial Neural Networks (ANNs) have been designed respectively to take Biceps and Triceps sEMG data as input, pass it through one hidden layer, containing 30 nodes, and produce three outputs each. The number of nodes is heuristically chosen to find the best model while avoiding over-fitting of data. The Levenberg-Marquardt algorithm is used due to its high computational speed [20]. The outputs are chosen to be the desired muscle activations corresponding to the muscle group for convenience. However, the choice of inputs is not as straightforward.

Evidence suggests that a 50 ms - 150 ms delay exists between the collected sEMG data and the movement performed by the subject [21]. Also, muscle activations are known to depend upon the time history of this activation. Thus, the relationship between measured sEMG activations and muscle activations is not linear [22]. This delay is accounted for within OpenSim as well. The input at a given time instance is expected to be dependent on 150 ms of information before that instant which corresponded to about 750 data points (depending on the duration of the entire motion). To reduce computation time while maintaining this dependence on activation history, the 751 data points (including the current time instance) have been down-sampled to 16 fixed data points. These 16 points are selected to reduce discrepancies. Thus, at a given time instance, for a given muscle group, 16 data points are passed as an input, and three data points are expected as the network's output.

Further, to separate the training and validation data sets, only five of the repetitions of the GA robot intervention trial are averaged and scaled to generate the inputs for the training set. The position data for the same trials is used as an input to OpenSim's CMC tool. This training set is used to train two ANNs for the Biceps and Triceps muscle groups respectively. The remaining four repetitions are averaged to generate the validation sEMG data set, which is then fed to the ANNs to estimate the corresponding muscle activations for OpenSim. These are then compared to the validation target muscle activations generated by OpenSim's CMC tool.

E. Forward Dynamics

OpenSim's Forward Dynamics tool uses muscle activations as control inputs to simulate the corresponding motion. This motion is the solution (integration) of the differential equations that define the dynamics of the musculoskeletal model [18, 19]. The measured sEMG data is passed through the trained ANNs to estimate the OpenSim muscle activations corresponding to the remaining robot intervention modes. These activations are then used with the Forward Dynamics tool to simulate the subject's motion. As OpenSim does not take into account the robot's intervention, the resulting motion is different from the actual movement performed by the subject. Thus, the Forward Dynamics tool allows for the unique opportunity to compare the subject's 'true

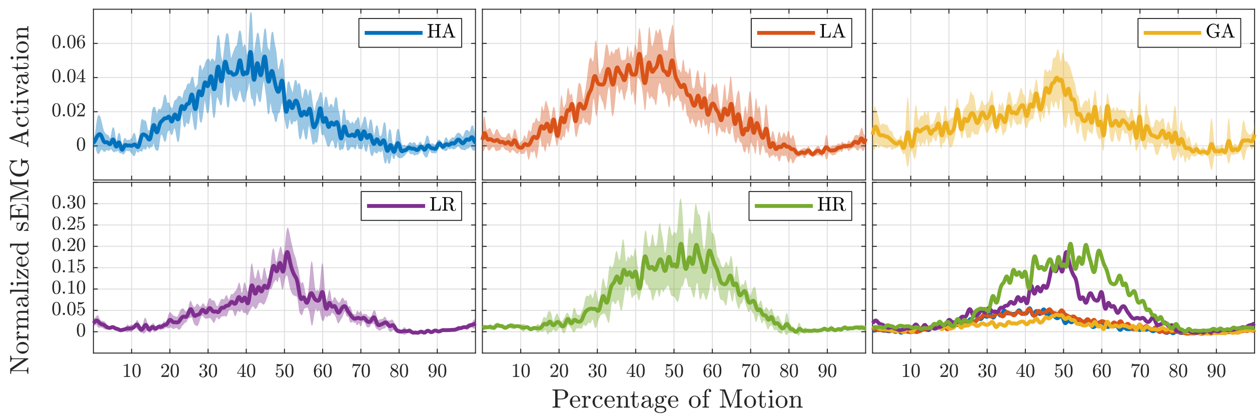


Fig. 6: **Averaged Biceps sEMG data:** The first five figures show the data for all five robot intervention averaged over nine repetitions, with the standard deviation shaded around the mean. The last plot in the bottom row compares the means for all five modes.

movement', and the movement performed as a result of the robot intervention.

III. Results

A. sEMG Comparison

The filtered and scaled sEMG data is compared for the five robot interventions (Biceps activations are shown in Fig. 6). As the motion performed in the first half of the trial is flexion, the flexor muscles (or Biceps) are expect to activate [23]. Conversely, during the extension half of the motion, the extensor muscles (Triceps) are expected to activate. As expected in the resistance conditions (LR, HR), the sEMG activations are higher than those in the GA condition. Further, the maximum sEMG activations increased from the LR to HR robot intervention trials. However, it was also observed that in both assistive conditions (LA, HA), the resulting sEMG activation was not lower than that in the GA mode, which was contrary to the intended effect of the intervention. In fact, during certain phases of the movement, the sEMG activation was higher in the assistance modes than in the GA mode. Investigation of the Biceps sEMG profile shows that the subject appears to be activating their muscles unexpectedly during the motion. To further analyze this anomaly, ANNs were trained and used to study the resulting simulated motion in OpenSim.

B. ANN validation

The OpenSim CMC muscle activations and ANN estimated actuations are compared in Fig. 7. These are the results from the validation set of four repetitions of the GA mode not used for training. The figure compares the estimates for three trained networks with 0, 15 and 20 data points of time history information passed as input to the network. At 15 time history points, the resulting trained network is able to generate reliable muscle actuations to be fed to the OpenSim Forward Dynamics tool. The averaged and scaled sEMG data for all the five robot intervention trials are then fed to the ANNs. The resulting muscle activations for the cases of interest (HA, LA and GA) can be seen in Fig. 8a. The estimated OpenSim muscle activations for the five robot intervention trials follow the same trend as the sEMG activations.

C. Motion Analysis

These muscle activations are used with OpenSim's Forward Dynamics tool to simulate the corresponding motion. The estimated elbow joint angles are shown in Fig. 8b.

IV. Discussion

The measured sEMG muscle activations are compared to understand the overall effects of the robot's intervention. The activations (Fig. 6) increase going from the GA mode to the LR to the HR modes as expected. This relates to the increasingly higher levels of resistance provided by the robot. However, the peak sEMG activations are higher in the LA and HA modes than the GA mode, even though the robot is nominally providing assistance to the subject. This result is intriguing as it corresponded well with the study performed by De Oliveria et al. [4]. The anomalous behaviour is believed to the result of unintended effects of the robot's intervention, which are further analyzed for the HA and LA modes.

Two ANNs are trained using the measured sEMG data and OpenSim CMC muscle activations for the GA mode (which is common to all five modes of the robot). The ANNs transform the measured muscle activations to the corresponding values estimated by OpenSim, with the ultimate goal of simulating the hypothetical motion that the subject is training for. As muscle activation is known to depend upon the time history of activation, the neural network inputs are designed to exploit this dependence. The resulting network is validated using trials of the GA intervention that are not used to generate the training dataset. Fig. 7 shows that passing time history information to the ANN significantly improved the prediction. Further, as the number of historical data points was increased beyond 15, over-fitting is observed. The performance of the ANN is improved by over 99% with the updated inputs than without the time history information.

The averaged and scaled sEMG data for the assistance modes is then run through these trained ANNs to generate the OpenSim muscle activation patterns (Fig. 8a). Next, these

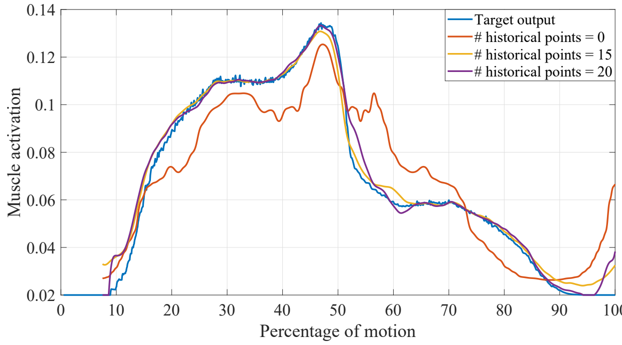
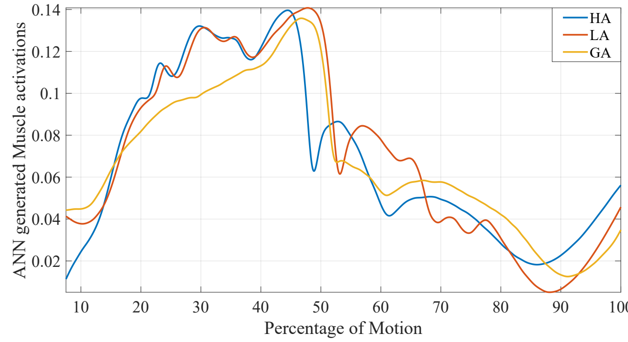


Fig. 7: **Validation of the ANN (BLH):** Comparison of the OpenSim CMC generated muscle activations (Target output) and the estimated muscle activations obtained as outputs of three ANN models for the Biceps Long Head muscle.

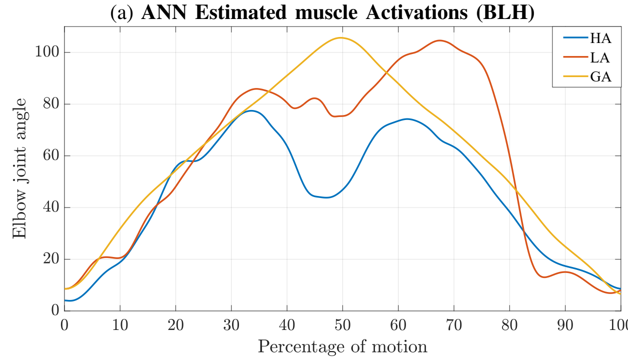
estimated muscle activations are used with OpenSim's Forward Dynamics tool to simulate the corresponding motion. The joint angles representing these motions, shown in Fig. 8b, do not follow the same pattern as the motion performed in the GA mode. Further, the simulated movement does not reach the same flexion angle in the HA and LA cases as in the GA case. This suggests that the unexpected high peaks seen in the measured sEMG data do not correspond to a more exaggerated simulated motion (higher flexion angle), but to a different motion trajectory altogether. Fig. 8b shows this trajectory to consists of two joint angle peaks (instead of one) in the HA and LA cases, providing some insight into the anomaly.

During the flexion phase of the motion, the subject is moving against gravity. The subject tries to move faster than the prescribed motion in order to compensate for the effect of gravity, and is thus restricted by the speed prescribed to the robot. The subject experiences a resulting unintended resistance applied by the robot, and the flexor muscles show a corresponding peak in activation. This corresponds to the first peak seen in Fig. 8b.

As the subject lowers (or extends) their arm, corresponding to the neutral (90°) position in the GA case, a second peak is observed. At this position, gravity is aiding the downward motion of the arm, and the subject is expected to first flex so as to slow down the movement to match the metronome, and then only extend the arm. However, the flexor muscles are seen to deactivate more abruptly than expected in the measured activations. Interestingly, the muscle activation increase occurring just before the second peak in the simulated motion is not as high as that before the first peak. The increase from the GA mode is also lower in the HA case than the LA case. This trend can also be explained by an unintended effect of the robot's intervention. Since the robot does not allow the subject to move faster than prescribed, the subject now experiences support against gravity. As a result, the flexor muscle activations die off faster in the assistance cases than in the GA case. Depending on the aim of the training protocol, the resistance that causes the two peaks in the subject's simulated motion may or may not be desired. This resistance could potentially be chosen deliberately for a desired training effect.



(a) **ANN Estimated muscle Activations (BLH)**



(b) **Forward Dynamics Simulated motion (BLH)**

Fig. 8: **Analysis of HA and LA modes (BLH):** Fig. 8a compares the muscle activations for the HA, LA and GA cases estimated from the corresponding sEMG data using the ANN. Fig. 8b shows the resulting motion generated using OpenSim's Forward Dynamics tool.

The ANNs trained in this paper are successful in transforming the measured sEMG data to the corresponding OpenSim muscle activations. This is valuable because these muscle activations can then be used to simulate the motion that the same muscle activations would result in given the hypothetical scenario where the robot does not apply an intervention. The simulated position data for the HA and LA cases allow for unique insight into the hypothetical movement that the subject is being trained for. The robot enforces the prescribed trajectory with the exact prescribed time signature, and as a result the subject experiences resistance even in the assistance modes. This observation further suggests that had the controller not resisted the subject in performing the motion at a speed faster than what was prescribed, the muscles would not have activated as much.

The class of controllers that use impedance control to supervise such interventions are called Assist-As-Needed (AAN) controllers. The results seen in this paper show that while the AAN controller used for the experiments performed as expected in the resistance modes, the same was not true in the assistance modes. This strongly supports the need to design such controllers with more care and with an emphasis on avoiding unintentional responses to intervention. For example, the minimal AAN controller proposed by Pehlivan et al. [24] allowed for unimpeded motion ahead of the reference trajectory. Any controller design must further be evaluated before being used in training, as this could help avoid detrimental effects, as well as allow for selection of specific training results.

Although this type of evaluation is difficult to perform in real time, the presented method enables this analysis offline. The method may be reproduced for any motion that can be reliably modeled and simulated using a software platform such as OpenSim. Thus, assuming that the estimated muscle activations and the corresponding simulated motions are representative of the true neural muscle activations and joint kinematics, the combination of OpenSim and trained ANN muscle activation estimators results in a powerful tool. In fact, this method can be used to analyze the way both healthy and affected subjects respond to physical intervention, be it robotic or otherwise. The results could be used to evaluate preliminary effects of a new protocol, or analyze the trends of the protocol on a number of subjects. This method also does away with the need for kinematic data in cases where such data may be noisy or hard to capture, in favor of sEMG measurements. Further, the method described here may be reversed to generate the training required to produce a desired rehabilitative outcome. For example, it might be possible to design a protocol to achieve a desired level of muscle activation, while restricted to a small workspace.

V. Conclusion

The aim of this study is to present a reliable method to establish a relationship between a subject's response and the applied robotic interaction. The method is demonstrated by varying the intervention applied by Harmony along the axis conceptualized in Fig. 2, going from high impedance assistance to high impedance resistance. The resulting sEMG data (Fig. 6) shows that the muscle activations do not perform as expected. Specifically, the maximum activation does not decrease going from the neutral to the assistance modes. The proposed method of analysis uses trained neural networks and the muscle activations for the assistance modes to provide insight into the true effects of the intervention. The results help characterize the unintended resistance applied by the robot on the subject's motion. Thus, the method is proven to be a reliable tool for the analysis of the true effects of robotic intervention on human motion. Further, the method may be used to preemptively evaluate such interventions as well as to develop new and more deliberate training protocols.

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