

Estimate Human-Force from sEMG signals for a Lower-Limb Rehabilitation Robot

Irاندokht Khanjani
Center of Excellence on Soft
Computing & Intelligent Information
Processing, Mechanical Engineering
Department, Ferdowsi University of
Mashhad, Mashhad.
irandokht.khanjani@mail.um.ac.ir

Vahab Khoshdel
Center of Excellence on Soft
Computing & Intelligent Information
Processing, Mechanical Engineering
Department, Ferdowsi University of
Mashhad, Mashhad.
vahab.khoshdel@gmail.com

Alireza Akbarzadeh
Professor
Center of Excellence on Soft
Computing & Intelligent Information
Processing, Mechanical Engineering
Department, Ferdowsi University of
Mashhad, Mashhad.
ali_akbarzadeh.prof@fms.um.ac.ir

Abstract— This paper presents an application of artificial neural network (ANN) to estimate human forces from Electromyogram (sEMG) signals. There are plenty of algorithms that are used to obtain the optimal ANN setting. The accuracy of ANN model is highly dependent on the network parameter settings and the accuracy of target data. However, in the majority of previous studies the force data, which are collected from the force sensors or dynameters, used as target data in the train phase. Whereas the force sensors only measured the contact force, while the EMG signals are included of contact force and limb's dynamics. Therefore, in this paper, we present the new model to estimate the force from sEMG signals. In this method, the sum of the limb's dynamics and the contact force is used as target data in the train phase. To determine the limb's dynamics, the patient's body and rehabilitation robot are modeled in the OpenSIM. The results indicated that presented model can estimate the human force from sEMG signals precisely.

Keywords-Artificial Neural Network; Taguchi Method; Analysis of variance; EMG signals

I. INTRODUCTION

Recently, a rehabilitation robot has received higher attention both by physiotherapists and robot researchers. There are a number of reasons leading to this increasing attention. The rehabilitation robot can consistently apply therapy over long periods without tiring. In addition, the use of sensors can highly improve the quality of the therapy. Moreover, it can provide some sort of therapy exercises that a therapist will not be able to do. Furthermore, the robot can bring a vivid decrease to the cost of physiotherapy process. There is also a great need from the side of many patients with movement disabilities to have session physiotherapy. Finally, the rehabilitation robot can be easily programmed by the physiotherapist to perform the suggested exercises [1].

Muscles activity can be recorded from selected muscles by using surface EMG electrodes (sEMG), while the user moves his arm. The muscular activity can be transformed to the force and kinematic variables that are used as inputs in control robot by a decoding procedure.

The sEMG is one of the most common biological signals, which we might find beneficial in robot control according to the user's intention. The sEMG can reflect the muscle activation level in real time directly [2-8]. In voluntary movements, force is associated with motor unit recruitment and variations in motor unit firing frequency [9]. At the same muscle length and during isometric conditions, a greater number of recruited motor units with major discharge frequencies (i.e. muscle activation) lead to a significant generation of force. Therefore, a linear relationship between EMG and muscle force is considered. Although, precise estimation of muscle force based on sEMG signals in real time provides valuable information for robot control system in order to perform effective therapeutic exercises, sEMG signals are random, continuous and nonlinear in nature [10, 11]. Therefore, sEMG signals should be processed in order to get a simple model for its amplitude, so the amplitude should be mapped for joint force.

Various methods have been proposed for sEMG-based force estimation such as mathematical models, artificial neural network (ANN) and neurofuzzy. It has been shown that ANN will yield efficient to estimate voluntary limb force [12]. It has been shown that the setting of network parameters, such as number of neurons, number of hidden layers and learning rate which have fundamental influence on the accuracy of ANN model. However, the selection of ANN design parameters is still an open question in the force estimation for rehabilitation robots.

Therefore, in this paper, sEMG experimental data are collected and the ANN parameters are regulated to train the ANN. To have precise estimation, we present the new model to estimate the force from sEMG signals. In this method, the sum of the limb's dynamics and the contact force is used as target data in the train phase. To determine the limb's dynamics, the patient's body and rehabilitation robot are modeled in the OpenSim. The results indicated that presented model can estimate the human force from sEMG signals precisely.

The paper is organized as follows: Section 2 sheds light on how robotic system. The force estimation model is presented in

section 3. In section 4, the procedure of experimentation are presented. The results and conclusion of this discussion are presented in section 5 and 6.

II. ROBOTIC SYSTEM

A. Overall View of FUM PHYSIO Rehabilitation Robot

FUM PHYSIO is a single DOF robot, which is designed to perform knee-therapeutic exercises.

As shown in Figure 1, the three main part of robot is a chair, an actuator set, and a monitor for graphical user interface.

The monitor shows virtual reality animation to help the patients in performing therapeutic exercises. Indeed, the patients move their knees according to the desired trajectory, which are showed in the monitor.

To control the robot, windows real time target has been used and servo motor drives are received the command signals from windows real time target. Servo motor with 1Kw power works in torque mode. A planetary reducer is designed. Then by using the linkage it is able to transmit motor motion to the patient's knee. The force sensors are attached to linkage and due to the mechanism of the force sensing, they have direct contact with leg.

On the other hand, in rehabilitation robots due to physical interaction with human's safety is a great challenge. Therefore, a high degree of safety is considered in the mechanical design of the FUM PHYSIO robot.

Some proximity sensors are located in order to limit the rotation angle of revolute joint. Hence, the robot is allowed to rotate in limited trajectory and proximity sensors turn the motor off when the linkage finishes its trajectory. Moreover, two mechanical stops are designed to limit the linkage's movement.

Moreover, emergency keys are located near the patient, physiotherapist to be reachable.

The rotation axis of patient's knee and robot's revolute joint must be collinear in order to measure leg's torque correctly. Chair and plate are designed with adjustable mechanisms so patient's knee of all dimension and size can be set in front of the revolute joint easily. Chair and actuator set are able to move vertically and horizontally, respectively.

B. Hardware Configuration

As shown in Figure 1, controller computes needed torque and send control commands to the motion card via Ethernet cable. Motor encoders and load cells determine angular position and contact force as control input, respectively.

Then, the driver of the actuator gives control command to its actuator. Drivers determines torque according to voltage sent by custom bard. Indeed, the custom board has been designed to facilitate the communication between motor driver and TSP MDI motion control card. It is noticeable that the Driver of force sensor amplifies and filters its sensors.

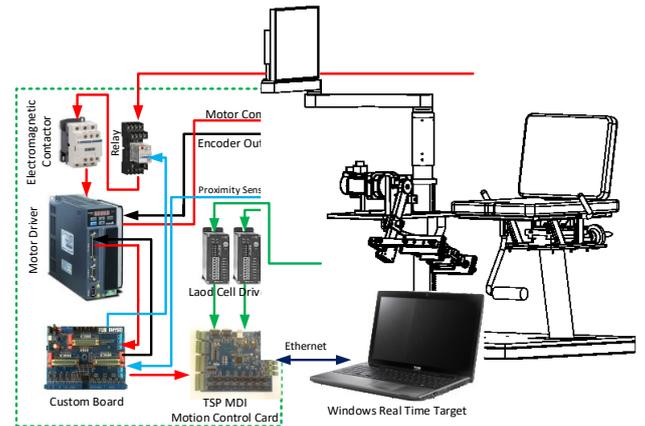


Figure 1. FUM PHYSIO robot Hardware Configuration.

C. Robot Modeling

Considering the human-machine interaction involved in the use of FUM PHYSIO robot and for specifying leg dynamic in rehabilitation exercises, the OpenSim simulator was chosen to implement and analyze the model from a biomechanical point of view.

Opensim is an open-source multibody dynamics engine developed by Stanford University to implement mathematical models of the musculoskeletal system and create kinematic and dynamic simulations of human movement.

OpenSim provides the capability to reconstruct motion. It assists researchers' review and analysis of the activities of the musculoskeletal system. OpenSim includes biomechanics algorithms such as inverse kinematics, computed muscle control and forward dynamics for a user to simulate and compute the kinematics, muscle activations and reaction forces for the customizable musculoskeletal models.

As shown in Figure 2, we modeled the FUM PHYSIO robot in OpenSim and the musculo-skeletal model used was the generic OpenSim model Leg6Dof9Musc which has 6 degrees of freedom and 9 muscles. Leg6Dof9Musc has Pelvis, Femur, Tibia, Patella, Talus, Calcn and Toes. Also, we used Inverse Dynamic Tool to calculate the moments of every part of the body.

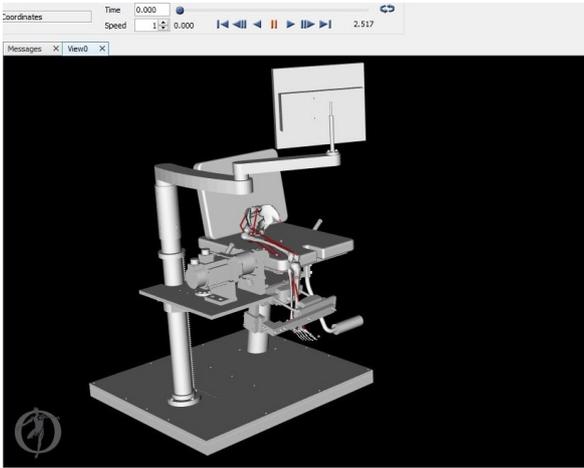


Figure 2. FUM PHYSIO in OpenSim.

III. FORCE ESTIMATION

In control system of rehabilitation robots, estimated force is used as an input signals. Nevertheless, raw sEMG signals are not suitable as input signals for controllers and must be processed prior to use.

In this paper, each EMG channel is independently processed in three steps. Step 1: Raw EMG signals must be filtered. In this step, a 5th ordered notch filter is used to remove the 60 Hz noise resulted from the power supply. Step2: EMG signal should be rectified. The absolute value of EMG signals is calculated in this step. Step3: The Online Moving Average (OMA) of rectified EMG signals is calculated as:

$$E(t) = \sqrt{\frac{1}{N} \sum_{i=0}^N E(t-i)^2} \quad (1)$$

Where N is the number of the segments ($N=100$) and $E(t)$ is the value of rectified EMG at its sampling point. The procedure of signal processing is shown in Figure 3. Finally, the Processed EMG (PEMG) signals are ready to be used as input for ANN estimator.

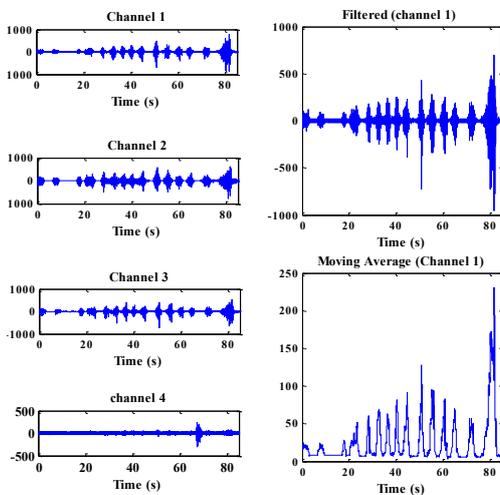


Figure 3. EMG processing for Neural network estimation.

The MLP and Cascade are the two most common structures of ANNs, which are used for force estimation. The detail structural design for feed-forward condition for the MLP and the Cascade is depicted in Figure 4.

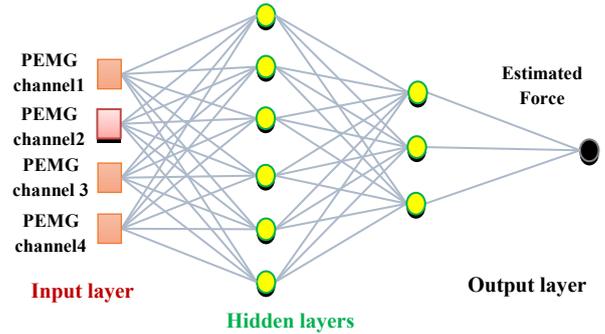


Figure 4. MLP Neural network structure.

We proposed the PEMG signals and the information of human dynamics as input for estimation; hence, the relationship between the sEMG signals and the human force is proposed as:

$$\tau_{loadcells} + \tau_{opensim} = \tau_{hest} = \begin{bmatrix} PE_{ch1}(t) \\ PE_{ch2}(t) \\ PE_{ch3}(t) \\ PE_{ch4}(t) \end{bmatrix} W^{hl1}_{6 \times n} W^{hl2}_{n \times m} W^{ol}_{m \times 1}$$

where τ_{hest} is the estimation of human force, $\tau_{opensim}$ is the calculated torque by OpenSim as result of patient's limb and $\tau_{loadcells}$ is recorded torque by force sensors, $PE_{ch_i}(t)$ is the processed EMG signal for i^{th} channel. $W^{hl1}_{6 \times n}$ and $W^{hl2}_{n \times m}$ are the neural network's weight matrices of the hidden layers and $W^{ol}_{m \times n}$ is the weight matrix of the output layer.

IV. EXPERIMENTS

A. Setup and sEMG data collection

Four channels of sEMG signals are used as main input signals to estimate the participant's real force. The locations of sEMG electrodes are shown in Figure 5. Each channel mainly corresponds to one muscle, as shown in Table 1. To determine the magnitude of sEMG signals of the knee extensors, our participants were seated on a dynamometer (Biodex - System3, Biodex Medical Systems Inc., USA) with hip angle of 85°.



Figure 5. The locations of sEMG electrodes.

TABLE I. MUSCLES FOR EACH SEMG CHANNEL

EMG Channel	Ch.1	Ch.2	Ch.3	Ch.4
Muscle	Vastus Lateralis	Rectus Femoris	Vastus Medialist	Bicep Femoris

Electrodes (Ag/AgCl) with an electrolytic gel interface were positioned above the midpoint of the muscle belly (with 2 cm distance on inter-electrodes) of the Rectus Femoris, Vastus Lateralis, Vastus medialis and Biceps Femoris (Fig3). Moreover, reference electrodes were located on the patella bone. The skin was carefully shaved and cleaned with alcohol to reduce skin impedance. To reduce motion artefacts of the electrodes they were further secured to the skin with an elastic tape, together with the preamplifier. Prior to the experiment, the leg was passively shaken to check mechanical artefacts of sEMG signals from each muscle. Several tests (e.g. contractions against manual resistance in knee flexion and extension) were performed to visualize whether a good signal was produced from each muscle. When artefacts or a poor signal were observed, the preparation procedure was repeated. ME6000 is used for recording the sEMG signal from muscle in Sport Sciences Research Institute of IRAN (SSRI). Data from EMG sensor was sampled using 2000 Hz sampling frequency.

V. RESULTS

In this study at first, we define an Isotonic exercise for the patient. Isotonic exercise is one method of muscular exercise that a constant resistance force is applied to the patient for the duration of the movement. In this study the patient must move her leg 3 times in each exercise. The evaluated dynamics of patient's limb during a therapeutic exercise by OpenSIM is shown in Figure 6.

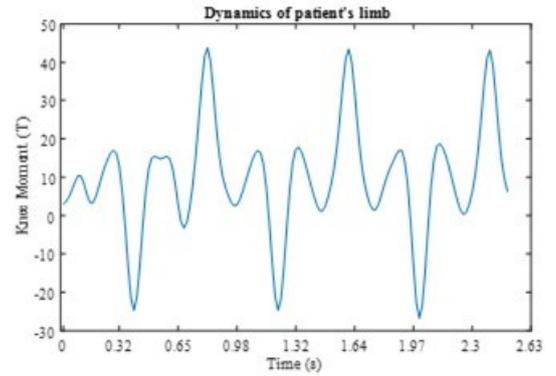


Figure 6. Calculated dynamics of patient's limb by OpenSim.

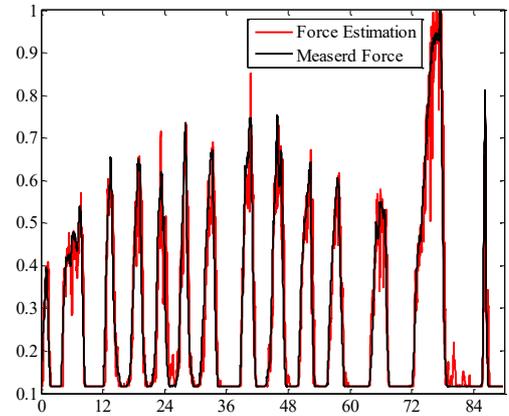


Figure 7. Force estimation by the optimized ANN.

Also, to evaluate the performance of proposed model, the proposed ANN model in (2) is simulated and compared with the commonly used ANN model presented by [6]. The ANN MATLAB toolbox is used for estimation force from EMG signals. As seen in figure 7, the performance of estimation increased when the patient's dynamic is considered.

VI. CONCLUSIONS

The main objective of this paper was to present a new ANN model to estimate the human force during therapeutic exercise. The authors theorize that whereas the majority of present studies used force sensors to estimate patient force from sEMG signals. However, this signals are related to the patient force which are consist of the limb's dynamic and the contact force. To determine the limb's dynamics, we model rehabilitation robot and patient in the OpenSim software as one of the best software for biomechanics modelling. Also the experimental sEMG data are collected form a volunteer person. Finally, the ANN is implemented to model real human force from sEMG signals based on limb's dynamics and measured contact force by FUM robot. The results demonstrated that presented model is an effective tool in estimating human force. The authors believe this model can be used in other applications too.

REFERENCES

[1] M.M. Fateh, V. Khoshdel, "Voltage-based adaptive impedance force control for a lower-limb rehabilitation robot", *Advanced Robotics*, 29(15), 961-971, (2015).

- [2] V. Khoshdel, A. Akbarzadeh Tootoonchi, "Robust Impedance Control for Rehabilitation Robot", *Modares Mechanical Engineering*, 15(8), 429-437, (2015).
- [3] R.K. Jain, S. Datta, S. Majumder, "Design and control of an IPMC artificial muscle finger for micro gripper using EMG signal," *Mechatronics*, 23(3), 381, (2013).
- [4] B. Dellon and Y. Matsuoka, "Prosthetics, exoskeletons, and rehabilitation (grand challenges of Robotics)," *IEEE Robot. Autom. Mag.*, 14(1), 30–34, (2007).
- [5] S. Wu, G. Waycaster, Xi. Shen, "Electromyography-based control of active above-knee prostheses," *Control Engineering Practice*, 19(8), 875–882, (2011).
- [6] K. Kiguchi, S. Kariya, K. Watanabe, K. Izumi, and T. Fukuda, "An exoskeletal robot for human elbow motion support—Sensor fusion, adaptation, and control," *IEEE Trans. Syst., Man, Cybern. B*, 31(3), 353–361, (2001).
- [7] J. Rosen, M. Brand, M. Fuchs, and M. Arcan, "A myosignal-based powered exoskeleton system," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 31, no. 3, pp. 210–222, (2001)
- [8] K. Kiguchi, M. H. Rahman, M. Sasaki, and K. Teramoto, "Development of a 3DOF mobile exoskeleton robot for human upper limb motion assist," *Robot. Autonom. Syst.*, 56(8), 678–691, (2008).
- [9] C. Fleischer and G. Hommel, "A human -exoskeleton interface utilizing electromyography," *IEEE Trans. Robot.*, 24(4), 872–882 (2008).
- [10] T. Moritani, M. Muro, "Motor unit activity and surface electromyogram power spectrum during increasing force of contraction," *Eur J Appl Physiol Occup Physiol*. 56(3), 260-5, (1987).
- [11] N. Hogan, "Myoelectric signal processing, Optimal estimation applied to electromyography—Part1: Derivation of the optimal myoprocessors," *IEEE Transactions on Biomedical Engineering*, 27(7), (1980).
- [12] S. Siegler, H.J. Hillstrom, W. Freedman, G. Moskowitz, "Effect of myoelectric signal processing on the relationship between muscle force and processed EMG," *Am. J. Phys Med*, 64(3), 130-149, (1985).
- [13] T.Y. Lin, H.C. Ping, T.H. Hsu, "A systematic approach to the optimization of artificial neural networks," *IEEE* 2011, 6, 76-79
- [14] E. Inhira, H. Yokoi, "An optimal design method for artificial neural networks by using the design of experiments," *J Adv Comput Intell Inform*, 11, 593-599, (2007).
- [15] Y.S. Kim, B.J. Yum., "Robust Design of Multilayer Feed Forward Neural Networks: An Experimental Approach," *Appl. Artif. Intell.*, 17, 249-263, (2004).
- [16] M.S. Packianather, P.R. Drake, H. Rowland, "Optimizing the Parameters of Multilayered Feed Forward Neural Networks through Taguchi Design of Experiments," *Qual. Reliab. Eng. Int.*, 16, 461-473, (2000).
- [17] S.M. Yang, G.S. Lee, "Neural Network Design by using Taguchi Method," *J. Dyn. Syst. Meas. Contr*, 121, 560-563, (1999).
- [18] J.F.C. Khaw, B.S. Lim, L.E.N. Lim, "Optimal Design of Neural Networks using the Taguchi Method," *Neurocomputing*, 7, 225-245, (1995).
- [19] P.P. Balestrassi, E. Popova, A.P. Paiva, J.W. Marangon Lima. Design of experiments on neural network's training for nonlinear time series forecasting, *Neurocomputing*, 72, 1160-1178, (2009).
- [20] R.K. Roy, "Design of Experiments Using The Taguchi Approach: 16 Steps to Product and Process Improvement", Wiley, (2001).
- [21] K. Lee, J. Kim, "Controller gain tuning of a simultaneous multi-axis PID control system using the Taguchi method", *Control Engineering Practice*, 8(8), (2000).