

TOWARDS AN INTEGRATED INTERVENTION AND ASSESSMENT OF ROBOT-BASED REHABILITATION

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ABSTRACT

This study presents robot-based rehabilitation and its assessment. Robotic devices have significantly been useful to help therapists do the training procedure consistently. However, as robotic devices interface with humans, quantifying the interaction and its intended outcomes is still a research challenge. In this study, human-robot interaction during rehabilitation is assessed based on measurable interaction forces and human physiological response data. And correlations are established to plan the intervention and effective limb trajectories within the intended rehabilitation and interaction forces. In the study, the Universal Robot 5 (UR5) is used to guide and support the arm of a subject over a predefined trajectory while recording muscle activities through surface electromyography (sEMG) signals using the Trigno wireless DELSYS devices. The interaction force is measured through the force sensor mounted on the robot end-effector. The force signals and the human physiological data are analyzed and classified to infer the related progress. Feature reduction and selection techniques are used to identify redundant inputs and outputs.

1 Introduction

Recently an increase in research interest has been shown in rehabilitation using robots and exoskeletons due to their capabilities in supporting physical therapy procedures [1–4]. The demand of such devices has increased partly due to an increasing rate of the aging community with motor impairments [5, 6]. Age related and other neuromuscular diseases such as muscular dystrophy (MD), amyotrophic lateral sclerosis (ALS), and multiple sclerosis (MS) can result in loss of independence due

to the associated hand impairments. About 800,000 Americans have strokes each year. The total cost of stroke in the United States is estimated at \$ 34 billion per year with the direct costs of medical care; and therapy are estimated at \$ 28 billion per year [7]. Stroke often causes paralysis or weakness of one or more of the muscles in the arm or shoulder. Diseases like these leave patients with greatly impaired or completely non-existent muscle function over time, making life for them tremendously difficult. An option to relieve the symptoms while medical research continues is rooted in assistive technologies. To this end, there has been considerable research directed toward the development of assistive devices to restore arm and hand functionality. For example, there are currently exoskeletons being used, largely in physical therapy, to help rehabilitate paralyzed or impaired movement of the upper-arm due to strokes and other similar medical problems [8–11]. However, due to the lack of quantifiable feedback regarding the degree of intervention at one point and the effectiveness of various training parameters (such as timing, intensity, etc.), the training protocols and their efficacy vary remarkably between institutions and therapists [12, 13]. In order to assess the efficacy of novel therapeutic methods and understand the potential contributions of incorporating innovative technologies into the training process, observing the variation in biomechanical and bio signal parameters are vital. In rehabilitation procedures, co-adapting interaction approaches with a behavior prediction power through data-driven models are needed for a quick and complete restoration of lost functions [14]. However, as robotic devices interface with humans, quantifying the interaction and its intended outcomes while maintaining the desired physiological movement is still a research challenge [15]. Maximizing the number of repeated movements and generating a

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correct physiological movement trajectory are the two most important factors in task-specific rehabilitation. People with upper-arm muscle weakness may not be able to carry the weight of their arms and can cause joint dislocations; a proper arm positioning and exercise after stroke can speedup recovery. Robotic devices have been significantly useful to help therapists do the training procedure efficiently and consistently. Assistive technologies can also guide/assist patients to follow a certain trajectory during the rehabilitation process. However, only few studies are available on how muscles are engaged in such interventions.

Universal Robots (UR) are considered as one of the collaborative robots (Cobots) that can be utilized in a human environment facilitating specific tasks in industries as well as clinics and hospitals [16, 17]. These robots are considered to have smooth movements being able to interact with human under different circumstances. This feature with some factors of safety, has been utilized in motor learning and interactive learning to develop effective neuro-rehabilitation methods [18]. Exploring and understanding of the potential effects of such assistive devices based on interventions and their interactions with the user are crucial. Some patients, such as PD patients are typically incapable of swinging their hands in a normal way, because the certain muscles that need to be recruited do not have enough strength [19]. These patients may not be able to trace a given circular path, however, with assistance through the end-effector mounted on the robot, they can complete the task. There have been numerous investigations and multidisciplinary studies on this issue each has approached the shortcomings from a different aspect [20,21]. However, it is still unknown on to what extent the robot recruits additional muscles from the upper arm to perform the task without introducing any complications in terms of force or stiffness on the patients. In this study, a task based rehabilitation with Universal Robot 5 (UR5) is assessed through muscle activities and robotic force sensors (FT300 sensor) mounted on the UR5. Using multiple IMU sensors to find position and orientation of points of interest, the study focuses on two main contributions: 1) a strategy to capture impact-based novel limb trajectories which can serve as a base for the intervention and input data for mechanism synthesis and 2) to develop an assist-as-needed (AAN) support strategy based on the targeted muscle activity and control of the highly correlated directional human-robot interaction force. The study envisions a model that can help physicians and therapists predict and quantify the efficacy of therapy for a given intervention pattern. The findings will help in prescribing the intervention with the right dosage and engaging robots in novel exercise than enhancing the traditional approaches.

2 Methodology

The study presents a systematic approach to develop a novel and controlled intervention procedure for upper-arm task-based rehabilitation. The specific tasks include 1) identifying effective

trajectories based on the muscle activity, 2) identifying correlations of interaction forces with targeted muscle responses, and 3) the implication towards an AAN control strategy. The methodology outlines the general procedure as well as its implication in a specific case study for upper arm rehabilitation using a circular trajectory.

2.1 Investigating Impact-based Limb Trajectories

This task is based on the rationale that harvesting and utilizing effective trajectories which can highly affect the muscle activity may result in reduced workspace and subsequently a reduced recovery time during rehabilitation. It has been established that the reduction in the number of degrees of freedom in the workspace provides a number of potential benefits in the clinical settings. However, the Degree of freedom (DoF)s that should be captured are neither arbitrary nor obvious. The workspace in many applications will greatly exceed the desired effective operational workspace of the device as well as the limb trajectory. Here, we introduced a new approach in which the muscle activities (EMG signals) and human motion via Inertial Measurement Unit (IMU) are integrated to get the effective and desired task(s) for the application of robot. The collected data include positions and angles from multiple locations on the human limb of interest. Effective cloud points will be collected and selected based on threshold values. The general outline for the this task is shown in Figure 1. For the upper limb rehabilitation, we have considered Biceps Brachii (BB), Triceps Lateral (TL), and Triceps Long (TLo) muscles; hence, placing surface electromyography (sEMG) hybrid sensors on these muscles and an IMU sensor at the upper arm can help to track position and orientation. A matlab script is developed to extract IMU data based on the RMS value of EMG, such that to maintain a set threshold of muscles activities. Finally, effective points for each muscle are analyzed individually, and the common points that have a potential effect on all the muscles are further characterized for their trajectory related implication. Studies have been done in the area of limb motion and corresponding muscle activities while following controlled joint and limb moments [22]. However, harvesting effective points within the range of motion of the limbs for rehabilitation requires more work and investigation. A preliminary analysis has also been done based on a selected motion of the upper arm as shown in Figure 2 and sEMG is collected at the targeted muscles: Biceps Brachii (BB), Triceps Lateral (TL), and Triceps Long (TLo) muscles. For this specific example, the red cloud points have a relatively higher impact on the corresponding muscles. At the same time, we can see differences in the three muscles, which opens an opportunity. Depending on the targeted muscle, effective points/trajectory can be defined or a common trajectory can be selected to affect the three muscles. Identifying such trajectories can also help as a base for novel mechanism synthesis; the traditional mechanism synthesis for an exoskeleton follow an intuitive approach by mimicking human-joint to robot-

joint which may not reach such effective points/trajectories due to joint constraints. Such approaches can also be used as a base to asses traditional therapy tasks and their implications on the targeted muscle, for example, following geometrical paths such as circular and elliptical shapes are utilized to asses upper arm strength and muscle weaknesses for stroke and Parkinson disease patients.

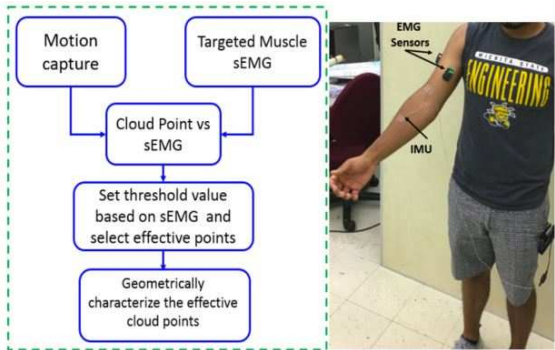


FIGURE 1. Experimental Setup for investigating impact-based limb trajectories

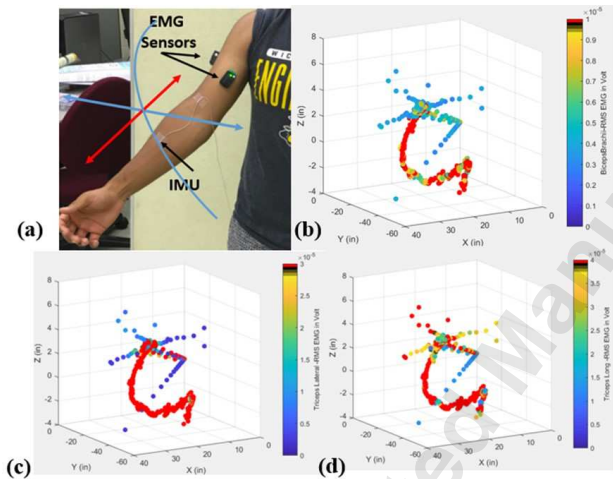


FIGURE 2. (a) Selected upper limb motions, (b) Biceps Brachii (BB), (c) Triceps Lateral (TL), and (d) Triceps Long (TLo) muscles.

2.2 Identifying Correlation Between Interaction Forces and Muscle Responses

The interaction force signals and the human physiological data can be analyzed to infer gestures and related progresses. In our preliminary study [23], an upper-arm, task-based rehabilitation with Universal Robot 5 (UR5) is assessed through a model-based approach. Universal robot5 (UR5) has been utilized to move an arm of healthy subjects over a circular path

while the muscle activities were recorded through sEMG; and interaction forces measured using Robotiq force sensors (FT300 sensor) mounted on the robot. This sensor provides forces in the three Cartesian coordinates (F_x , F_y , and F_z) also the couple about those directions (M_x , M_y , and M_z). A dynamic model has been developed through system identification to relate the resultant force with the level of muscle activity in the upper-arm. Based on the preliminary result obtained from the five healthy subjects, the model has provided a good accuracy in capturing the dynamics. However, in that study, the resultant force was utilized instead of directional forces; utilizing the resultant force for modeling is not a good approach from an implementation perspective, as it is easier to control forces in a certain direction than the resultant one. Understanding the interaction between directional forces and muscle responses in an effective limb trajectory is vital to employ robots in novel intervention protocol that can provide an effective and controlled outcome.

3 Case Study: Upper Arm Task-based Rehabilitation

Currently, robots do not introduce any novel rehabilitation methods; instead they enhance the traditional approaches [24]. Thus, either a new approach, or a novel modification of traditional devices is needed to develop a more convenient assistive training. In this case study, a typical geometrical path (circular) that is frequently utilized for upper arm rehabilitation is used to demonstrate how the selected task recruits the upper arm muscles, how directional interaction forces correlate with the muscle responses, and its implication for implementation and engagement perspectives. Within a wide variety of different geometries, drawing a circle has been the center of attention in lots of studies to detect the pattern movements, joint excursion and roundness precision so that a comprehensive therapeutic technique can be developed to help the therapist in the optimized rehabilitation process [25]. In another study, torque distribution of the shoulder and elbow have been observed while subjects were drawing various shapes and lines [26]. We have selected this well applied task based exercise (circular path) to establish interaction force and muscle response at the selected muscle groups. In this study, after obtaining the required Institutional Review Board (IRB) approval, a Universal Robot 5 (UR5) has been utilized to move an arm of healthy subjects over a circular path while the muscle activities are recorded through sEMG; at the same time, all components of the forces applied to the robot have also been measured using Robotiq force sensors (FT300 sensor). Five healthy male subjects, ranging from 24 to 29 years old, and weighing within the range of 62Kg to 86 Kg have been recruited to investigate the robot-based rehabilitation and its efficacy on the upper arm muscle recruitment. The subjects have been tasked to follow a given circular trajectory with robot assistance. Universal Robot (UR5) has been used for the assistance and the forces at the tip of the robot has been recorded while the robot is used in the training. The sEMG signal is also recorded from the Brachii (BB), Triceps

Lateral (TL), and Triceps Long (TLo) muscles while the subjects are performing a circular trajectory.

3.1 Experimental Setup

An ergonomic knob (green knob) has been designed and fixated on the gripper, so that subjects can place their right hand during the training. Additional strapping mechanism is used to securely hold subjects' hand and to avoid wrist rotation. During the training, real-time measurement of the force interaction between the user and UR5 has been recorded; all components of the forces are measured using Robotiq force sensors (FT300 sensor) mounted on the robot. Muscle activities are captured using sEMG sensors, Trigno wireless DELSYS device (Fig. 3). The hybrid sensors have accelerometer as well as sEMG electrode. Sensors are placed on the three aforementioned muscles of all subjects and the robot runs through the same circular trajectory with the same pace. This is a simulation of upper-arm therapeutic movement that is usually done by a therapist. The trajectory of the robot while holding the knob is confirmed by the circular trace in a similar setting shown in Fig 3. Kinematics of the motion is designed in such a way that the jerk is minimal so subjects could have a secure environment and trust the machine during the rehabilitation process. Post processing built-in module provided by the Delsys has been applied to filter and smooth the signals. Fig. 4 demonstrates EMG data at the Triceps long muscles for all five subjects. The raw data indicated that the triceps long muscles are relatively insensitive for the selected task and force interaction combination regardless of the anatomical differences of the subjects. This suggests that the need of new trajectory/task in order to engage TLo muscle groups (Fig. 4). Similarly, the corresponding forces on the robot have been recorded to analyze its implication on the upper-arm muscle activities. Understanding the associated interaction directional forces are vital for the controlled intervention. For instance, in the circular task some of the forces and couples have no or minimal changes indicating their effect on the targeted muscles. A sudden change of such unnecessary directional forces might lead to discomfort or affect muscles other than the targeted ones. An example of the RMS values of sEMG data and the corresponding interaction forces for one of the subject can be visualized in Fig.5.

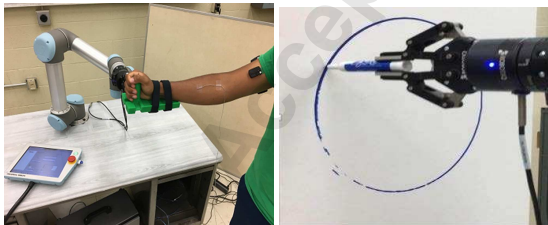


FIGURE 3. sEMG sensor setup and UR5 with its trajectory

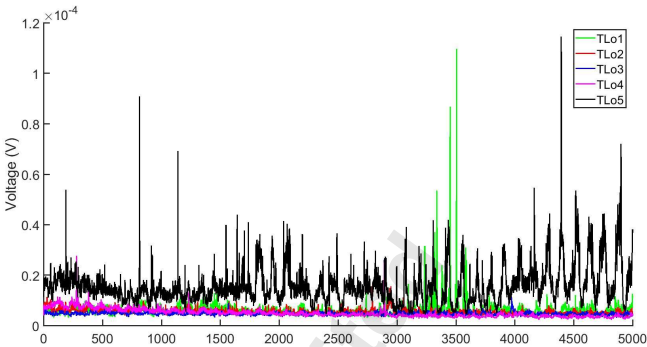


FIGURE 4. (a) RMS-filtered sEMG response of the Triceps Long (TLo) muscle of the five subjects' (X axis is # of samples)

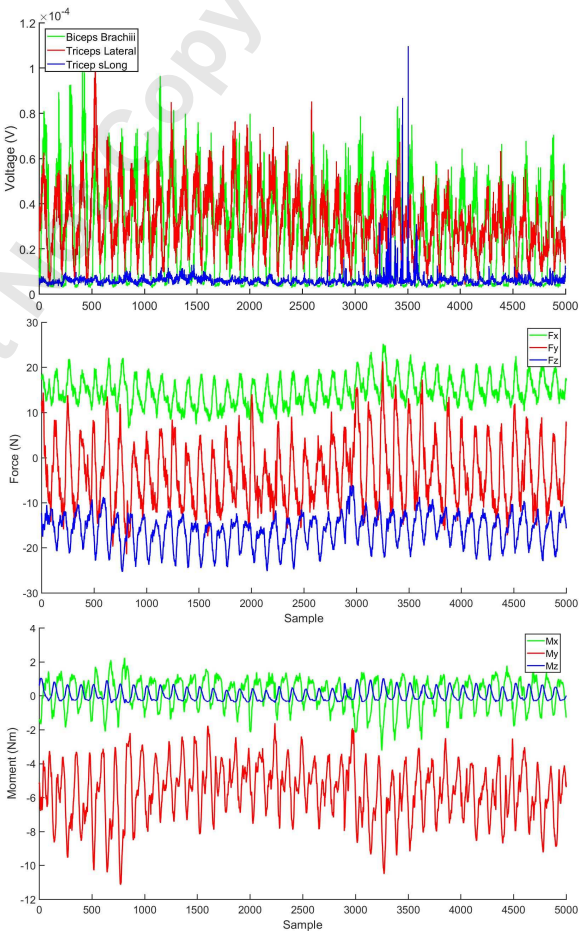


FIGURE 5. (a) RMS-filtered sEMG response of a subject's while straight arm is trained by UR5, (b) the measured interaction force and (c) moments

3.2 Correlation Analysis

The association between the directional forces and muscle responses have been analyzed based on the Pearson product-moment correlation criteria.

3.2.1 Correlation of force and couple components: In this study, we have analyzed the correlation and impact of each force and couple components for a better understanding and implementation. Such analysis is important to better define the process main parameters.

We used the Pearson’s Product Moment Correlation Coefficient ([27], [28]) given the ordinary distribution of the variables in the problem of interest. Preliminary analysis of data linking forces with EMG signals shows that the dimensionality of the vector of forces can be initially reduced by eliminating forces with high correlation (for example, in five subjects, we have found Fy and Mx have a correlation of = -0.99 (Fig 6), thus one of these parameters can be eliminated from the analysis). With that, key independent factors are recognized to be part of the correlation analysis as they are impactful towards identifying an effective model using reduced parameters. As shown in Fig 6, Mx and Fy are highly correlated in a reverse fashion. The same is applicable to My and Fz, as well as My and Fx with lower levels of comparability. This means My parameter could convey the effects of Fz and Fx on the model as we reduce the number of main factors. This demonstration indicates how three forces, three moments; and three EMG values of the targeted muscles are related within several training trails by five subjects. Moreover, by comparing the information between muscle activity level and Force/Torque data, it is noticed that TLo activity does not even have marginal correlation to any force or torque collected from the UR5. In other words, the selected training is not a promising way to engage TLo muscle fibers. In addition, Fx, Fy, Mx, and Mz do not have major association with BB and TL muscle activities as well. There is plenty of useful information embedded in the table that can be instrumental to therapists and physiologist as they prescribe a particular rehabilitative training method to better help the patients recover.

3.2.2 Correlation Between Interaction Forces and Muscle Responses: To administer the right task and interaction force control, understanding the interdependence of muscles and forces is required. For example, as it is stated earlier, the TLo correlation to any of the forces, as well as to other muscle groups, is minimal. An analysis of the relationship between forces and muscle activity shows significant differences between such relationships for different subjects, both in terms of patterns and variability. This supports the need for the more comprehensive data collection and analysis. Moreover, correlation of the EMG signals collected from each individual muscle group has been investigated to further observe how dependent muscle signals are from one another. This has been discussed for each individual subject (Fig.7 - Fig.11). For all cases except for one, TLo activity is more related to TL than to BB; which is reasonable as both are elbow extensors. Here it is confirmed that for virtually all cases, Fy and Mx intercorrelation is high enough to narrow them down to one representative factor. My and Fz are another

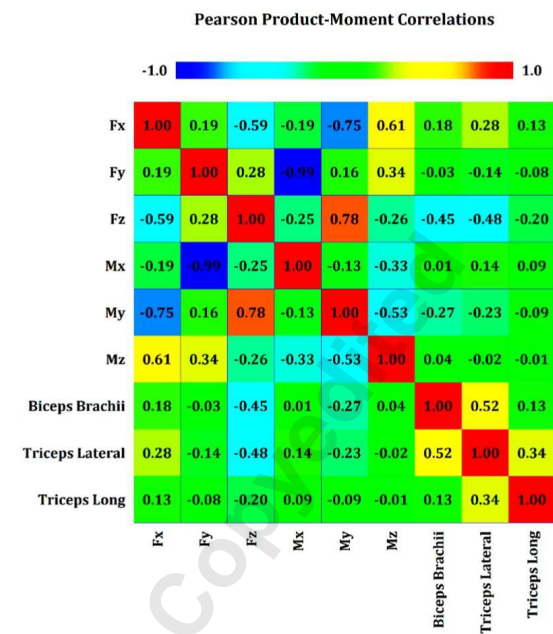


FIGURE 6. Correlation Between Interaction Forces and Muscle responses for five subjects

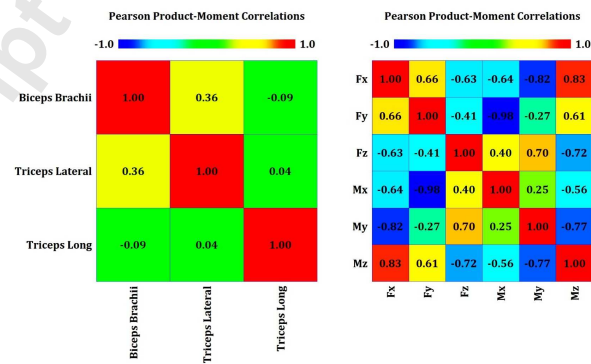


FIGURE 7. Correlation Between Interaction Forces/EMG the muscles for subject 1

pair of parameters that are somewhat correlated to one another; however, there are several others such as My and Fx that are usually of high correlation factor yet there is also inconsistencies at times. Integrated correlation table and individual correlation tables would help therapist to come up with a more robust and effective procedure for training and rehabilitation.

4 Trajectory and Muscle activity Correlations

This task is based on the rationale that if the effective trajectories and associated human-robot interaction force are known, we should be able to predict/estimate the corresponding muscle activity. This finding and prediction model can lead

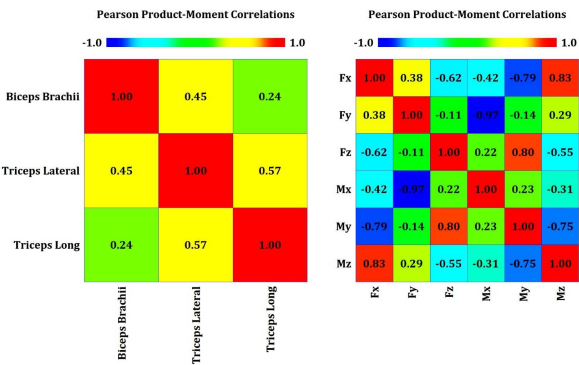


FIGURE 8. Correlation Between Interaction Forces/EMG the muscles for subject 2

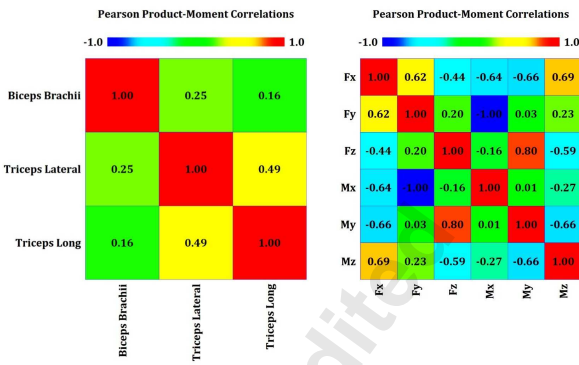


FIGURE 11. Correlation Between Interaction Forces/EMG the muscles for subject 5

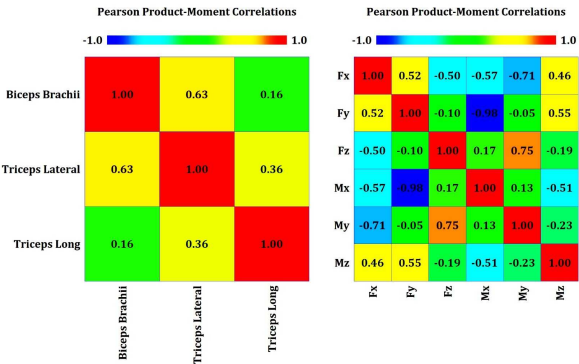


FIGURE 9. Correlation Between Interaction Forces/EMG the muscles for subject 3

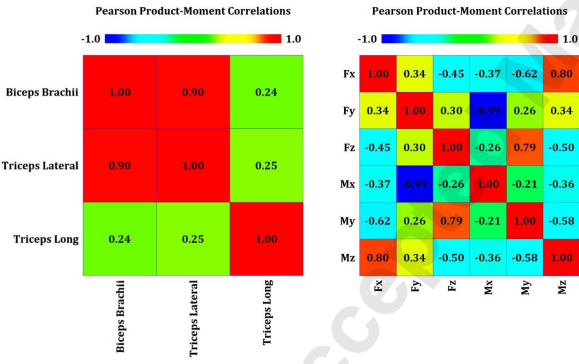


FIGURE 10. Correlation Between Interaction Forces/EMG the muscles for subject 4

to prescription-based rehabilitation. Once the effective trajectory/cloud points are identified, the implementation part will discuss controlling the robot. The robot can be programmed to pass

smoothly and safely through the selected cloud points in two ways: (1) systematically by feeding the points sequentially. This approach is good, especially when the effective cloud points formulate a quantifiable trajectory; and (2) to search cloud points based on maximizing the sEMG patterns. Following the experimental setup shown in Fig.3, another experiment has been conducted using three subjects to identify the impact of a trajectory on the muscle recruit and to demonstrate the idea. The overall idea is to propose an integrated approach that involves a trajectory with a desired interaction force to better recruit and positively affect the targeted muscle groups. In this experiment, two IMU sensors have been placed on the upper arm and lower arm so that one can measure the relative position and orientation of the whole limb for further investigations on the trajectory of proximal or distal limb, respectively. For this case, the data for the sensor on the upper arm close to the muscles has been utilized to be associated with their level of activity i.e. BB, TL, and TLo muscles (Fig.12). Fig.12 shows the IMU placement as well as cloud points marked as three subjects move their right arm through a constant circular path for the training exercise.

The captured EMG data for each muscle is associated with location of the motion tracking sensor and the speed of the robot as it loops through the circular path. After that, an appropriate threshold value has been selected and applied so as to filter out data points in the 3D workspace that are below that particular value; hence, remaining points represent those that are highly impactful on the designated muscle. This perspective provides a targeted trajectory within which we are confident that training will be more effective; such techniques lead to lower training duration delivering the same result that can help patients recover quickly. Fig.13, Fig.14 and Fig.15 illustrate the filtered EMG values for each targeted muscle while using color to convey the concept of effective trajectory and its influence on each muscle group.

Based on Fig.13, sections with more dense distribution of

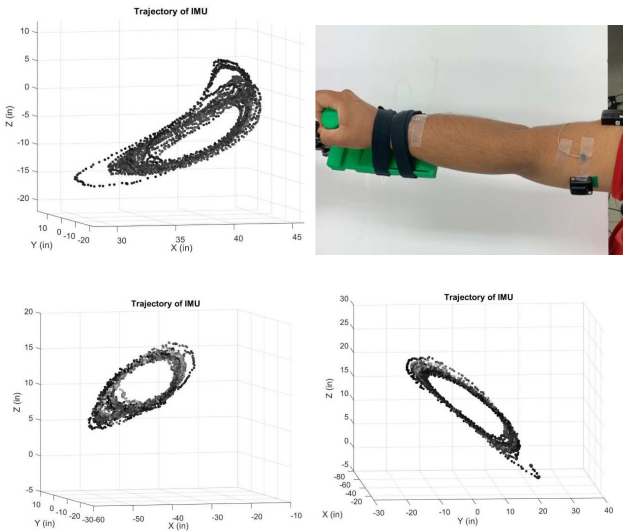


FIGURE 12. Trajectory of all three subjects

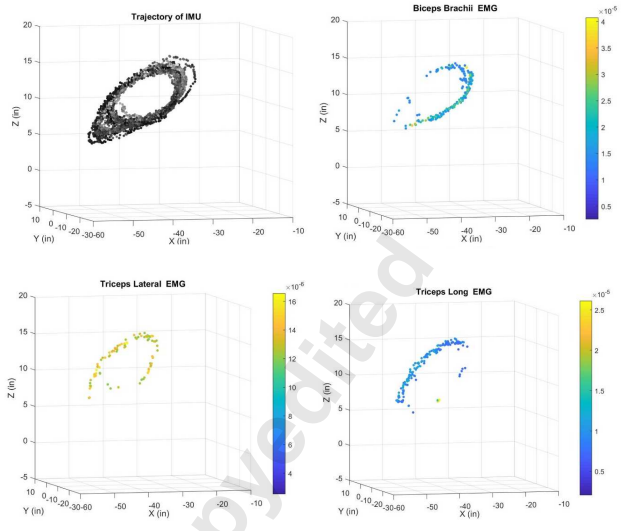


FIGURE 14. Effective trajectory based on the EMG signal of BB, TL, and TLo muscles for subject2

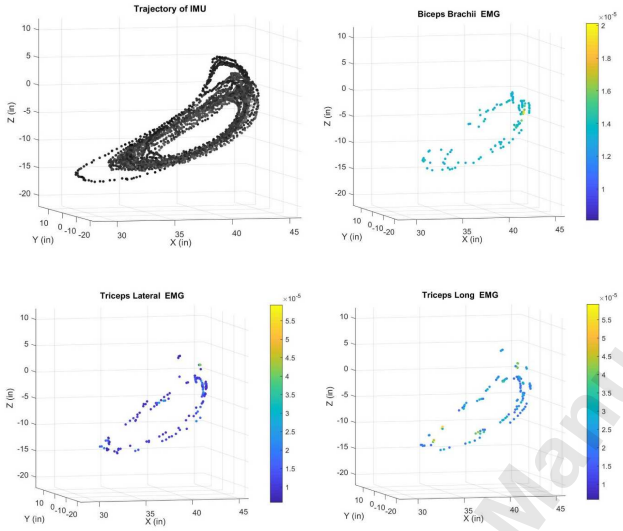


FIGURE 13. Effective trajectory based on the EMG signal of BB, TL, and TLo muscles for subject1

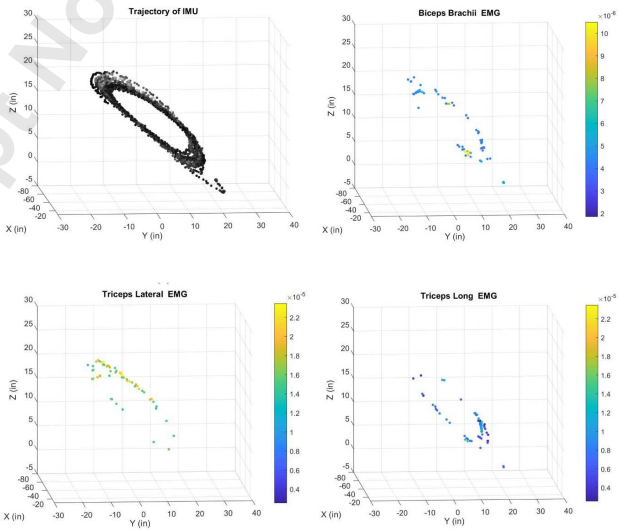


FIGURE 15. Effective trajectory based on the EMG signal of BB, TL, and TLo muscles for subject3

points imply that as the IMU on the upper arm pass through that region, the designated muscle experiences a higher level of recruitment. Therapists can use this information to design the therapy path. So as Fig.14 and Fig.15 indicate, the effective region is not necessarily similar for different muscles. In Fig.14, the upper left hand side of the loop is almost open which means moving the arm through that section of the loop does not contribute much toward triggering BB muscles. Same analogy holds for TL and TLo as lower parts of the loop does not have many designated point whereas the upper part where more points are concentrated. This indicates the productive region of the movement. This re-

gion is tremendously subjective as Fig.15 shows a different set of trajectory points as the most effective ones. This will help to provide a greater emphases while planning and controlling a robot to work within the part of the trajectory that have a better impact/influence on the muscle, and may potentially reduce the recovery time and associated rehabilitation costs by reducing the total duration of the therapy.

5 Implementation Strategy

Defining the desired, effective trajectory alone is not enough for a quick recovery of the patient. Acknowledging progresses made by the patients during an intervention is crucial while providing assistance when needed. Traditionally, the rehabilitation therapist manually assists patients in performing movements, providing only as much assistance as needed to complete the movement, i.e., "assist-as-needed". Researchers are attempting to automate this principle with robotic movement training devices and several robot control algorithms have been designed to automate the process [29, 30]. However, more investigation is still required to provide autonomy to the user by involving human physiological signals and motor unit activities in the loop, for both, operating the device and monitoring the level of recovery. EMG signals have shown promising results in controlling robots with correct human motion intention interpretation, and detection of medical conditions, such as level of injury and recovery [31].

This section is designed to provide a general outline for the implementation of the assist-as-needed strategy while following effective trajectory. The task involves system identification to relate muscle activity and interaction forces based on the outline shown in Fig. 16. The outline helps to engage the robots in an outcome-based rehabilitation protocol, which includes following the desired trajectories and actively learn from the real-time data to adjust its assistance during the interaction.

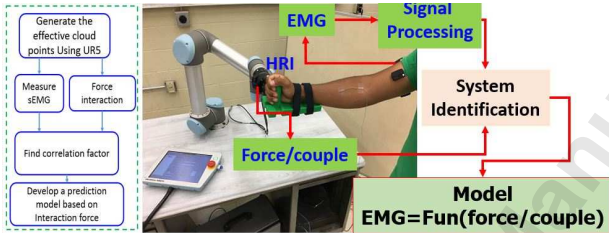


FIGURE 16. Model Prediction Outline

To implement the controller strategy, the kinematic and dynamics of the robot and the interaction force at the end-effector are required. The controller interface will have two main systems (i) task-planner and (ii) joint-torque control using inverse dynamics.

(i) Task-planner: The task planner module will send data (end-effector position and orientation) based on the intended task and the identified effective trajectories. The robot motion will be programmed using Python to command the robot to move as well as collect data from the robot. To achieve this online, socket communication, a TCP/IP protocol communication is created between the robot and the computer.

(ii) Joint-torque control: The inverse kinematics analysis will then be conducted to obtain the values of the angular position of the robot joints to satisfy the given end-effector trajec-

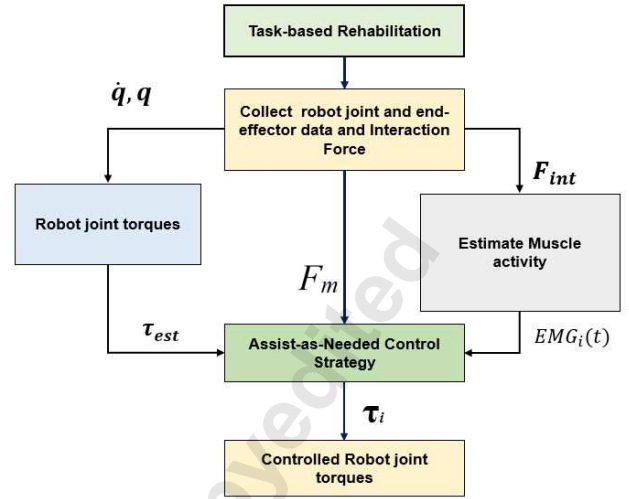


FIGURE 17. The assist-as-needed control strategy

tory. This allows to compute torques using the Euler-Lagrange Equation shown in equation 1.

$$\tau = M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + \beta[[J]^T[F_{in}]] \quad (1)$$

where $M(q)$ is the Mass Inertia Matrix of the system, $C(q, \dot{q})$ is the matrix that defines the Centrifugal and Coriolis forces, $g(q)$ is the gravity vector and τ is the Torque acting at the robot joints. $M(q)$ matrix is calculated using Equation 2.

$$M(q) = [\sum_{i=1}^n (m_i J_{v_i}^T J_{v_i} + J_{\omega_i}^T R_i I_i R_i^T J_{\omega_i})] \quad (2)$$

where J_{v_i} and J_{ω_i} are the linear and angular part of the Jacobian Matrix J_i .

The matrix $C(q, \dot{q})$ elements (c_{ij}) are calculated using the mass inertia matrix m_{ij} .

$$c_{ij} = \sum_{k=1}^n \frac{1}{2} \left(\frac{\partial m_{ij}}{\partial q_k} + \frac{\partial m_{ik}}{\partial q_j} - \frac{\partial m_{kj}}{\partial q_k} \right) \quad (3)$$

The gravity vector $g_i(q)$ is calculated as:

$$g_i(q) = \frac{\partial P}{\partial q_i} \quad (4)$$

This method takes into account the moment of inertia of the individual links and thus provides a more realistic representation of the motion. To implement the AAN support strategy, a dynamic scaling vector β to account the muscle activity and its correlation with the directional interaction force is used so that it can control the torque/power demand due to the interaction force (F_{in}). This interaction force has six dimensions, the three forces and moments in x, y, and z directions. The β value will keep the power/torque demand as needed at each major joints to gener-

ate the directional force as interface as needed for the targeted muscle. A higher value of β is needed during at the beginning of the intervention and a lower value of β is needed when the patient is recovering and contributing to the motion. For example, if more assistance is needed based on the predicted model or measured sEMG, the β value will be increased in the desired direction of force or moment to influence the total torque demand for the robot. For the specific task/trajectory, β can be set based on the correlation factor of the interaction force and targeted muscle, so that the highly correlated component of the load is maximized. Essentially, the β factor plays the element of compensation role which is the intent in AAN controllers yet it will be adjusted intelligently based upon the correlation analysis.

6 Conclusions

In this study, UR5 robot is utilized for an upper-arm task-based rehabilitation, and the interaction between the robot and the user's upper arm muscles has been analyzed based on task specific trajectories. Correlation analysis is utilized to capture the relationship between the force interaction and the muscle activities(sEMG) in the upper-arm, while following a circular path. Based on the preliminary result obtained from the five healthy subjects, the analysis has provided a good insight to infer the muscle activity in the upper-arm based on the force data. Highly correlated parameters suggest that they could be referred to as one representative factor which is the most effective and could serve as the main parameter when physicians are prescribing training and defining the procedure. Muscles with low dependencies will not be influenced by that particular configuration and driving forces must change so as to engage such muscles. Moreover, targeted trajectory approach will reinforce the idea of finding a robust yet constructive operation by selection of the optimized path and impact rehabilitative movements as well as the right dosage of applied force and other parameters that have already been assessed in correlation analysis. This result will layout a foundation to establish research strategies to understand how human muscles are recruited during a task-based robot assisted rehabilitation that eventually leads to a clear and concise rehabilitation prescription. For instance, after the predicted model is applied to the UR5 force input, having an outliers peak or continuous misalignment in the result may suggests that not only the robot is not helping the patient but also it has applied counter force to the arm which needs an immediate attention.

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