Experimental Study of Robot-Assisted Exercise Training for Knee Rehabilitation Based on a Practical EMG-Driven Model*

Long Peng, Zeng-Guang Hou, Liang Peng and Wei-Qun Wang

Abstract— **This paper proposes two robot-assisted exercise training methods for knee rehabilitation based on a practical EMG-driven model, aiming to beneficially exploit the patient's ability through neurorehabilitation process. The EMG-driven model is a simplified representation of the musculoskeletal system, with acceptable accuracies to predict the muscle forces and active torque of knee joint. Thus the patient's voluntary contribution can be introduced to the control loop through admittance controller. Preliminary experiments verify that the model prediction performance is able to reflect the subjects' motion intention in real-time and assist the subjects to perform exercise training with a lower limb rehabilitation robot. The information recorded during exercise training could be useful to understand the process of recovery and make quantitative evaluations to the patient's motor abilities.**

I. Introduction

The quality of a person's life can be greatly compromised following a neurological disorder disease such as stroke or spinal cord injury (SCI). Rehabilitation devices show great potential for aiding people with movement disabilities in their recovery [1]. Rehabilitation robots can not only execute intensive tasks continuously with precision, but also present various rehabilitation therapies that were formerly unavailable. Increased motivation can be achieved via human-machine interactive environments. The sensors integrated within the robots could obtain patient's motion parameters and provide a quantitative evaluation on the recovery process objectively.

Surface electromyography (sEMG) signal reflects degree of activity in specific muscle and can be detected ahead of movement (about 30-100 ms [2]), making it promising as the human-machine interface (HMI) to control rehabilitation robots or assistive devices.

Torque estimation using sEMG signals is a widely research method to control robots or assistive devices. Many EMG-based models are built based on machine learning algorithms, such as neural network [3] and regression method [4]. These approaches focus on model accuracy without considering the relationship between the EMG signals and internal muscle forces. However, knowledge of internal forces and torques during movements can be used to understand the body status and rehabilitation progress of the patients. Establishing EMG-driven musculoskeletal models can overcome above-mentioned deficiency [5], [6]. Nonetheless, muscle parameters vary among individuals, and too many related parameters need to be optimized. This process is time consuming [7] and may cause its estimation performance in various conditions to be poor, which may confine the practicability of EMG-driven model. Based on an opinion that a rough estimate of torque may be enough to perform the robot-assisted exercise training, we have proposed a simplified representation of the musculoskeletal system to simulate knee-joint movements [8]. Dual population genetic algorithm (DPGA) [9] is applied to optimize the model parameters. This EMG-driven model can reduce the model complexity and time cost for parameter optimization process, while maintaining a relatively high accuracy.

The goal of the research presented herein is to develop robot-assisted exercise training methods for knee rehabilitation based on the proposed EMG-driven model. The developed training methods hope to provide assistance in the rehabilitation of three major neurological populations: people who have survived a stroke, traumatic brain injury (TBI), or incomplete SCI.

II. Methods

We use the *i*Leg rehabilitation robot (see Section II-A) to perform the rehabilitative exercise training. The EMG-driven model (see Section II-C) is used to estimate muscle forces and active torque of knee joint from EMG signals. Then the admittance controller (see Section II-D) is used to transform the active torque to the robot control signal, so as to implement the conversion from motion intention to actual motion.

A. *iLeg Platform*

The data acquisition and exercise training experiments were conducted on *i*Leg−a horizontal exoskeleton for lower limb rehabilitation developed at our laboratory, whose mechanical structure is shown in Fig. 1. Joints 1, 2 and 3 correspond to the hip, knee and ankle joints of human limbs respectively. A torque sensor, an absolute encoder and a relative encoder are installed at each joint.

B. *EMG Processing*

EMG signals were recorded with a gain of 1000 and filtered by a bandpass filter of 20 to 200 Hz and a notch filter of 50 Hz. Then the signals were digitized with a sampling frequency f_c = 2048 Hz and a 12-bit quantization (Art TechnologyCo., Inc., China). We have integrated

*This work is supported in part by the National Natural Science Foundation of China (Grants 61421004, 61533016).

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Fig. 1. Mechanical structure of *i*Leg platform.

these components to an 8-channel EMG acquisition device shown in Fig. 1.

The digitalized EMG signals were post-processed to obtain the linear envelopes (LEs), which provide rough estimates of the exerted forces. The LEs were obtained online through full-wave rectification of the digitalized EMG signals and then filtered by a second-order lowpass Butterworth filter with a 3 Hz cutoff frequency to perform the smoothness of the signals [10].

Finally, the LEs were normalized with the resting state value and maximum voluntary contraction (MVC) of EMG. The EMG processing can be described as follows:

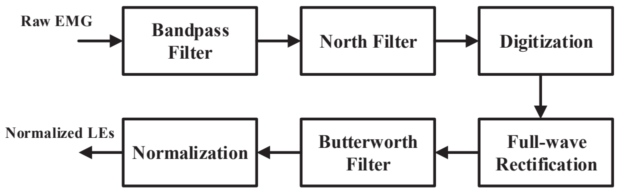

Fig. 2. Flowchart of the procedures for EMG processing.

The normalized LEs give an indication to the muscle activation levels and are input to the EMG-driven musculoskeletal model to compute the muscle forces and active torque of knee joint.

C. EMG-Driven Musculoskeletal Model

Briefly, the EMG-driven model consists of two main modules: a muscle tendon model to compute the muscle force of each muscle group, and a proposed musculoskeletal model. The muscle tendon model is built based on the work by R. Riener and T. Fuhr [11]. The muscle force is calculated using following equation:

$$F = LE_{\text{emg}} \cdot F_{\text{max}} \cdot f_{\text{fl}} \cdot f_{\text{fv}} \tag{1}$$

where LE_{emg} is the normalized output from EMG processing; F_{max} is the maximum isometric force; f_{fl} and f_{fv} describe the force-length and force-velocity relations respectively, which can be described as follows:

$$f_{\text{fl}} = \exp\left[-\left(\frac{\bar{l}-1}{\varepsilon}\right)^2\right] \tag{2}$$

$$f_{\text{fv}} = 0.54\arctan(5.69\bar{v} + 0.51) + 0.745 \tag{3}$$

where $\bar{l}$ is the normalized muscle length; ε is a shape factor; $\bar{v}$ is the normalized muscle velocity (see [11] for details).

The musculoskeletal model simulates the knee joint with a union of simplified muscle and bone structures, which is shown in Fig. 3. Three main muscle groups are considered in this study: the quadriceps femoris (Qf) muscle, which causes knee extension; the hamstrings (Ha) and gastrocnemius (Ga) muscles, which cause knee flexion. The red arrows show the main forces generated by the three muscle groups, which are represented as F_{Qf}, F_{Ha} and F_{Ga} respectively. The moment arms for torque calculation are labeled as MA_{Qf}, MA_{Ha} and MA_{Ga}.

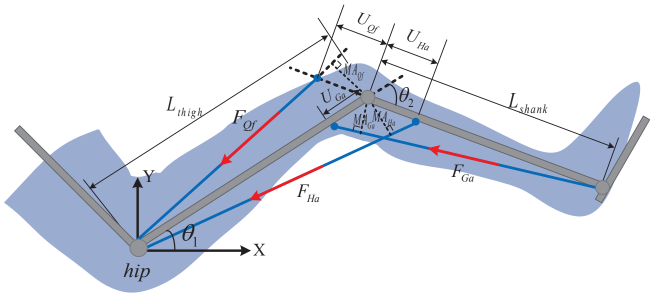

Fig. 3. Musculoskeletal model of the knee joint.

Considering knee flexion as the positive direction, the active torque of knee joint is given by

$$\begin{aligned} T_{\text{act}} = {} & K_{\text{Ha}} \cdot F_{\text{Ha}} \cdot MA_{\text{Ha}} + K_{\text{Ga}} \cdot F_{\text{Ga}} \cdot MA_{\text{Ga}} \\ & - K_{\text{Qf}} \cdot F_{\text{Qf}} \cdot MA_{\text{Qf}} + \Phi(\theta_1, \theta_2) \end{aligned} \tag{4}$$

where K_{Ha}, K_{Ga} and K_{Qf} are correction constants due to the simplification of model. Φ is an correction function considering the changes in joint angles, which is approximated by gravitational torque of the shank:

$$\Phi(\theta_1, \theta_2) = 0.02M_{\text{weight}} \cdot \text{g} \cdot L_{\text{shank}} \cdot \cos(\theta_1 + \theta_2) \tag{5}$$

where M_{weight} is the body weight (kg) ; $\text{g} = 9.8\text{m/s}^2$ is the constant of gravitational acceleration.

The musculoskeletal model has totally 6 parameters to be further optimized. DPGA is employed to determine ideal values for these 6 model parameters. The details for the establishment of the EMG-driven model and DPGA algorithm can be found in [8].

D. Control System for Robot-Assisted Exercise Training

The control program was realized in C# using Windows operating system, whose structure is shown in Fig. 4. The raw EMG signals recorded from three muscle groups are input to the muscle tendon model to calculate muscle force for each muscle group after the EMG processing procedure

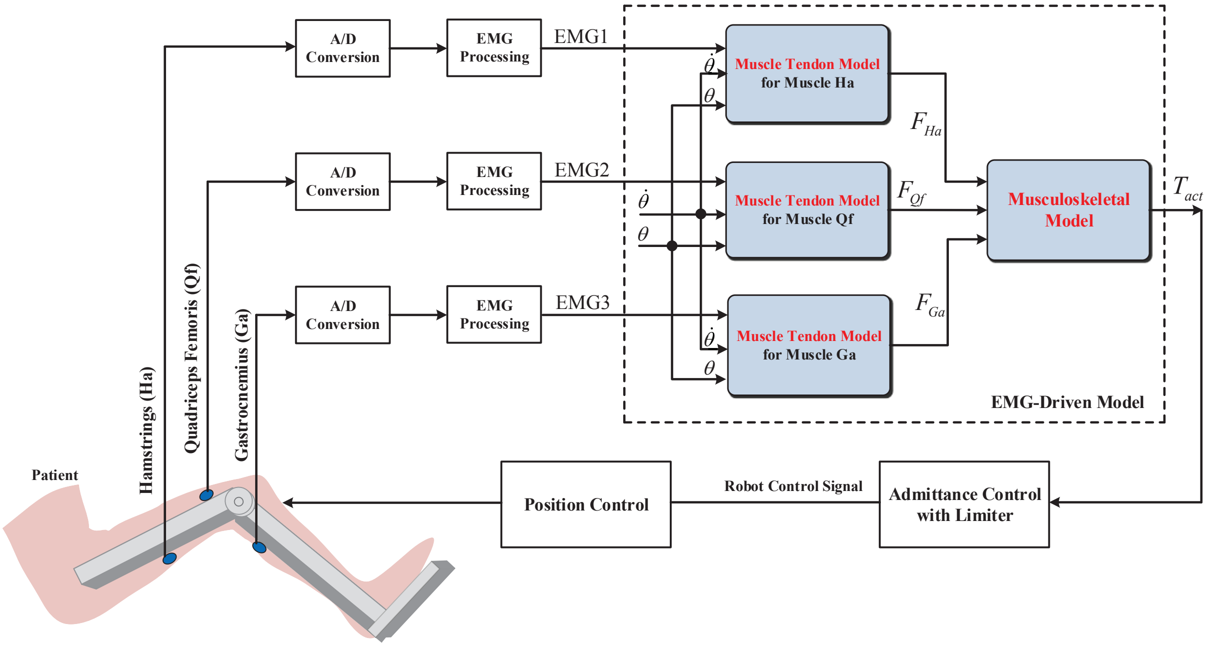

Fig. 4. Control structure for robot-assisted exercise training.

(see Section II-B). Then the muscle forces are input to the musculoskeletal model to estimate the active torque T_{act}. Finally, the admittance controller is used to transform the active torque T_{act} to the robot control signal and a commercial PID controller (Copley Controls Corp., USA) is used to achieve position control. Therefore, this training strategy could be called "patient-driven voluntary exercise training".

The admittance control strategy could be considered the opposite of impedance control. In this study, the admittance control is applied to establish a dynamic relationship from the interaction force to the position deviation in the joint space, defined as:

$$T_{\text{act}} = M(\ddot{\theta} - \ddot{\theta}_0) + B(\dot{\theta} - \dot{\theta}_0) + K(\theta - \theta_0) \qquad (6)$$

where T_{act} is the active torque of knee joint exerted on the robot by human, θ is the actual position of knee joint, and θ_0 is the desired position of knee joint. The admittance control parameters, i.e. inertia M, damping B and stiffness K, are set to 5, 62, 80 respectively. These typical values meet the equality $B = 3.1\sqrt{M \cdot K}$, which could reduce the robot system oscillation effectively [12]. The positive and negative amplitudes of output signal θ_0 are limited to some predetermined value by a limiter, above which the peaks become flattened. The limiter guarantees smooth movement of the robot system because patients usually perform the rehabilitation training with a relatively low speed.

Since patient's muscle activity degree and muscle weakness should be improved through neurorehabilitation process, they may need to re-learn how to activate different muscles. On the basis of the training strategy described above, another training strategy called "muscle-triggered patient-driven voluntary exercise training" is proposed to enhance muscle performance, which allows specific muscle(s) to trigger the robot action to perform the first training strategy. The information recorded during the training, such as whether selected muscle(s) could trigger the robot action and how long does it take, could be useful to provide an objective evaluation to the muscle performance.

III. Data Acquisition and Model Tuning

Three healthy subjects (males, 27-28 yrs) took part in the data acquisition and the following experiments. The study was approved by the Institutional Review Board of China Rehabilitation Center, Beijing, China. All subjects gave their informed consent before participation. Two types of movements were performed to calibrate the EMG-driven model since a varied range of dynamic contractile conditions may enhance the robustness of the tuned model.

The end-point reference trajectory of the first movement was a back-and-forth pedaling movement in a straight path, with the start point at [0.52 0.05], the midpoint at [0.62 0.1] and the motion period as T = 10 s (Cartesian coordinate system shown in Fig. 3), which is represented as:

$$\begin{cases} x = -0.1\cos(0.2\pi t) + 0.62 \\ y = -0.05\cos(0.2\pi t) + 0.1, \end{cases} \qquad (7)$$

The end-point reference trajectory of the second movement was a cycling movement in clockwise direction that commonly used for rehabilitation exercise, with the center at [0.62 0], the radius as r = 0.15 m and the motion period as T = 10 s, which is represented as:

$$\begin{cases} x = 0.1\cos(0.2\pi t) + 0.62 \\ y = -0.1\sin(0.2\pi t), \end{cases} \qquad (8)$$

EMG signals were acquired by Ag/AgCl bipolar surface electrodes, which are separated from each other by 2 cm over the muscle belly [13]. Before data acquisition, the resting state value and MVC of EMG were recorded for normalization of the LEs. During data acquisition, the subject's right leg was drived by the robotic leg to perform these two types of movements individually, which is shown in Fig. 1. The subjects were asked to exert their voluntary effort randomly during the movement and perform several periodic trajectories at each trial with their own willingness. Three trials of cycling movement and one trial of straight movement were completed by each subject, with no resting period between consecutive trials. Since the torque sensor installed at knee joint can obtain the actuating torque generated by robot, the active torque T_{act} was obtained online through a dynamic parameter identification method (see [14]).

The acquired data, which are normalized LEs, joint kinematics and active torque T_{act}, were used to tune the EMG-driven model. The model was tuned by the first half data of each trial, then the tuned model was used to predict the active torque of the second half of that trial through EMG and joint kinematics. The identification result of model parameters by DPGA is shown in Table I. Root-mean-square error (RMSE) was used as the criterion to show the prediction performance of tuned EMG-driven model (Table II).

TABLE I

IDENTIFICATION RESULT OF MODEL PARAMETERS FOR EACH SUBJECT

Subject	U_{Qf} (m)	U_{Ha} (m)	U_{Ga} (m)	K_{Qf}	K_{Ha}	K_{Ga}
1	0.026	0.024	0.006	0.896	0.737	0.909
2	0.028	0.018	0.007	0.830	0.983	0.969
3	0.021	0.019	0.008	1.194	0.808	0.956

TABLE II

RMSE OF THE TUNED MODEL TO PREDICT ACTIVE TORQUE OF KNEE JOINT (NM).

Subject	Cycling1	Cycling2	Cycling3	Pedaling1	Mean $\pm$ SD
1	4.19	6.08	6.85	3.60	5.18 ± 1.54
2	6.61	5.40	5.90	4.63	5.64 ± 0.83
3	5.90	7.31	6.08	4.90	6.05 ± 0.99

Figure 5 shows one trial of torque prediction result using the tuned model for subject 3. It can be seen that the prediction performance could reflect the human motion intention in real-time.

IV. EXPERIMENTS AND RESULTS

Voluntary exercise is considered to be an essential factor to improve functional performance of patients with neurological injury. It was confirmed that voluntary exercise induces neurogenesis in the adult CNS [15] and enhances the neuroplasticity [16], [17]. Two different voluntary exercises were conducted. Only knee joint was considered in this study, so the hip and ankle joints of *i*Leg were set to be fixed angles.

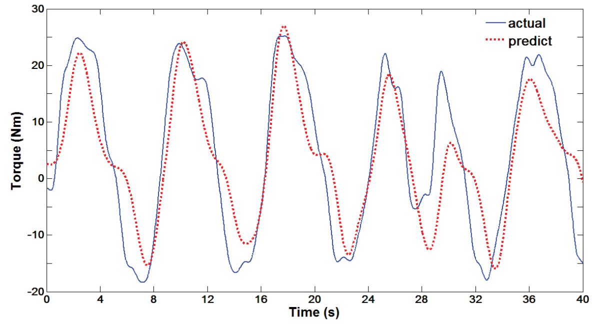

Fig. 5. One trial of torque prediction result using the tuned EMG-driven model. RMSE = 7.31 Nm.

A. Experiment I: Patient-Driven Voluntary Exercise Training

Three subjects participated in this experiment and they all were able to complete robot-assisted voluntary exercise of knee joint. No target was provided to the participants and they just performed the training at their free will. Fig. 6 shows a typical recording from subject 2. It is indicated that the angle of knee joint is entirely controlled by the active torque exerted by that subject. The knee joint performs an extension movement when the value of active torque is greater than 0, otherwise performs a flexion movement. When the subject relaxes during the time period labelled as "A", the knee joint remains still.

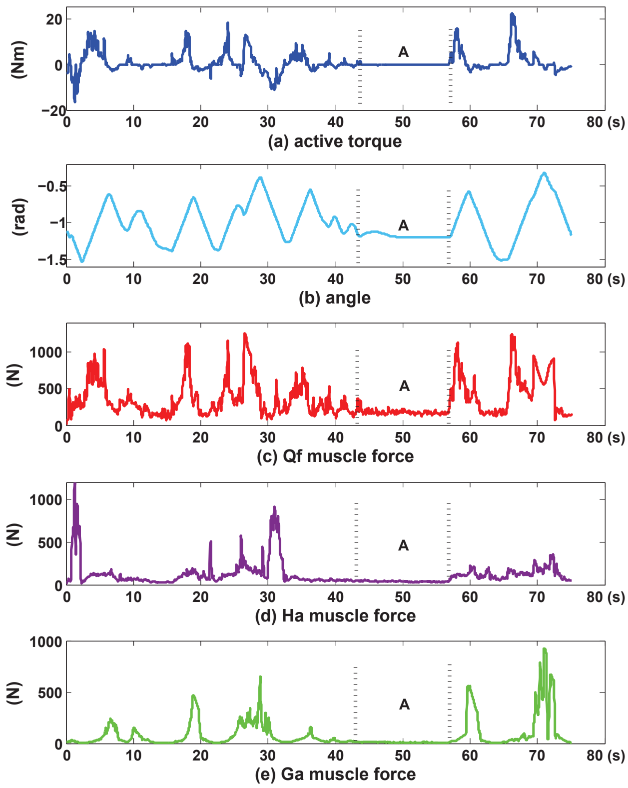

Fig. 6. A typical recording of experiment I.

The aim of this exercise training is: the movement is driven by the voluntary effort of the patient's paralyzed limb, rather than imposing a fixed reference trajectory. Thus, patient's ability could be beneficially exploit to allow a patient to actuate the human-machine system dynamics. Different levels of intensive training could be implemented by adjusting the admittance parameters. This method could inspire the enthusiasm of patients to perform rehabilitation training and may increase the functionality of the paralyzed limb through motor learning.

B. Experiment II: Muscle-Triggered Patient-Driven Voluntary Exercise Training

A subject's attempt to trigger the onset of the robot action is detected by monitoring muscle force(s) computed by the muscle tendon model. The single-threshold detector was applied in this experiment, and multiple-threshold detector could be realized through the logical OR (or AND) operator similarly. Fig. 7 shows a typical recording from subject 1 when the calculated Qf muscle force is greater than 800 N (threshold) to trigger the robot motion. The threshold could be adjusted according to the patient's training needs.

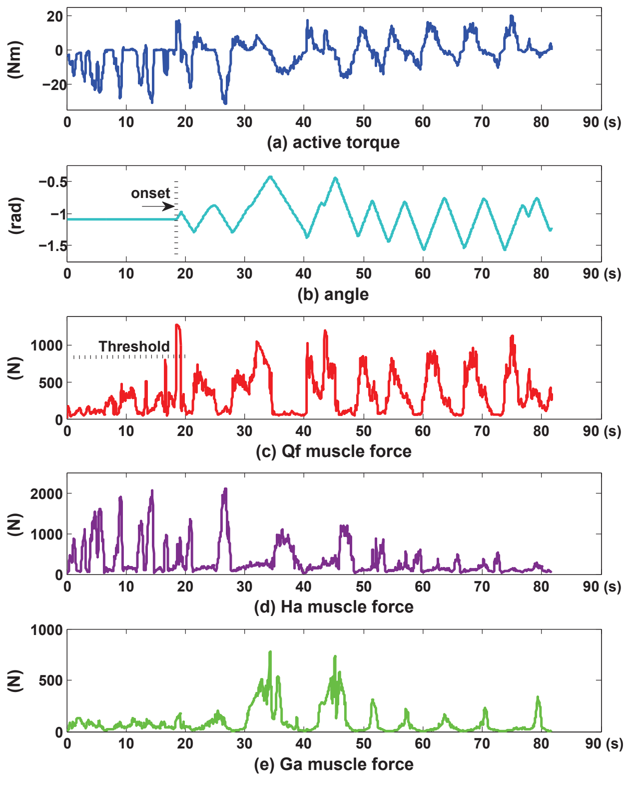

Fig. 7. A typical recording of experiment II.

The muscle-triggered exercise training may provide the following advantages: it could be used to train specific muscle(s) of the patient based on customized rehabilitation requirements to enhance muscle performance; the information, such as trigger time and changes of the selected muscle force(s), could be useful to make quantitative evaluations to the patient's motor abilities.

V. Conclusion

Two robot-assisted exercise training methods for knee rehabilitation based on a proposed EMG-driven model have been developed and tested on healthy subjects in this study. In such voluntary exercise training patterns, the patient is able to influence and control the trajectory of human-robot system. Thus, the patient's voluntary contribution is introduced to the control loop, known as "patient-centered" controller, which is opposed to the "robot-centered" controller. The long term goal of this work is to expand the practical EMG-driven model to other joints and implement multi-joint coordinated rehabilitation training with *i*Leg.

References

[1] J. C. Perry, J. Rosen and S. Burns, Upper-limb powered exoskeleton design, IEEE/ASME Trans. Mechatronics, vol. 12, no. 4, pp. 408-417, Aug. 2007.

[2] P. R. Cavanagh and P. V. Komi, Electromechanical delay in human skeletal muscle under concentric and eccentric contractions, European journal of applied physiology and occupational physiology, vol. 42, no. 3, pp. 159-163, 1979.

[3] R. Song and K. Y. Tong, Using recurrent artificial neural network model to estimate voluntary elbow torque in dynamic situations, Medical and Biological Engineering and Computing, vol. 43, no. 4, pp. 473-480, 2005.

[4] K. Ullah and J-H. Kim, A mathematical model for mapping EMG signal to joint torque for the human elbow joint using nonlinear regression, International Conference on Autonomous Robots and Agents (ICARA 2009), pp. 103-108, 2009.

[5] D. G. Lloyd and T. F. Besier, An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo, Journal of biomechanics, vol. 36, no. 6, pp. 765-776, 2003.

[6] Q. Shao, D. N. Bassett, K. Manal and T. S. Buchanan, An EMG-driven model to estimate muscle forces and joint moments in stroke patients, Computers in biology and medicine, vol. 39, no. 12, pp. 1083-1088, 2009.

[7] J. W. L. Pau, S. S. Q. Xie and A. J. Pullan, Neuromuscular interfacing: Establishing an EMG-driven model for the human elbow joint, IEEE Trans. Biomed. Eng., vol. 59, no. 9, pp. 2586-2593, Sep. 2012.

[8] L. Peng, Z-G. Hou, L. Peng and W-Q. Wang, A practical EMG-driven musculoskeletal model for dynamic torque estimation of knee joint, IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 1036-1040, 2015.

[9] T. Park and K. R. Ryu, A dual population genetic algorithm with evolving diversity, Proc. IEEE Congr. Evol. Comput., pp. 3516-3522, 2007.

[10] A. T. C. Au and R. F. Kirsch, EMG-based prediction of shoulder and elbow kinematics in able-bodied and spinal cord injured individuals, IEEE Trans. Rehabil. Eng., vol. 8, no. 4, pp. 471-480, Dec. 2000.

[11] R. Riener and T. Fuhr, Patient-driven control of FES-supported standing-up: A simulation study, IEEE Trans. Rehabil. Eng., vol. 6, no. 2, pp. 113124, Jun. 1998.

[12] A. Denève, S. Moughamir, L. Afilal and J. Zaytoon, Control system design of a 3-DOF upper limbs rehabilitation robot, computer methods and programs in biomedicine, vol. 89, no. 2, pp. 202–214, 2008.

[13] C. J. DeLuca, The use of surface electromyography in biomechanics, J. Appl. Biomech., vol. 13, pp. 135-163, 1997.

[14] L. Peng, Z-G. Hou, N. Kasabov, J. Hu, L. Peng and W-Q. Wang, sEMG-based torque estimation for robot-assisted lower limb rehabilitation, IEEE International Joint Conference on Neural Networks, pp. 1-5, 2015.

[15] G. Kempermann, H. Van Praag and F. H. Gage, Activity-dependent regulation of neuronal plasticity and self repair, Prog. Brain Res., vol. 127, pp. 35-48, 1999.

[16] F. Gómez-Pinilla, Z. Ying, R. R. Roy, R. Molteni, Voluntary exercise induces a BDNF-mediated mechanism that promotes neuroplasticity, J. Neurophysiol., vol. 88, no. 5, pp. 21872195, 2002.

[17] G. S. Griesbach, D. A. Hovda, R. Molteni, A. Wu, F. Gomez-Pinilla, Voluntary exercise following traumatic brain injury: brain-derived neurotrophic factor upregulation and recovery of function, J. Neurosci., vol. 125, no. 1, pp. 129-139, 2004.