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MAGNI Dynamics: A Vision-Based Kinematic and Dynamic Upper-Limb Model for Intelligent Robotic Rehabilitation

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***Abstract*—**This paper presents a home-based robot-rehabilitation instrument, called "MAGNI[1] Dynamics", that utilized a vision-based kinematic/dynamic module and an adaptive haptic feedback controller. The system is expected to provide personalized rehabilitation by adjusting its resistive and supportive behavior according to a fuzzy intelligence controller that acts as an inference system, which correlates the user's performance to different stiffness factors. The vision module uses the Kinect's skeletal tracking to monitor the user's effort in an unobtrusive and safe way, by estimating the torque that affects the user's arm. The system's torque estimations are justified by capturing electromyographic data from primitive hand motions (Shoulder Abduction and Shoulder Forward Flexion). Moreover, we present and analyze how the Barrett WAM generates a force-field with a haptic controller to support or challenge the users. Experiments show that by shifting the proportional value, that corresponds to different stiffness factors of the haptic path, can potentially help the user to improve his/her motor skills. Finally, potential areas for future research are discussed, that address how a rehabilitation robotic framework may include multisensing data, to improve the user's recovery process.

***Keywords*—**Human-robot interaction, kinect, kinematics, dynamics, haptic control, rehabilitation robotics, artificial intelligence.

I. Introduction

A job or traffic accident, a misfortune even or an unforeseen stroke can lead to brain or musculoskeletal injuries, that impact motor and cognitive functions. Modern physical rehabilitation has proven to be instrumental in the ability to partially or fully heal patients with impaired motor capabilities. During the last two decades, the use of robotic instruments for upper-limb rehabilitation has increased as robot-based rehabilitation provides an accurate evaluation of motor recovery and automates simple tasks that burden caregivers. Nowadays, as the number of people that require physical rehabilitation has increased, the need has arisen to create low-cost home-based robotic instruments that are simple, acceptable and provide easy monitoring, smart assessment, and adaptable training [1]. However, an element that is poorly designed in the current rehabilitation robotics systems is the incorporation of the user in the robot's control loop, to provide personalized and adaptable training. To achieve that we present an accurate and safe motion analysis system that does not rely on wearable sensors [2]. The system estimates the user's force/torque state which can be used as a visual feedback to the robot's control loop system. Moreover, the system can be used by physicians and occupational therapists to monitor the physical state of the patient's upper-limb, while performing repetitive exercises. To prove the intellectual merit of the algorithm, we validate our previous kinematic and dynamic estimation system [3] by utilizing electromyographic signals from the Delsys [4] device and by correlating the electromyographic values with torque estimations.

Due to the increasing number of senior patients that require physical rehabilitation, there is a growing need for therapist and nurses that are able to provide home-based assistance and training. In our work, we proposed to automate the physical rehabilitation by building a robotic system that introduces home-based robotic instruments. In Fig. 1, we envision a home-based rehabilitation system that consists of a robotic arm, a monitor system, such as a depth camera, and a virtual reality exergame system that displays instructions, as well as allows communication with the therapists.

In the field of rehabilitation robotics, there are two types of robots developed for upper extremity exercises, the end-effector and the powered exoskeletons devices [5]. The end-effector robots were the first devices to be implemented and tested in stroke rehabilitation research due to their straightforward design. On the other hand, the powered exoskeletons carry the distinct advantage of enabling both accurate measurements of the torques that affect each joint, as well as the precise recording and monitoring of motion

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[1]MAGNI is the God of strength in Norse mythology

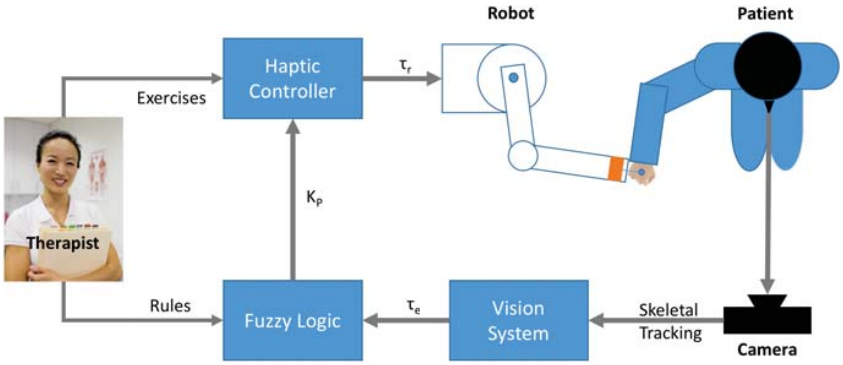


Fig. 1 Proposed home-based robotic rehabilitation system

trajectories in joint space [6]. Unfortunately, the powered exoskeletons constrain the user's range of motion due to their complex configuration. In our work, we utilize the Barrett WAM manipulator [20] for its advanced mechanical structure and high haptic resolution in conjunction with the Kinect skeleton tracker [21] to achieve highly dynamic adaptation, force feedback and torque sensing to deliver an unobtrusive, safe and guided physical therapy system.

As seen from Fig. 1, the system is consisted of the following components: The RGBD camera sensor that provides skeletal tracking information, which is fed into the proposed vision system. Note that this system is thoroughly analyzed in our past work [3], [23]. Furthermore, the estimated torque (τ_e) of the user is passed to a fuzzy controller. The fuzzy controller acts as a high intelligence system that shifts the gains (K_P) of the haptic controller, according to some abstract rules that have been defined by the therapist in a linguistic manner, and the performance of the user. As a result, the fuzzy intelligence system adjusts the control input signal (τ_r) of the robot to provide adaptive/assistive training.

II. Related Work

Joint torques are of main importance for physicians and occupational therapists to analyze the effects of rehabilitation and to obtain an indicator of patient's functional capacity to perform a motion [7]. A joint's strength is assessed through the measurement of the maximal joint torque, which represents the resultant action of all muscles crossing the joint. Manual muscle testing (MMT) is a measure of upper and lower body strength that occupational and physical therapists often complete as part of a clinical evaluation and to measure progress in therapy. MMT is a graded scale (typically on a scale from zero to five) that is used to assess patients with neurological or orthopedic impairments [8]. A score of zero indicates that there is not any muscle contraction to five indicates that strong pressure can be applied. Many issues arise because MMT can be subjective based on many factors. The validity and reliability of MMT are dependent upon a variety of factors including training of the therapist; the patients diagnosis, pain level, and other physiologic issues; which muscle is tested; the position of the patient; hand placement of therapist during testing; and variability between therapists [9].

The rehabilitation therapists may change the parameters of the exercise or activities (commonly referred to as grading) between or during treatment sessions, based on confounding patient factors such as pain or fatigue [10]. For example, the therapist may change the number of repetitions, the number of sets, and/or the amount of resistance given to the patient. These parameters may remain consistent over time or need to be changed during each session based on the patients performance and muscle fatigue. Multiple researchers have attempted to generate models for muscle fatigue based on joint torques and muscle contraction levels. For example, the authors in [11] utilized electromyographic data and derived an analytical muscle model, taking into account physiological and anatomical data, to estimate the joints' torque. This model helps them to generate joint torques and stiffness values while the user is interacting with a rehabilitation instrument.

One simple exercise in rehabilitation is to repetitively follow pre-described trajectories to help users strengthen their weakened muscles or regain motor control. A haptic path can be defined as a virtual tunnel that uses force feedback to help users move through that path or constrain them from deviating in other directions. The authors in [12] use gait trajectories to help users while doing exoskeleton gait training on the treadmill. They proposed a haptic controller designed to be 'assist-as-needed' system, which can apply suitable forces on the patient's leg to help him move on the desired trajectory. Similarly, in upper limb rehabilitation, [13]-[15] tracking the performance and progress of the users, can be achieved by comparing their measured trajectories with the Dynamic Time Warping (DTW) algorithm [25]. The literature has shown that haptic feedback/guidance can help the users improve their tracing abilities by following a prescribed trajectories [16], [17]. This haptic feedback can be by probing the user's hand through the path or by providing perpendicular forces that prevent the user's hand to deviate from the desired path.

A considerable amount of research has been conducted to implement a robotic rehabilitation system that adapts its behavior according to the patient's performance and physiological state. Rajibul et. al. [18], have presented preliminaries studies in developing a fuzzy logic intelligent system for autonomous post-stroke upper-limb rehabilitation. In their work, an intelligent system estimates the muscle fatigue of the patient and tunes the control parameters

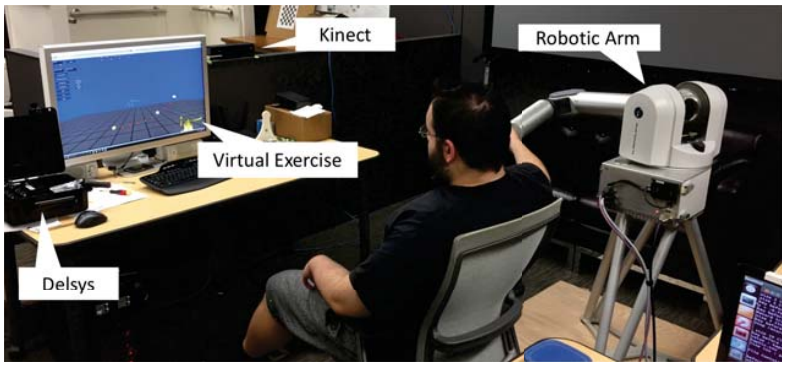


Fig. 2 Robot-based Rehabilitation system

to generate different haptic effects. Badesa et. al. [19], have incorporated multisensory data in the control loop to adaptively and dynamically change in real-time the therapy. The aforementioned results demonstrate the potential to create a fuzzy system that adapts the robot's behavior and delivers personalized rehabilitation sessions. Similarly, in our work, we incorporated a fuzzy logic module that controls the haptic forces which are exerted upon the user.

The following sections of the paper are dedicated to the thorough analysis and representation of the proposed intelligent rehabilitation system. In Section III we recap the algorithm that is used by the proposed vision system and we justify the correctness of each estimation. Moreover, in Section IV, we present the developed haptic force-field impedance controller and we test its application with an chronic stroke patient and an unimpaired user. Lastly, we provide some future discussion on how to make this robotic framework capable of making decisions that would improve the user's performances over time.

III. Human Arm Kinematic and Dynamic Vision System

A. Algorithm

At this point, we would like to recap our previous work [23] that used a biomechanical model and the Kinect depth camera to reconstruct upper-limb kinematics and dynamics in the joint space. Algorithm 1 presents the steps for the extraction of the human arm kinematics and dynamics from a Kinect camera. As an input, the system must capture the person who is performing the exercise with the Kinect, according to the configuration that Fig. 3 suggests. Once the trajectory of the subject's arm has been captured, the Kinect passes the cartesian positions of the chest, shoulder, elbow and wrist frames to the first unit of the system.

The system then applies a median filter to the Kinect data to eliminate any abnormal behavior from the skeleton tracking algorithm of the Kinect. The result of this module produces a smooth cartesian trajectory that is used by the Inverse Kinematics Solver (IK Solver) to provide an estimation of the angles of the human arm joints. Afterward, the system produces the first estimation in joint space. In the next iteration, the system makes sure that all data in joint space are characterized by a polynomial profile function. This happens because the motion of all rigid bodies, such as our Kinematic Model, must be expressed with a polynomial function that can produce a second, third or even forth derivative (jerk) [24]. Lastly, as an output, the system provides an estimation of the torques that affect the subject's arm with the RNE method. Interested readers can read our previous work, which explains in great detail the formulation of the forward and inverse kinematics equations [3].

Algorithm 1 Steps to calculate human arm dynamics using Kinect camera system and a robotic arm

1: **INPUT1**: A sequence $\{P_t\}_{t=1}^{N}$ of frames recordings from Kinect, where each $P_t = (P_{W_t}, P_{E_t}, P_{S_t}, P_{C_t})$ consists of the cartesian position of the wrist, elbow, shoulder and chest.
2: **INPUT2**: Import user height and weight and extract anthropomorphic data for the human body segments for the length and mass of the upper and lower section.
3: **INPUT3**: Add the external forces ${}^{B}f_{robot}$ from the robotic arm that are exerted to the user's wrist.
4: Reconstruct a raw model from the captured $\{P_t\}_{t=1}^{N}$ frames according to the proposed kinematic model using the Homogeneous transformations of our previous work [3].
5: Apply a moving median filter to the raw position data.
6: Utilize the proposed Inverse Kinematics (IK Solver) to generate an estimation of the joint angles $\{\theta_r(t)\}_{t=1}^{N}$ and $r = [1, ..., 4]$
7: Apply a higher-order polynomials to the $\theta_r(t)$ in order to fit the joints estimation $\theta_e(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5$ to the trajectory sequence (exercise).
8: Generate estimated angles: $\{\theta_e(t)\}_{t=1}^{N}$ and $e = [1, ..., 4]$
9: Recreate the kinematic model according to the forward kinematic equations as per [3].
10: Apply the Recursive Newton-Euler [22] dynamics algorithm (RNE) and propagate the external force ${}^{B}f_{robot}$ from the robotic arm to the user wrist joint.
11: **OUTPUT**: Export the human arm joint velocity, acceleration and torque profiles $(q, \dot{q}, \ddot{q})$ for the recorded trajectory sequence with the applied forces of the robotic arm.

B. Experimental Setup

In order to fully validate that the torque estimation derived by our biomechanical model is correct, we conducted a series of experiments that involves primitive arm movements that isolate the shoulder axis and muscle activations. Fig. 4 shows

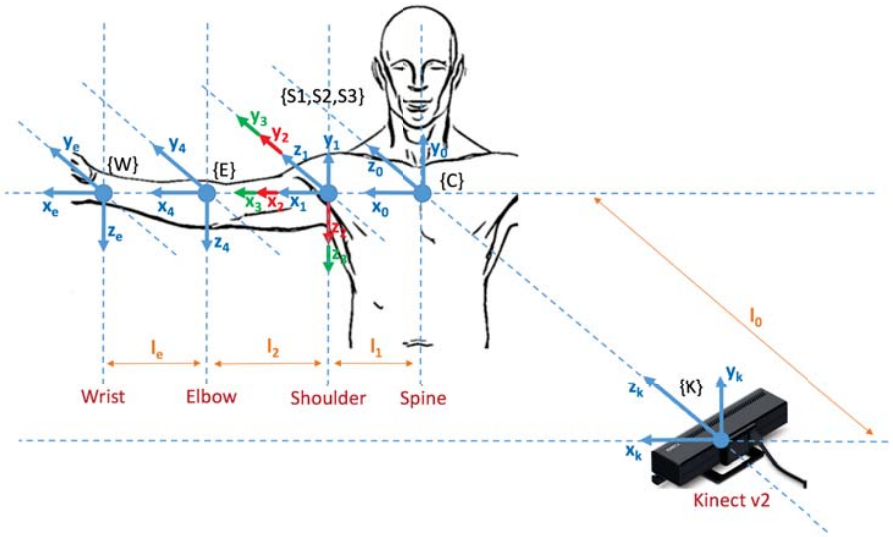


Fig. 3 4 DoF Kinematic Model of the Human Arm

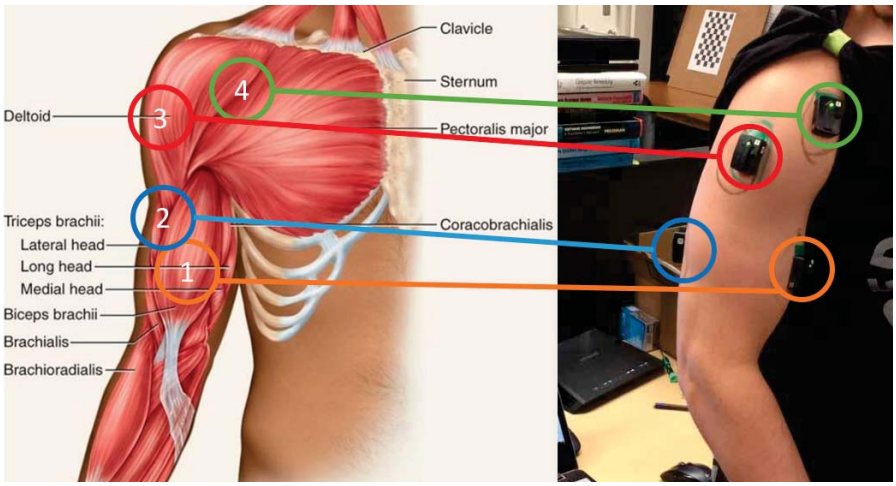


Fig. 4 Muscles to sensor placement

the Delsys sensors placement in the user's arm and the muscles area that are associated.

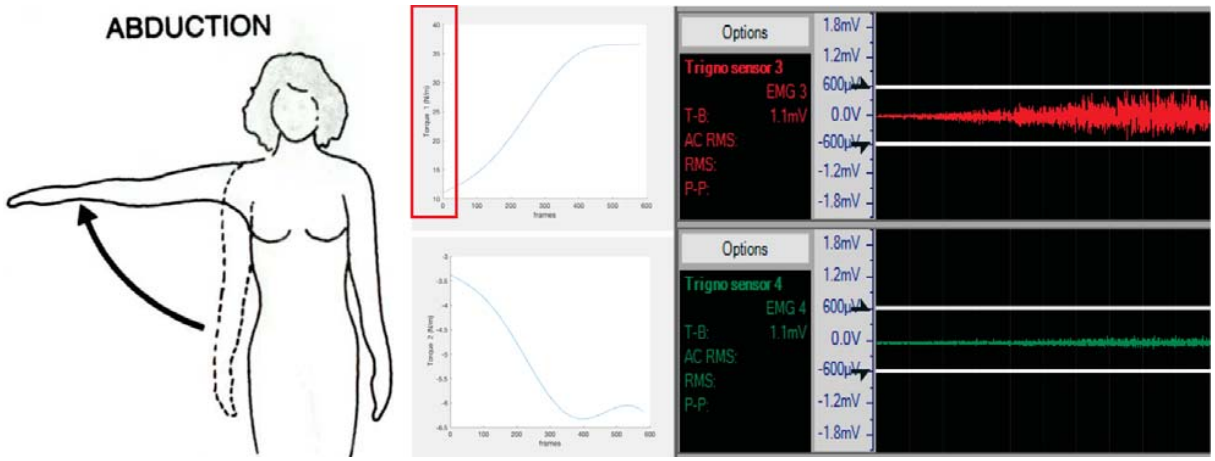
Our initial goal is to correlate the joints' frame placement, according to Fig. 3, with the muscles that are triggered and move the shoulder at each axis. For this reason, sensor 3 has been placed on the Lateral Deltoid muscle, sensor 4 has been placed to the Anterior Deltoid muscle area, connecting to the clavicle, and sensor 1 and 2 were placed to the biceps and triceps respectively. The exercise that is first chosen is the shoulder abduction (Fig. 5a). This allows the first frame of the shoulder to rotate along axis z_1 in the positive direction. The second exercise is the shoulder forward flexion (Fig. 5b) that allows the second shoulder frame to rotate along axis z_2.

From the experimental results, in Fig. 5a, it is obvious that the first exercise triggers the third sensor more which correlates the deltoid's muscle movement. The torque values of the frame 1 at the beginning are close to 11 N/m and when the shoulder is fully abducted they reach 36 N/m. For the frame 2, the absolute torque values increased slightly exactly like the correspondence muscle contraction (sensor 4).

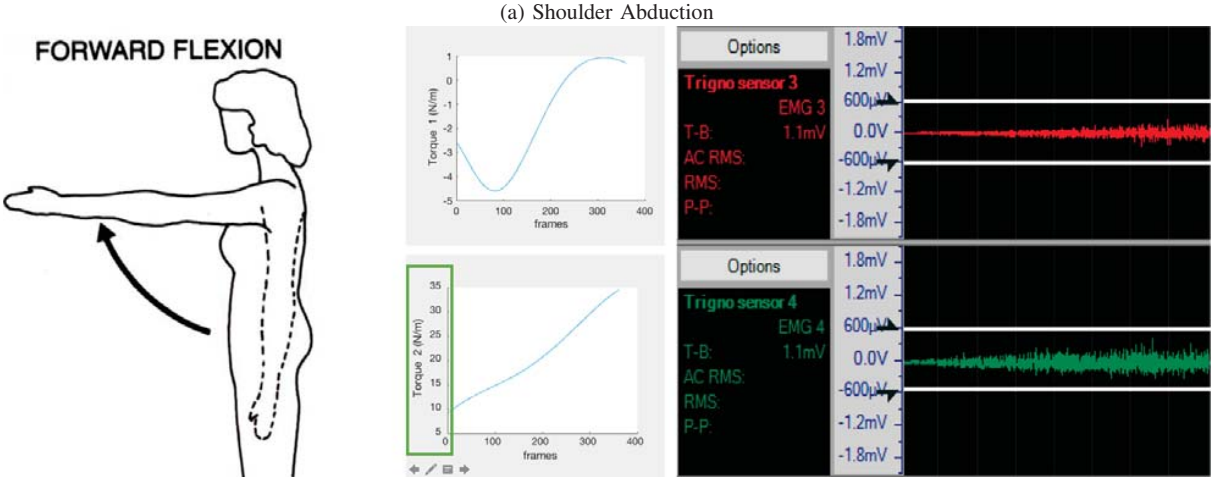
The second experimental results (Fig. 5b) show the opposite torque value estimation which corresponds with the muscles' activation. The torque values of the second frame are increased from 9 N/m to 34 N/m relatively as sensor 4 jumps. The frame 1 torque values show some discrepancy but this is caused because of the axis z is crossed while the user is flexing forward his arm. Also, sensor 3 is reacting to this motion as the deltoid muscle is triggered slightly. It should be mentioned that is difficult to isolate the muscle's activation at the shoulder as they are wrapped together to help the shoulder's rotation to the three axes.

C. Experimental Analysis

To analyze the electromyographic (EMG) data, the collected signal was first filtered. Filtering was done in 3 stages: High Pass filter, Low Pass filter and Notch Filter. A butterworth



(a) Shoulder Abduction



(b) Shoulder Forward Flexion

Fig. 5 Experimental results for the Shoulder Abduction and Shoulder Forward Flexion Motions

filter was used to design these filters. The corner frequency of the high-pass filter was 10 Hz while the corner frequency of the low-pass filter was 500 Hz and the frequency of the notch filter was 50 Hz. This process removed any noise below 10 Hz, above 500 Hz and at 50 Hz.

After the filtering process, the peaks of the EMG were found. These peaks were used to find a relationship between the torque extracted from the Kinect data and the EMG extracted from the Delsys. We used the inbuilt peak detection function in MATLAB to detect the peaks. Furthermore, both the EMG and the torque data were downsampled to 1 HZ, resulting in one data point per second. This was done for EMG data too. Peak data at each second was calculated as the mean of the EMG peaks for 500 ms on either side of the second mark.

Lastly, the relationship was found by using Kendalls Rank Correlation method. This is a nonparametric correlation method. It operates by assigning ranks to each datapoint and calculating the concordant and the discordant pairs. Consider a data point in a set, any data point below the considered one is assumed to be a concordant pair if the rank for the new data point is smaller than the rank for the considered data point. It is a discordant pair if the rank for the new data point is greater than the initial data point. Kendalls correlation calculates τ by using the following formulae:

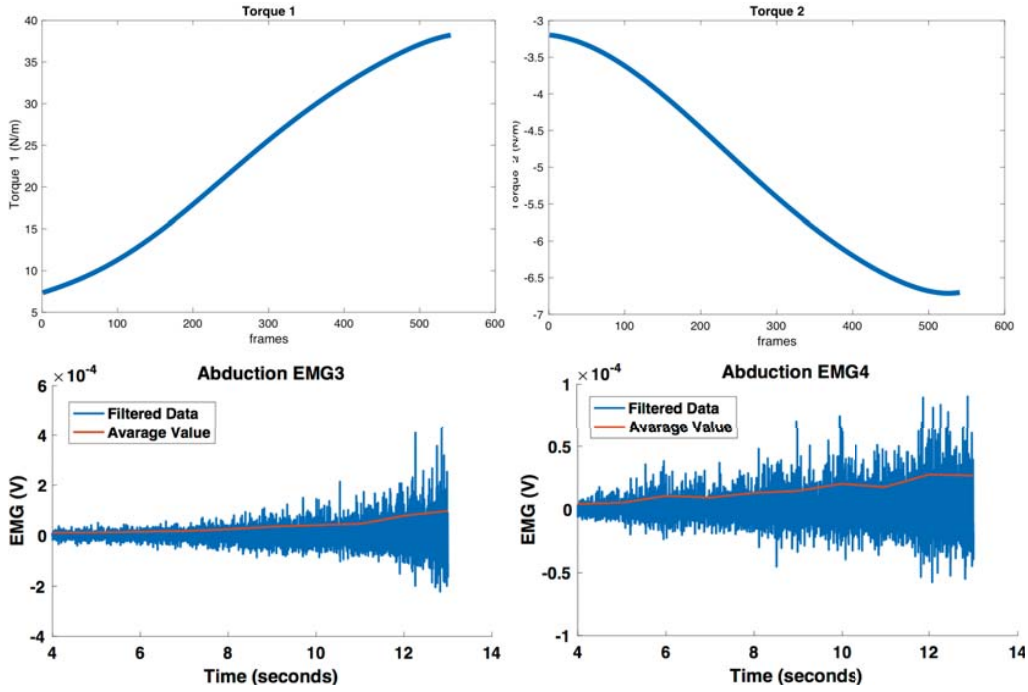
$$\tau = \frac{\sum D - \sum D}{\sum D + \sum D} \quad (1)$$

where C are the Concordant Pairs and D are the Discordant Pairs. This yields a value between -1 and 1 where -1 indicates a strong negative correlation and '+1' indicates a strong positive correlation. 0 indicates no correlation.

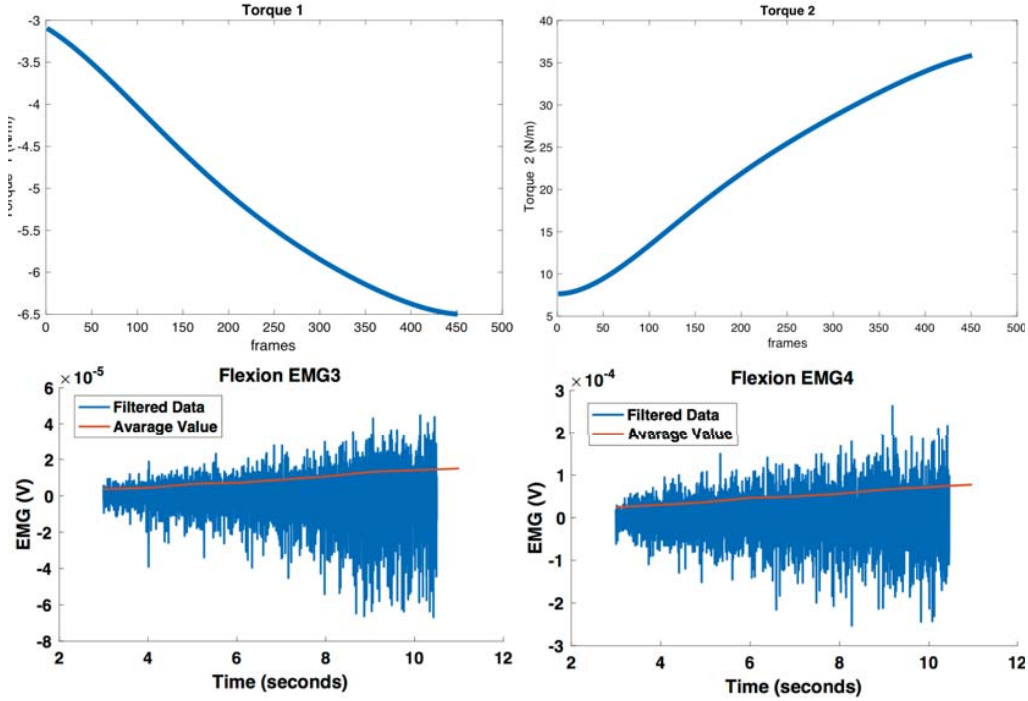
Figs. 6a and 6b show the opposite correlation of the torque values estimated by our biomechanical model and

TABLE I
CORRELATION VALUES BETWEEN TORQUE AND ELECTROMYOGRAPHIC SIGNAL

Exercise	Sensor	Tau	P
Abduction	*EMG3*	1	5.51E-07
	EMG4	-0.82222	3.58E-04
Forward	*EMG3*	-1	4.96E-05
Flexion	*EMG4*	1	4.96E-05



(a) Shoulder Abduction



(b) Shoulder Forward Flexion

Fig. 6 Experimental Analysis for the Shoulder Abduction and Shoulder Forward Flexion Motions

the electromyographic filtered signal after the analysis. These results confirm our hypotheses for torque estimation per axes with the isolated muscle to electromyographic data analysis. Specifically, in Table I we can see that the correlation values for the shoulder abduction motion give $\tau = 1$ and $\tau = -0.82222$ for the EMG3 and EMG4 respectively. This means that the $torque1$ value has linear increasing rate such as the EMG3 signal. On the other hand, $torque2$ value follows closely the linear decreasing of the signal. An analogous trend is observed in the shoulder forward flexion EMG and torque correlation graph (Fig. 6b), because the increments rates are opposite. Thus, we can justify the torque values and claim that our biomechanical model can be used for shoulder torque estimation in rehabilitation exercises.

IV. Haptic Path

In this work, the robotic arm can help guide the user to follow a precise trajectory as dictated by previously recorded exercises done by a physical/occupational therapist. The user can attempt to perform the prescribed exercise and if he/she deviates from the prescribed trajectory, an appropriate correctional force is applied by the robotic arm to guide him/her back to the correct trajectory. Besides spatial, the deviation can also be temporal, i.e. the user performs the exercise much slower or much faster than the therapist. When either of the two deviation types occurs, an error-correction force is applied to bring the patients hand position closer to the prescribed trajectory.

A. Haptic Forces

In order to assist the user to stay close to a prescribed path in the 3D space, a force-field (Fig. 8a) is rendered from the given start position ${}^{B}p_{start}$ to the end target position ${}^{B}p_{end}$ of the path, as Fig. 8b depicts. If the user deviates from the given path, a perpendicular force will be applied in order to push the users arm to stay close to the path. At each moment, the robot's end-effector position ${}^{B}p_t$ searches for the closest point at the haptic path. The direction and magnitude of the force in the end-effector position ${}^{B}p_t$, is calculated by the ${}^{B}p_N$ point and the absolute distance d_t respectively.

The haptic path has been reconstructed with the use of an impedance control mechanism that controls the position of the robot's end-effector (${}^{B}p_t$) at the corresponding trajectory point (${}^{B}p_{NN}$). The impedance control aims to increase or decrease the compliance (stiffness) of the robot in order to allow the user to deviate more or less from the predefined trajectory. This stiffness values (K) constrains the user to the trajectory and acts as the spring constant. The force generated (f_t) is equivalent to $f_t = K \times d_t$. The proportional gain (P) that represents the stiffness of the force-field of the impedance controller, behaved similarly to the K spring constant value. By changing the P value we are able to bring the patient's hand closer to the therapist's prerecorded trajectory.

B. Haptic Control

The control chart of the proposed control system can be found in Fig. 7. The Barrett WAM robot is directly interacting with patients arm τ_p. All motion parameters that associate the kinematics of the robot are measured with internal sensors. In our case, the measurements are provided through the Barrett WAM's Puck sensor that operates in 500 Hz. The forward kinematics of the robot is used to calculate the actual end-effector position, which is fed into the visual interface implemented in the Unity 3D game engine. This provides a visual feedback about the end-effector's trajectory as well as the start position p_{start} and target position p_{target} that defines the haptic path. This information is used to calculate the nearest neighbor point p_{NN} on the path and the tangential vector $f_{assist/resist}$ by means of the end-effector position. The transposed Jacobian $J^T(q)$ is used to calculate the corresponding joint torques τ that accelerates the robot. Additionally, the compensation model τ_{comp} which is consisting of the friction, gravity and spring compensation module, provides the necessary torque to keep the arm stationary.

C. Haptic Experiments

In order to test the compliance of the impedance controller, we recruited one chronic stroke patient and we conducted three experiments with different proportional values. Then, we analyzed the effects of the haptic controller by using the Dynamic Time Warping method to derive spatial or temporal error deviations in the user's cartesian trajectory. Figs. 9a and 9b illustrates the Cartesian position in the plane during the haptic path exercise. In particular, the desired trajectory is shown with red targets to the stroke patient (Virtual Exercise) (Fig. 2) and is represented by the red line in Fig. 9a. The stroke patient was instructed to perform each exercise (Haptic path) with the best of his abilities and try to reach all the red virtual targets.

D. Haptic Response

Three exercises were performed with the stroke patient with small breaks of 5 minutes (Fig. 9a). In the first, exercise (A) the stroke patient was unassisted ($P = 50$) and his error deviation was $error = 4.9114$. At the second execution (B), the stiffness value of the impedance controller was ($P = 100$) and the stroke patient's error trajectory deviation from the prescribed path was $error = 0.65122$. Finally, we increased the robot's assistance (C) with ($P = 800$) and he managed to execute the exercise correctly ($error = 0.22548$).

Similar experiments were conducted with an unimpaired user. In Fig. 9b the user's performance did not change drastically as he manages to control the motion of his hand successfully and his error deviation is getting better as long the robotic arm constrains him to the prescribed trajectory. It is clear that when the applied rendered forces constrain the users to the prerecorded exercises, the error deviation is getting smaller. This phenomenon implies that patient will be able to increase hand coordination and improve motor skills with the passage of time.

V. Conclusions and Future Work

In this work, we presented an unobtrusive home-based rehabilitation system that consists of an RGBD camera, an

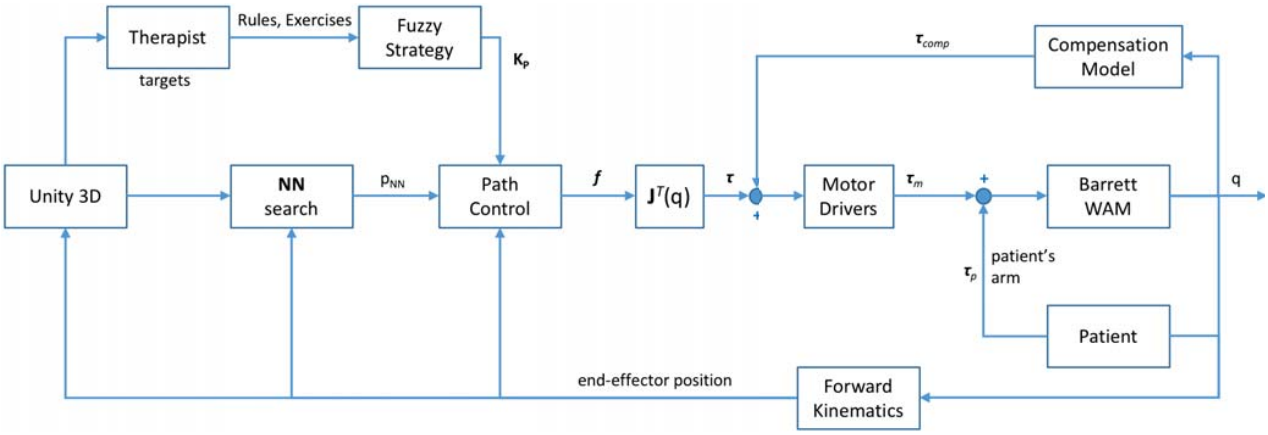
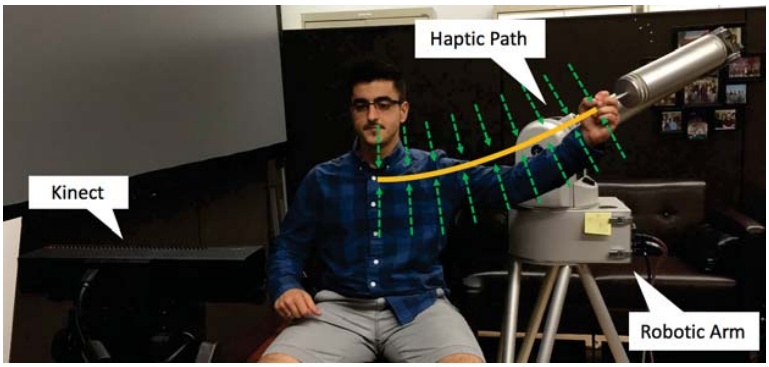
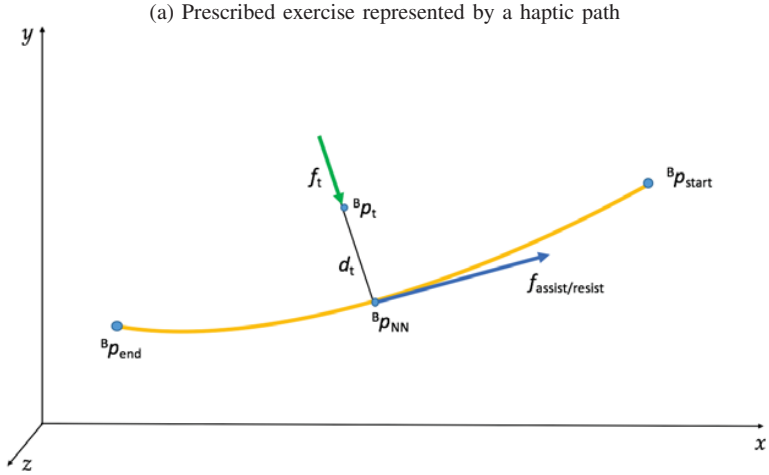


Fig. 7 Control chart of the impedance haptic path controller implemented in the Barrett WAM robot

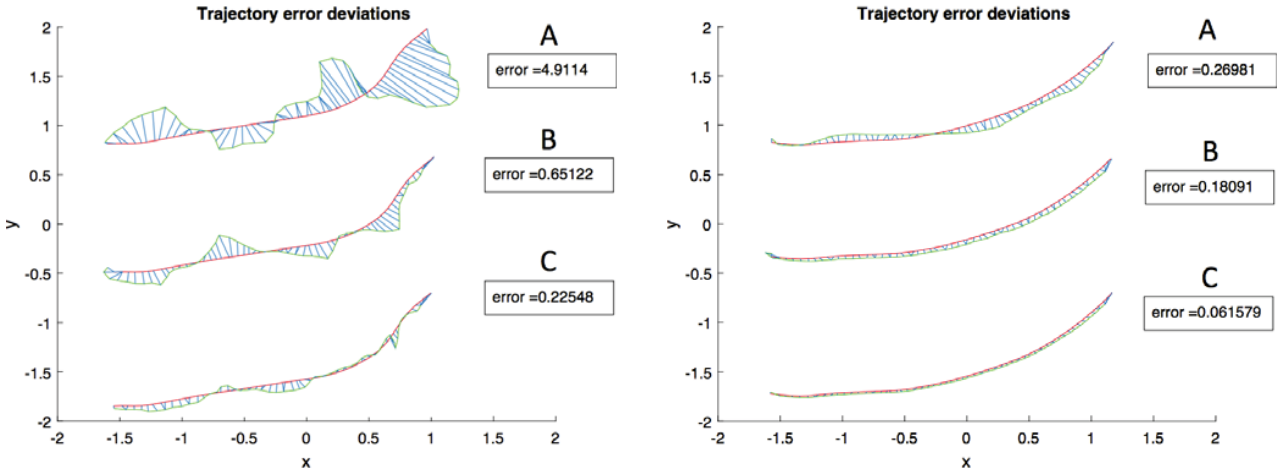


(a) Prescribed exercise represented by a haptic path



(b) Prescribed exercise represented by a haptic path

Fig. 8 Prescribed exercise represented by a haptic path



(a) Stroke patient (b) Unimpaired user

Fig. 9 Error deviation for three difference proportional values: A) P = 50; B) P = 100; C) P = 800

end-effector robotic arm, an intelligent control module that allows therapists to change the input parameters, and a haptic controller that adjusts the control input signal of the robot. Particularly, we validate our previous proposed vision-based system with electromyographic signals from the Delsys device for primitive motions. Furthermore, we investigate the developed haptic controller's response in exercises performed with a chronic stroke patient and an unimpaired user.

In the future, we plan to integrate our home-based robotic rehabilitation system with multisensory data coming from physiological sensors, such as the Microsoft Band. These data will estimate the user's arousal and muscle fatigue in real-time using a hierarchical fuzzy logic controller. It is estimated that such a multisensing upper-limb intelligent rehabilitation system will be able to adapt the robot's behavior and deliver personalized rehabilitation sessions.

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