Simplified EMG-driven Model for Active-Assisted Therapy*

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***Abstract*— Home-based motion therapy assisted by a mechatronic device is a new alternative for patients that must undergo rehabilitation therapy but cannot regularly visit a health care center. A mechatronic rehabilitative device must include a sensing system that provides feedback and quantifies the effort required to move a limb. A simplified EMG-driven model was designed to address this need. The hypotheses were that 1) the sum of neural activation from the biceps and triceps muscles can show good correlation with forearm flexion–extension movements, and 2) data from a motion sensor can be used to correct the prediction. The proposed EMG-driven model was tested in real time to determine the prediction accuracy of motion profiles provided by twelve healthy subjects. The model accuracy across subjects (97.4–98.6%) and across different types of exercises (97.9–98.4%) is within the required tolerance (96–100%). The model replicates each subject's motion trajectory with high correlation (0.99–1.00). The error of prediction is equal to the sensitivity of human joint positioning. Thus, reported results indicate that the simplified model has achieved the desired goal accuracy for rehabilitation purposes.**

***Keywords*— electromyography; EMG-driven model; elbow; biceps; triceps; rehabilitation.**

I. Introduction

Joint related pathology can involve connective tissues, bones, nerves, muscles and tendons. Despite the variety of joint lesions, physical therapy modalities and postoperative therapeutic exercise play an essential role in the rehabilitation of joint injuries. Treatment includes (a) passive movements that are done by a therapist or with the help of a continuous passive motion (CPM) machine and (b) active programs that are performed at health care centres or at home. Although CPM machines and orthotics with rubber bands or springs are effective for joint rehabilitation, they are inappropriate for patients that are at the active-assistive stage of rehabilitation. Active-assistive range-of-motion exercises are generally prescribed for 3–4 weeks in total [1]. Despite the benefits of rehabilitation, many patients are not compliant with their rehabilitation program due to the need to travel long distances to medical centers, social responsibilities, forgetfulness, lack of motivation, boredom and/or lack of instant feedback [2]. Thus, a promising option for this group of patients may be a home-based therapy assisted by a mechatronic device (smart brace, orthotic or exoskeleton) that 1) maintains patient motivation and 2) monitors and measures movements outside the clinical setting. To address these two needs, a mechatronic device should include a sensing system that provides feedback and quantifies the effort required to move a limb. A safe and noninvasive way to measure this effort is through electromyography (EMG) sensors.

EMG-driven models quantify upper arm muscle activity in order to predict elbow motion and force [3–14]. A device employing such models can send predicted motion profiles as commands to the actuators to assist in the movement. Nevertheless, due to the complexity of the models, their associated long calibration processes and resulting low accuracy, the current approaches cannot be used for motion-based rehabilitation. Thus, there is a need for a simple EMG-driven model for elbow motion rehabilitation.

The aim of this paper is to describe a test case of a proposed EMG-driven model for upper limb motion prediction. The validation process was designed for upper arm muscles that perform elbow flexion–extension (FE). As human limb positioning and movements are controlled by receptors with specific precision, the goal of this research is to predict the motion with sensitivity equal to that of human joint positioning.

II. EMG-Driven Model for Elbow Rehabilitation

A. Goals and Requirements

The objective of this project is to validate a simplified EMG-driven model that predicts subject's motion for people that need support when lifting their forearm during active-assistive motion therapy. The sensitivity of joint position sensing for the elbow is 2 degrees [15]. This was confirmed by an expert who stated that elbow FE position error can vary between 2 and 5 degrees. As an elbow's range of motion (ROM) is 0–130°, the error of limb positioning can be between 96–98.5%, corresponding to 5° out of 130° (equivalent to 96% accuracy) and to 2° out of 130° (equivalent to 98.5% accuracy).

The model was designed to deal with active-assistive motion therapy that requires slow elbow motion (average speed of 15°/s). At the end of a rehabilitation program, a patient should be able to lift at minimum a 1-kg load during the elbow FE motion. Thus, from the combination of the slow

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speed and the 1 kg of load, it is concluded that the goal accuracy should be performed for low torques. For anthropometric data for males and females at the 95th percentile [16], the maximum torque required to overcome gravity is 11.3 Nm and 8.4 Nm respectively. Therefore, the proposed model is expected to accurately mimic a motion profile for a torque range of 0–11 Nm.

B. Simplified EMG-Driven Model for Elbow Rehabilitation

Over the past 5 years, several research groups have developed EMG-driven models that quantify upper arm muscle activity to predict elbow FE motion [3–14], see Table I. The models' aim is to describe limb motion as a function of its EMG signal. At first, Hill-based models were using knowledge about the dynamics of individual sarcomeres within a fiber [17] to link extremity motions to their muscle activity [11]. Later, it was shown that a mapping technique (e.g. classification models, artificial neural networks and support vector machines) could achieve better accuracy than Hill-based models [12–14].

The error of prediction for models [3–14] was estimated to be in the range of 1.20–11.85%. As motion rehabilitation requires the accuracy of an EMG-driven model to be within 96–98.5%, only three models [11,13,14] meet this requirement. Despite good accuracy, these models are restricted to specific exercise conditions: isometric contractions (i.e., stationary contraction of the muscles) [11], normal and high speeds [13] and limited ROMs [14]. Nevertheless, the proposed strategies were used as guidelines for selecting an optimal prediction technique for slow motion therapy. The proposed EMG-driven model combines the main ideas from [14] and [5]. The hypotheses were that 1) the sum of neural activation from the biceps and triceps muscles can show good correlation with the forearm FE movements, and 2) data from a motion sensor (e.g., accelerometer, potentiometer, or optical tracking system) can be used to correct motion prediction. The proposed model uses EMG data from the biceps and the triceps simultaneously for elbow FE prediction.

III. Methods

Twelve healthy subjects (7 males, 5 females) that do not have neural or musculoskeletal disorders were recruited for the trial. The subjects were between 20 and 35 years old. Each subject was seated comfortably on a chair and asked to put his/her arm in an adjustable mechanical brace (InnovatorX, OSSUR®). The subject's arm was then secured to the linkage of the brace using straps. The brace restricts the movement of the limb to the sagittal plane when the upper limb is in the neutral position (upper arm against torso).

Two pairs of surface EMG electrodes were placed on the skin overlying the biceps brachii (BB) and triceps brachii (TB) muscles. A reference electrode was placed on the bony area (at the proximal head of ulna). The skin was prepared only in those areas where the EMG electrodes were placed. According to the SENIAM's (Surface EMG for a Non–Invasive Assessment of Muscles, 1999) recommendations for skin preparation, the skin was cleaned with alcohol pads. As the alcohol vaporized, EMG electrodes were placed parallel to the muscle fibers (2 cm apart), over the muscle belly, two thirds of the distance between the shoulder and the elbow, see Fig.1.

To compare the performance of the model with real-world motions, an accelerometer was placed on the inside of the forearm. The sensor was placed on the skin and secured with the help of adhesive strips. It was observed that the best place for the accelerometer was between the two cuffs of the lower arm of the brace. Thus, a specific distance that satisfies this requirement for each subject was assigned as being 17 cm from the elbow joint (Fig.1, distance between point A and point B).

TABLE I. Description of the EMG-driven models.

Ref.	Method	RMSE (%)	Limitation
[3]	Acceleration data and RMS of the EMG data was mapped with the help of a Kalman filter	11.85	The model was designed to predict tremor, thus may be only suitable for fast motions. Low accuracy.
[4]	Artificial neural network	10.49	Low accuracy
[5]	Modified Hill-based model and a Kalman filter	9.46	Low accuracy and long calibration process. The model was tested only for the EMG signal from the biceps.
[6]	Mapped model and a Kalman filter	8.30	Low accuracy
[9]	Classic Hill's model	7.50	Low accuracy and long calibration process.
[10]	Artificial neural network that uses MMG* in combination with EMG	7.00	Low accuracy and the model was tested for isometric contractions
[11]	Artificial neural network	6.20	Low accuracy
[12]	Hill-type model	5.22	The model was tested for moderate speeds
[13]	Hill's model [17] with a Calcium concentration rule	3.97	Limited to isometric contractions at a stationary elbow position (90°)
[14]	Fuzzy-neuro modifier	6.27	Low accuracy
[15]	Switching the model between two different modes (velocity and force)	3.63	The model is restricted to normal and high speeds (25–80°/s)
[16]	Mapping models	1.20	It is not clear how the model will perform for a ROM between 90 and 130°

*MMG - mechanomyography

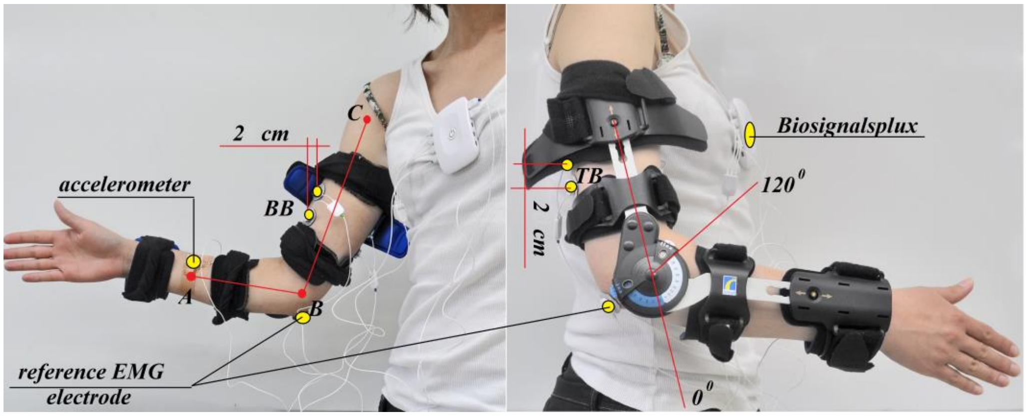

Fig. 1. Example of placement of the EMG sensing system and the mechanical brace.

Muscle activity and forearm acceleration data were tracked at a sampling rate of 1000 Hz with the help of a Wearable Body-Sensing Platform "Biosignalsplux" (Plux®). The sensed data were stored in a temporary file with the help of the "OpenSignals" software (Plux®). The proposed EMG-driven model and the conversion of the acceleration data to angular profiles was implemented and computed using MATLAB (MathWorks®). Each volunteer was asked to perform a maximal BB contraction. The EMG signal from BB and TB were recorded for 3 s of rest and 3 s of maximum contraction. The average EMG values during one full rest and one full contraction phase were used to identify the minimum and maximum values of the EMG signals for normalization purposes. The normalized EMG data (represented as a percentage) shows the strength of the signal from the muscles with respect to the maximum value for each subject. Hence, further calculations of neural activities are unitless.

After calibration, each subject performed six sets of FE movements, while holding a 1 kg load. Subjects were instructed to move their forearm with a speed of less than 20°/s. Practice trials were first completed to teach subjects how to perform slow motions with minimal shoulder movement.

For each set of movements, a unique ROM was selected: 1) 0–45 degrees, 2) 0–60 degrees, 3) 0–90 degrees, 4) 0–120 degrees, 5) 45–105 degrees and 6) 90–120 degrees. Subjects were instructed to complete three elbow FE repetitions for each set. In order to eliminate the effects of muscle fatigue, subjects rested 2–5 minutes between each set.

A. Data Processing

The raw EMG signal was processed as recommended in [5, 18], by completing the following steps: 1) data were high-pass filtered (4th order Butterworth filter with a cutoff frequency of 10 Hz) to remove any direct current offsets or low frequency noise caused by possible movements of the electrodes [18], 2) then rectified (take the absolute value of the EMG signal), and 3) then individually normalized for each subject according to the prerecorded maximum and minimum EMG value from the BB and TB muscles.

The data from the accelerometer were converted to an angular position profile and high-pass filtered with a 2nd order Butterworth filter with a cutoff frequency of 2 Hz. The normalized EMG signal $e(t)$ was used to calculate the neural activity [19], $u(t)$, as follows:

$$u(t) = \alpha \cdot e(t-d) - \beta_1 \cdot u(t-1) - \beta_2 \cdot u(t-2),$$

where d is the electromechanical delay (EMD), and α, β_1 and β_2 are coefficients. For all trials, the coefficients used were calculated following the method outlined in [19], as: α=0.0021, β_1=-1.78 and β_2=0.7821. In general clinical practice, the EMD is inconsequential [20]. Thus, for the trial the EMD is assumed to be zero.

B. Kalman Filter

A Kalman filter (KF) consists of two phases — prediction and correction, see Fig.2. Each iteration goes through two steps: 1) the KF takes the motion prediction X_{k-1} computed earlier and updates X'_k according to the information from a motion sensor U_{k-2}, 2) it then predicts the one-step-ahead signal X_k of the motion profile at the correction phase according to the noise Q and R. More details can be found in [5, 6].

The calculated muscle activity from the BB and TB muscles was added together to create the first input signal (X_k) to the KF. Motion data from the accelerometer were used

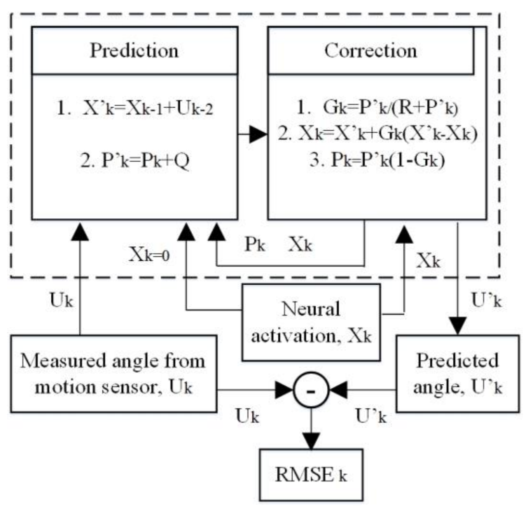

Fig.2. Flowchart of data in Kalman filter, where X_k is the sum of the neural activity from the BB and TB muscles, Q is the process noise, R is the measurement noise, P_k and G_k are function of the noise, U_k is the data from the motion sensor, U'_k is the predicted motion profile (equal to the X_k value at the correction phase), $RMSE_k$ is the error between the real motion profile and the predicted signal from the KF at each iteration. The KF takes the motion prediction made earlier and updates it according to the information from a motion sensor. During the correction phase, the KF predicts the one-step-ahead signal of the motion profile according to the noise.

as the second input signal (U_k). Prediction of motion X'_k relies on a previously corrected value of X_k and on the history of the signal U_k from the motion sensor. Two variables, P_k and G_k, are used in the process of correction. Both of them are functions of the noise. The process noise Q and the measured noise R were defined for each individual during manual calibration of the KF according to the method described in [5]. The goal of the calibration was to achieve an RMSE ≤ 2.0±0.1% for a full FE movement that required the forearm to move from 0° to 120°. The output signal (U'_k) from the KF is the predicted motion profile (output frequency f=1000 Hz).

The RMSE of the model prediction with respect to the estimated variable and the Pearson correlation coefficient (CC) were used to estimate the accuracy and correlation between the model results and the observations. The correlation coefficients range from –1 to 1 where values close to 1 or -1 represent a high correlation.

IV. Results

The proposed EMG-driven model was tested in real-time to determine the prediction accuracy of motions provided by healthy subjects. All subjects completed all trials. Recorded data were used as input signals to the model. A summary of the accuracy results for all subjects is presented in Figs. 3 and 4. An example of a recorded EMG signal from the BB and TB muscles and their corresponding calculated neural activity is present in Figs. 5.A and 5.B, respectively. The model predicted forearm motion trajectory (CC=1) with high accuracy (RMSE=1.67%), as shown in Fig. 5.C.

The model accuracy across subjects (97.4–98.6%) and across different sets of exercises (97.9–98.4%) is within the required tolerance (96–98.5%). It can be seen in Fig. 4 that the error increase for lower torques occurs during the 0–45° and the 90–120° phases. The model replicates the subjects' motions trajectory with high correlation (CC=0.99–1.00). However, additional trials with a large group of patients are necessary to understand model behavior with signals from healthy and restored nerves.

V. Discussion

The results have validated that using EMG data from the biceps and triceps muscles provide better prediction accuracy than using only biceps muscle data as in [5], and that KF is a powerful tool for correcting the EMG-to-motion mapping technique (compared to the pure mapping strategy presented in [14]). The accuracy requirements gathered from the experts and the literature was between 88.0 and 98.0%. The results of the trials show an accuracy of 97.4–98.6% across all subjects. Therefore, the model is able to predict elbow flexion and extension motion more accurately than most of the previous efforts defined in the literature. The simplified motion prediction model also offers two other advantages: ease of implementation and low computation cost compared to other models. Across all subjects, the upper limit of the position prediction accuracy reaches the goal of 98.5%; on the other hand, the best accuracy across all sets does not achieve the goal by 0.1%. The lower bound accuracy (97.4%) across

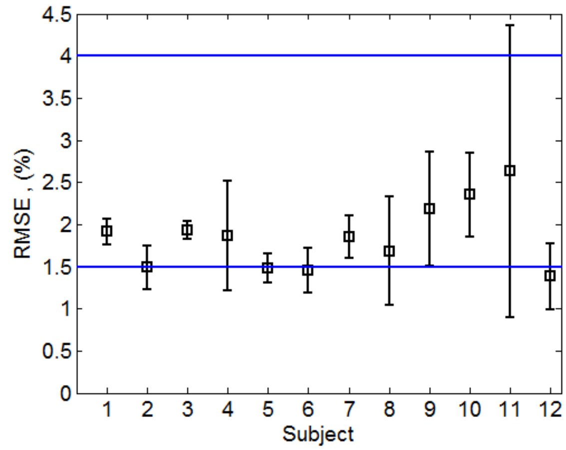

Fig. 3. Error distribution across subjects

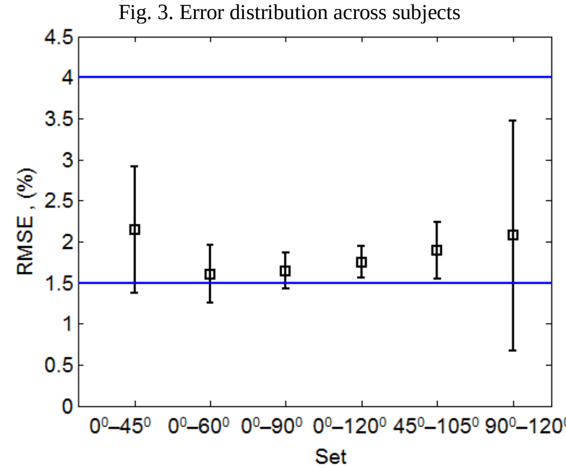

Fig. 4. Error distribution across different trial sets.

subjects corresponds to a position error of 3.4 degrees. Therefore, the accuracy of the model provides a worst-case position error that lies within the acceptable range (2-5 degrees).

The variability of EMG signals caused by a vast amount of conditions and non-voluntary shoulder motions created a different error distribution for each subject (e.g., Fig. 3, Subject 11). Although no control was implemented for some subject-related parameters (posture, mental state and temperature), the model was able to make predictions with the desired accuracy.

The raw neural activity from the BB and the TB muscles that has not been corrected by a KF (Fig.5.B) has shown good correlation with real motion data (e.g., CC=0.8664 for Subject 12, set No. 3). Due to the EMG signal processing procedure used, the neural activity of the BB and TB muscles had an amplitude within 0 and 1. In order to link the neural activity to the motion profiles, it was necessary to use a KF as it can handle signal-scaling issues. The designed filter predicts motion based on the history of real position and the current neural signal. The proposed model uses EMG signals as the main controlling signal. Therefore, if at some moment of therapy, the subject is not able to complete the desired motion, the model will predict the effort required to move the limb according to the EMG signal and the previous angular position.

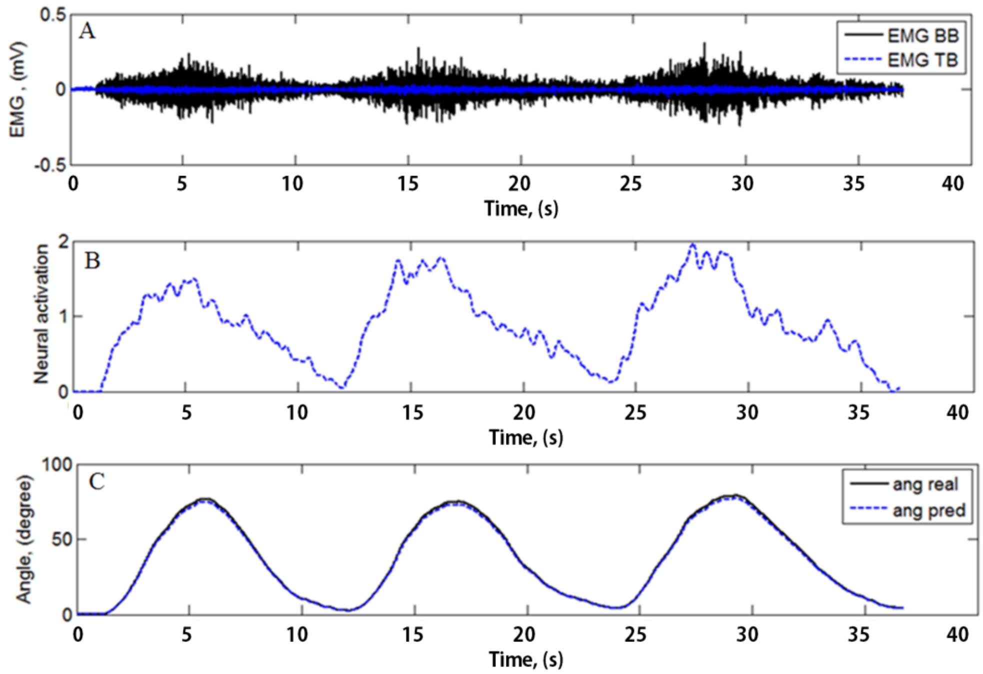

Fig.5. Example of data from Subject 12 for set No. 3 (ROM 0–90^0). Each FE motion was completed within 12 s.
A) EMG signal from BB (black) and TB (blue) muscles, B) Resulting neural activation (sum of BB and TB neural activation),
C) Measured motion profile (black solid line) compared with predicted motion from model (blue dashed-line). RMSE=1.6696 %, CC=1.

The proposed prediction model will help mechatronic devices aimed at active-assistive motion therapy by providing increased safety and decreased cost. A model that can produce very accurate position or torque predictions is essential to ensure that device motion does not overshoot the boundaries of the patient's range of motion or deviate far from the patient's desired motion. An overshoot of even a few degrees can cause pain and damage to weak tissues. Decreasing the likelihood of causing further tissue damage will increase safety for the user. The model offers a cost saving opportunity to devices by simplifying control system structures. Due to model simplicity, implementation and testing phases related to using the model as part of a control system will be shorter compared to more complicated models. Financial benefits will be seen as a reduction in labour hours, software module complexity and required circuitry. Simpler systems are also easier to debug, maintain and repair.

A. Sources of Error

For the elbow FE motion, each muscle must produce a different level of force. At the 90° position, the force reaches its peak. For 45–0°, force smoothly decreases as it approaches 0°, whereas for 90–120°, force smoothly decreases as it approaches 120°. The number of motor units, i.e. neural pathways and all the muscle fibers they innervate, control the mechanism of generating force. The force can be produced in two ways [1]: (1) by increasing the number of active motor units, or (2) by increasing the frequency of stimulation to a motor unit. Since motor units are arranged in parallel [21], the total force is equal to the sum of the individual motor units. A frequency threshold *f* for a slow motor unit is 20 Hz, while for a fast motor unit it is 50 Hz. If the stimulation does not exceed the threshold, the muscle will show a series of individual twitches. In case the stimulation frequency *Vs* is above the threshold, then a second pulse will stimulate the muscle before the force effects of the first pulse have completely subsided (Fig. 6). Therefore, the principal frequency of the EMG signal is concentrated in the 30–500 Hz range [22]. On the other hand, the main energy is concentrated in the range of 0–500 Hz [23]. Thus, filtering of the EMG signal may cut down useful information that corresponds to the smallest force produced by the muscle. An increase in the error for the 0–45° and 90–120° ranges may be attributed to this concept.

Using optimization techniques, a smaller accuracy error may have been attained when compared to using a manual model parameter calibration. However, optimization techniques are computationally expensive. In addition, optimized parameters can take longer to compute than the entire time devoted to the trials of one subject depending on which optimization technique is used. Lastly, EMG signals fluctuate naturally due to fatigue, temperature, environment and other factors. Therefore, the optimization would need to occur for every usage of the device housing the proposed model. The time constraints these factors place on parameter optimization are the reasons why manual calibration was chosen for the experiment.

B. Integration into Control Systems

The model currently considers a narrow view of the control requirements: predicting torque or position based on EMG signals. To account for other control system characteristics, modifications such as additional accelerometers and saturation limits could be added to the model. Additional accelerometers will allow for the effects of posture and segment movement on prediction errors to be discovered. An accelerometer on the upper arm segment would allow for shoulder movement to occur while being able to mitigate the

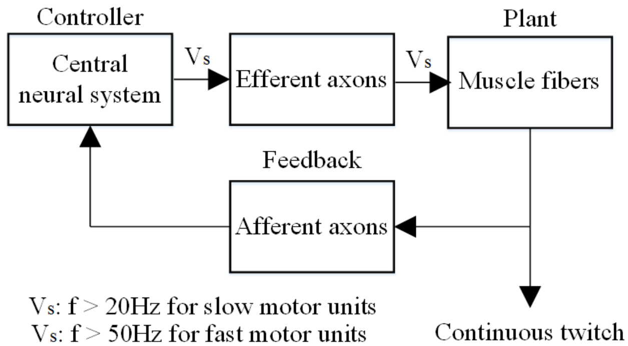

Fig.6. Muscle force control. Afferent axons deliver information about the contractile status of the muscle to the central nervous system, while efferent axons deliver signals for contraction from the central nervous system [23].

errors it may cause in prediction. A similar case is possible for all other limbs. If posture or segment position can be related to errors in control system output or rehabilitation outcomes, corrective feedback could be given to the patient. Saturation limits will allow the control system to function within the patient capabilities. Even if the model predicts values greater than expected, the control signals will not exceed the therapist specified values due to saturation of the output signal. Setting the limits properly will ensure that the control system will be unable to reach positions or torques that are outside the patient's safe motion range. Another issue with integration of the model into a control system occurs with the output frequency. The smaller the output frequency, the easier it is for the control system to respond to a command signal from the model. Hence, the model output must be down sampled to a lower frequency. The preferred range for the desired frequency should not be less than the frequency of normal elbow motions, i.e. 0–5 Hz [24]. Therefore, a 10 Hz output frequency will increase system stability without signal loss.

VI. Conclusion

A simplified EMG-driven model for prediction of elbow motion has been developed and experimentally validated on twelve healthy subjects. Despite the different age, gender, anthropomorphic data and torque levels, the model showed high correlation with slow motion trajectories (CC=0.999–1), as well as high accuracy (97.4–98.6%) of prediction for "best case" scenario. For future work, the proposed model will be integrated into the control system of a mechatronic brace for rehabilitation. Modifications required for control system usage as well as further testing with jerky motions and patients with upper limb disabilities will be conducted to accomplish the future objectives.

References

[1] F. Wilson, J. Gormley, J. Hussey, Ed., "Exercise therapy in the management of musculoskeletal disorder," John Wiley & Sons, 2011.

[2] A. Howard, D. Brooks, E. Brown, A. Gebregiorgis, C. Yu-Ping, "Non-contact versus contact-based sensing methodologies for in-home upper arm robotic rehabilitation," Rehabilitation Robotics (ICORR), 2013 IEEE International Conference, pp. 1–6, 24–26 June 2013.

[3] F. Widjaja, C. Y. Shee, W. T. Latt, W. L. Au, P. Poignet, W. T. Ang, "Kalman Filtering of Accelerometer and Electromyography (EMG) Data in Pathological Tremor Sensing System," Proc. IEEE Intl. Conf. Robot. Automat., May 2008, pp. 3250 - 3255.

[4] Y. Chen, X. Zhao, J. Han, "Hierarchical projection regression for online estimation of elbow joint angle using EMG signals," Neural Computing and Applications, Sept. 2013, vol. 23, issue 3–4, pp. 1129–1138.

[5] Q. Ding, A.B. Xiong, X.G. Zhao, J.D. Han, "A novel EMG-driven state space model for the estimation of continuous joint movements," Systems, Man, and Cybernetics (SMC), 2011 IEEE International Conference, 9–12 Oct. 2011, pp. 2891–2897.

[6] Q. Zhang, R. Hosoda, G. Venture, "Human joint motion estimation for electromyography (EMG)-based dynamic motion control," Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE, 3–7 July 2013, pp. 21–24.

[7] K. Mountjoy, "Use of a Hill-based muscle model in the fast orthogonal search method to estimate wrist force and upper arm physiological parameters," Masters thesis, Department of Electrical and Computer Engineering, Queen's University, Oct. 2008.

[8] W. Youn, J. Kim, "Estimation of elbow flexion force during isometric muscle contraction from mechanomyography and electromyography," Medical & Biological Engineering & Computing, Nov. 2010, vol. 48, issue 11, pp. 1149–1157.

[9] C. Loconsole, S. Dettori, A. Frisoli, C. A. Avizzano, M. Bergamasco, "An EMG-based approach for on-line predicted torque control in robotic-assisted rehabilitation," Haptics Symposium (HAPTICS), 2014 IEEE Conference, 23–26 Feb. 2014, pp.181–186.

[10] J.W.L Pau, S.S.Q. Xie, A.J. Pullan, "Neuromuscular interfacing: establishing an EMG-Driven model for the human elbow joint," Biomedical Engineering, IEEE Transactions, Sept. 2012, vol. 59, issue 9, pp. 2586–2593.

[11] H. Wagner, K. Boström, B. Rinke, "Predicting isometric force from muscular activation using a physiologically inspired model," Biomechanics and Modeling in Mechanobiology, Dec. 2011, vol. 10, issue 6, pp. 955–961.

[12] K. Kiguchi, Y. Hayashi, "Motion estimation based on EMG and EEG signals to control wearable robots," Systems, Man, and Cybernetics, 2013 IEEE International Conference, 13–16 Oct. 2013, pp. 4213–4218.

[13] P. K. Artemiadis, K. J. Kyriakopoulos, "Bio-inspired mechatronics and control interfaces," Perception-Action Cycle, Springer Series in Cognitive and Neural Systems 2011, pp. 749–775.

[14] K. Ullah, K. Jung-Hoon, "A mathematical model for mapping EMG signal to joint torque for the human elbow joint using nonlinear regression," Autonomous Robots and Agents (ICARA 2009), 4th International Conference, 10–12 Feb. 2009, pp. 103–108.

[15] G. C. Burdea, Ed.,"Force and touch feedback for virtual reality," New York: Wiley, c1996.

[16] R. Huston, "Principles of biomechanics", CRC Press, 2008, p. 442.

[17] A.V. Hill, "The series elastic component of muscle," Proc. R. Soc. Lond. B. Biol. Science, 1950, vol. 141, pp.104–117.

[18] D. Farina, R. Merletti, R. M. Enoka, "The extraction of neural strategies from the surface EMG," J. Appl. Physiol., Apr. 2004, vol. 96, issue 4, pp. 1486–1495.

[19] F. E. Zajac, "Muscle and tendon: properties, models, scaling and application to biomechanics and motor control," Critical Reviews in Biomedical Engineering, 1989, vol. 17, pp. 359–411.

[20] A. Celli, L. Celli, B.F. Morrey, "Treatment of elbow lesions: new aspects in diagnosis and surgical techniques," Ed. Milano, Ed., New York: Springer, c2008.

[21] M. Epstein, W. Herzog, Ed.,"Theoretical models of skeletal muscle: biological and mathematical considerations,"New York: Wiley, c1998.

[22] C. J. De Luca, "Surface electromyography: detection and recording," Delsys Incorporated, 2002.

[23] G. Lee, Ed., "Biomedical Engineering and Environmental Engineering," WIT Press, 2014.

[24] G. Grimaldi, M. Manto, Ed., "Mechanisms and emerging therapies in tremor disorders," Springer, 2012.