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Neural Network-based EMG-driven Model for Patient Torque Estimation Applied to Rehabilitation Robotics[1]

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Abstract

This paper deals with EMG-driven modeling of patient torque estimation during robot-aided rehabilitation. Electromyographic (EMG) signals, taken from selected muscles acting during flexion and extension movements, are processed to get the muscles activations. First, a simplified and optimized musculoskeletal model is used to compute the estimate of patient torque. The model optimization is performed by comparing the estimate torque with the torque generated by the inverse dynamics tool of the OpenSim software, considering a scaled musculoskeletal model. As a complementary solution, a multilayer perceptron neural network (NN) is proposed to map the EMG signals to the patient torque. This solution simplifies the torque estimation by decreasing the number of paramters to be optimized. It is also presented an EMG-driven Torque Estimation of Environment created to analyze the data obtained from the application of the proposed approaches considering a set of subjects wearing a knee active orthosis and preforming a protocol created for user-exoskeleton interaction analysis. A database with data from five healthy subjects is also made available in this paper. Finally, the results obtained by applying the NN-based EMG-driven model is presented.

Keywords: active orthosis, impedance control, rehabilitation robotics, series elastic actuator, torsion spring.

1. Introduction

Neurological disorders are diseases of the central and peripheral nervous system, resulting in motor control disturbances which affect motor functions, such as walking or upper limb movements. Cerebral Vascular Accident (CVA or stroke) is the leading cause of permanent disability in developed and developing countries, being the cause of 10% of deaths worldwide. Each year 15 million people suffer a stroke, five million of them die and five million staying with a residual disability (Mackay, Mensah, Mendis, & Greenlund, 2004). Spinal cord injuries are approximately half a million people worldwide each year from traffic accidents mostly. For low- and middle-income countries, only 15% of people with this type of injury have the access to assistive devices they need (Lukersmith, 2013).

Reduction of walking abilities is the main result caused by neurological diseases, and loss of mobility is the activity of daily living with greater value for patients. The impact on patients is huge, with negative results on their participation in social, professional, and recreational activities (Robinson, Shumway-Cook, Ciol, & Kartin, 2011).

Strengthening exercises in lower limbs and training tasks can be used to recovery of walking abilities in people with neurological disorders (Patton, 2004; Teixeira-Salmela, Olney, Nadeau, & Brouwer, 1999). In current clinical practice, the gait restoration with robotic devices is an integral part of rehabilitation program of patients with this type of disorder (Sale, Franceschini, Waldner, & Hesse, 2012).

The most successful robot-aided therapy is based on learning. Repeating the therapy process with high intensity provides the stimulus for the brain to re-acquire movement control and coordination (a typical session of robot-aided therapy involves over a thousand movements, whereas a typical session of human-administered therapy involves about eighty); this is confirmed by the observation that the patient's active participation is essential (passively moving a patient's limbs may help improve joint mobility but it yields no improvement of motor function). Due to physical interaction, the dynamics of an object (in this case, a patient) coupled to the robot may profoundly affect the robot controller's stability.

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This challenge was identified in the earliest days of research in robotic. Given a sufficiently detailed knowledge of the object's dynamics, but in this application, the *object* is a neurologically-impaired human (Hogan, 2014).

The field of robot assisted treadmill training has evolved significantly during the last ten years, and the robotic devices can be divided into exoskeletons and end effector-based system device. In particular early research in powered human exoskeleton devices began in the late 1960s with Hardiman, developed by General Electric and US Department (Bogue, 2009).

The use of exoskeletons, an external structural mechanism with joints and links corresponding to those of the human body, has very different objectives such as using in the neuro-recovery therapy, but the common problem arises: design of a human-robot interface able to understand user intent and react appropriately to provide the necessary assistance.
A widely investigated methodology to achieve this objective is based on the estimate of joint torques to perform the movement, and the provision with a fraction of the estimated torque to decrease the effort of the user (Kong & Tomizuka, 2009). The expected result is, thanks to the help mediated robot, the subject can perform the desired task with less muscular effort (Gordon & Ferris, 2007).

A possible strategy for estimating the torque needed to perform a movement consists in measuring the activation of the involved muscles through electromyography (EMG). EMG signals, resulting from the motor neuron impulses that activate the muscle fibers, can be correlated with the force produced by muscles and the resulting torque at the joint level. The main drawback of EMG-based torque estimation methods is intrinsic in the complex subject- and session-dependent calibrations that are required to produce an accurate and reliable model (Lenzi, De Rossi, Vitiello, & Carrozza, 2012).

This paper shows the development of an optimized EMG-driven model of patient torque for rehabilitation robotics. First a musculoskeletal model is used to compute the estimated patient torque. For this, the torque estimation approach starts with the neural command and then uses a simplified muscle contraction model to compute the joint torque. These joint torques are also computed using inverse dynamics tools and position data from the robotic device. An optimization procedure, where the EMG-driven model's parameters are adjusted, is performed aiming to minimize the difference between the estimate joint torques.

Although the proposed simplified muscle contraction model is effective if properly adjusted, it considers a high the number of parameters to be optimized. Besides, musculoskeletal parameters are bounded to possible physiological values, requiring the optimization procedure to be a constrained one. To solve this problem, we have implemented a multilayer perceptron neural network (NN) to map the EMG signals to the patient torque. The inputs for the NN are the processed EMG signals from five muscles involved in the movement and the output is the estimated patient torque.

It is also presented an EMG-driven Torque Estimation of Environment created to analyze the data obtained from the application of the proposed approaches considering a set of subjects wearing a knee active orthosis presented by (dos Santos & Siqueira, 2014). A specific protocol was created to analyze the user-exoskeleton interaction, consisting of a set of flexion and extension movements of the knee, with and without robot assistance. A database with data from five healthy subjects is also made available in this paper. Finally, the results obtained by applying the NN-based EMG-driven model is presented.

The paper is organized as follows: Section 2 describes the EMG-driven musculoskletal model; Section 3 presents the torque estimation procedures based on the musculoskeletal model and on the NN model; Section 4 shows the EMG-driven Torque Estimation of Environment used to evaluate the data; Section 5 shows the protocol and the database created to analyze the user-exoskeleton interaction; Section 6 shows the results obtained by applying the NN-based EMG-driven model to the data obtained; and a short conclusion is given in Section 7.

2. EMG-driven torque estimation

In this section the EMG-driven musculoskeletal model for torque estimation is presented. The torque estimation based on EMG starts with a measure of neural command using surface electrodes. This signal is preprocessed and generate muscle activations through a function of neural activation; then, we compute the resulting force using a muscle contraction model and, using the moment arms, compute the torque τ_{EMG}.

We are considering a simplified muscle contraction model to compute the muscles forces, with active and passive components depending only on the muscle length. No velocity-dependent components are taking into account. The simplified model is justified since it will be implemented in an online adaptive control strategy of adjusting the robot assistance (Pena, Jauregui, Santos, & Siqueira).

2.1. *Muscle activation*

The postprocessed EMG signal (with DC offset elimination, rectification and subtraction of the measured offset when the muscle is relaxed, and low-pass filtering) is transformed to muscle activation through the function:

$$a(u) = \frac{e^{AuR^{-1}} - 1}{e^{A} - 1} \tag{1}$$

where u is the post-processed EMG value, R a mean value of maximum voluntary isometric contraction, and A a nonlinear shape factor defining the curvature of the function with $A < 0$. For $A \rightarrow 0$, the function approximates a linear relationship.

2.2. *Musculoskeletal model*

Once the muscle activation is obtained, we can estimate the force using a simplified Hill-type model (Fleischer, 2007) of muscle contraction Figure 1

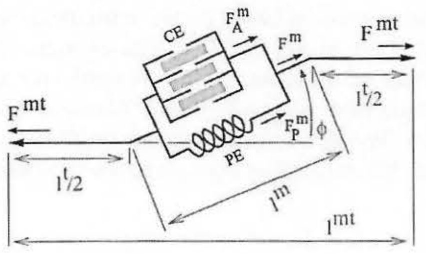

Figure 1. Muscle Model

It consists of two elements: a contractile element producing the active muscle force, F_A^m, and a parallel elastic element that produces the passive force, F_P^m, when the muscle is stretched. The muscle force is given by:

$$F^m = F_A^m + F_P^m \tag{2}$$

The force of the contractile element is calculated by:

$$F_A^m = f_A(\tilde{l}^m) F_0^m a(u) \tag{3}$$

where $f_A(\tilde{l}^m)$ is the normalized active force-length function, F_o^m is the maximum isometric force at optimal muscle fiber length l_o^m, $a(u)$ is the muscle activation, and $\tilde{l}^m$ is the normalized muscle fiber length given by:

$$\tilde{l}^m = \frac{l^m}{l_0^m} \tag{4}$$

where l^m is the muscle fiber length. The passive force is calculated as a product of F_o^m and the normalized passive force-length function $f_P(\tilde{l}^m)$:

$$F_P^m = f_P(\tilde{l}^m) F_0^m \tag{5}$$

According to Figure 1 the force of the musculotendinous unit F^{mt} is calculated by:

$$F^{mt} = (F_A^m + F_P^m) cos\phi \tag{6}$$

The angle between the orientation of muscle and tendon fibers, named pennation angle, ϕ, can be compute by:

$$\phi = arcsen\left(\frac{l_0^m\, sen\phi_0}{l^m}\right) \tag{7}$$

where ϕ_0 is the pennation angle at optimal fiber length.

2.3. Joint torque

Once the muscle forces are estimated (Eq.(6)) and the moment arms (data taken from software Opensim) of all chosen muscles acting on the joint are available, we are able to convert the muscle forces to joint torque τ by means of the following equation:

$$\tau = \left|\sum_{i=1}^{n} F_i^{mt} r_i\right|_{Agonist} - \left|\sum_{j=1}^{m} F_j^{mt} r_j\right|_{Antagonist} \tag{8}$$

where n and m are the number of agonist and antagonist muscles acting on the joint, respectively.

3. Optimization process

In this section, it is presented the optimization procedure proposed by (Jauregui, Pena, Santos, & Siqueira) to adjust the EMG-driven model's parameters aiming to minimize the difference between the EMG-based estimate joint torque, τ_{EMG}, and the ID-based one. The optimization process based on the muscoloskeletal model is shown in Figure 2. We are using the open-source software OpenSim (Delp et al., 2007). It allows users to develop musculoskeletal models and create dynamic simulations of a wide variety of movements. In this work, we are using the OpenSim inverse dynamics tool which, considering position and torque data from the robotic device and the musculoskeletal proprieties, provides us a reliable estimate of the joint torque. We are considering the Gait2392 model, a 23-degree-of-freedom model of the human musculoskeletal system, with 92 musculotendon actuators representing 76 muscles in the lower extremities and torso.

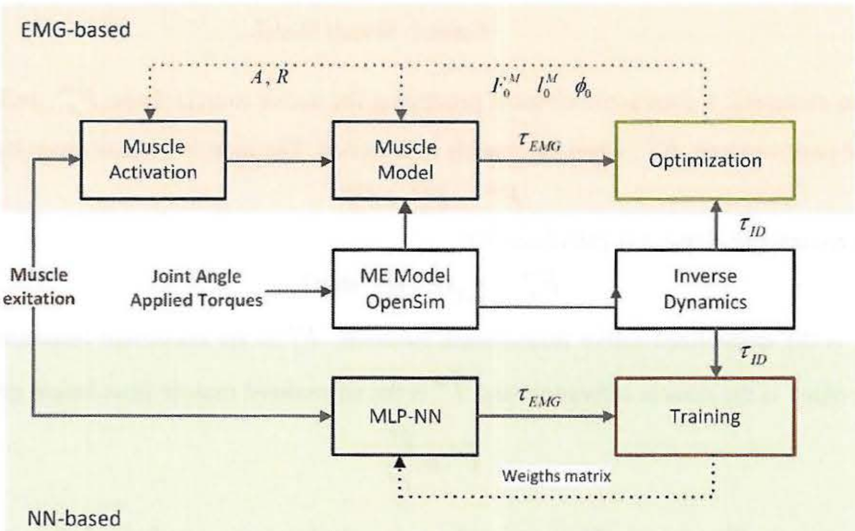

Figure 2. Optimization procedure. Based on EMG torque estimation (top), and MLP – Neural Network (bottom)

The EMG signals pass through signal processing (with DC offset elimination, rectification, low-pass filtering, and subtraction of the measured offset when the muscle is relaxed); the processed signal is introduced into the muscle activation function; and the result is used in the contraction model to generate muscle forces. Finally, the estimated torque is computed considering the moments arms, obtained from the OpenSim model.

On the other hand, joint positions and applied torques obtained from an active knee orthosis are loaded to the OpenSim model, and the Inverse Dynamics tool is used to compute the user's torque, τ_{ID}. The active knee orthosis is shown in Figure 3. The orthosis' actuator is an rotary series elastic actuator, which allows to set the mechanical impedance of active knee orthosis, (dos Santos & Siqueira, 2014).

Figure 3. Active knee orthosis

Although the proposed simplified muscle contraction model is effective to be implemented in an online adaptive control strategy as presented by (Pena et al.), the number of parameters to be optimized, even if it is considered only few muscles, is big. Besides, musculoskeletal parameters are bounded to possible physiological values. For example, the maximum isometric force can not assume values very different from those usually found in the literature.

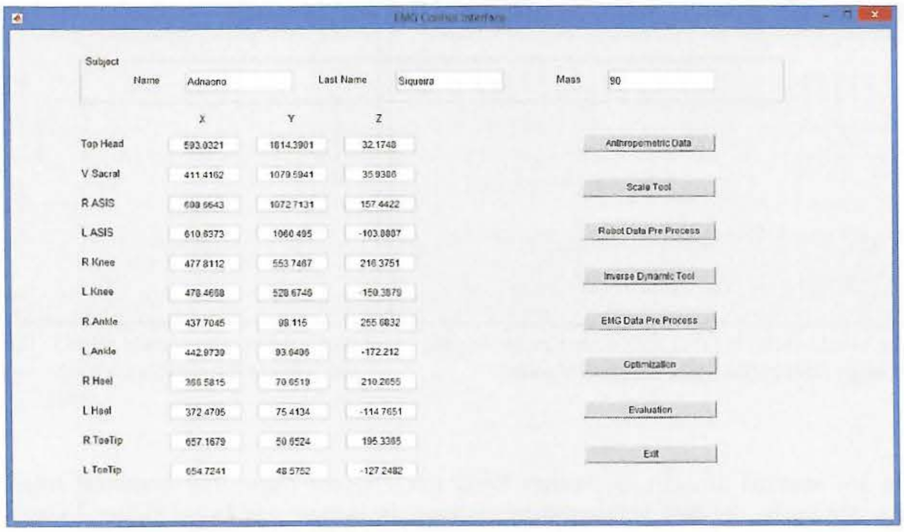

Figure 4. EMG-driven Torque estimation environment.

To solve this problem, we have implemented a multilayer perceptron neural network (NN) to map the EMG signals to the patient torque. The inputs for the NN are the processed EMG signals from five muscles involved in the movement of flexion/extension of knee: Rectus femoris, Vastus lateralis and Vastus medialis of the extensors group; and Biceps femoris e Semitendinosus, of flexors group. Also, 10 hidden neurons and 1 output neurons, related to the patient's estimated torque, complete the NN structure. The following parameters were considered during the training phase: 1000 epochs, learning rate, $\alpha = 0.3$, and momentum, $\omega = 0.89$. Figure 2 (bottom) shows the training process of the NN, where the desired output signal is the patient's torque estimated from the OpenSim Inverse Dynamic tool, τ_{ID}.

4. EMG-driven torque estimation environment

A Matlab-based computing environment was developed to facilitate the analysis of the optimization process of estimating the patient torque. The environment also uses the software OpenSim to perform the scheduling process of the musculoskeletal model, the calculation of the inverse dynamics, and to obtain the initial parameters of muscles.

The graphical interface of the environment is shown in Figure 4. In the top of the interface, the user can enter the name, surname, and the mass of the subject whose data will be studied. In the left part of the interface, it is shown the measures obtained from the subject, corresponding to the markers of the OpenSim musculoskeletal model. By clicking on the button *Antropometric Data*, a dialog box shows the options of files .mat to be loaded. When you select the file, the program inserts the values of the measures from the .mat file in the markers' fields.

The scaling process is performed through the button *Scale Tool*. By clicking this button, a dialog box shows the available models: gait2392_simbody.osim and its corresponding in a sitting position, gait2392_simbody_sitted.osim. Based on the selected model, the markes' measures, and the mass value, OpenSim scale tool generates the scaled model of the subject.

After obtaining of the scaled model, it is possible to insert the position data of the knee joint over time and the torque applied by the orthosis. By clicking the button *Robot Pre Process Data*, the graphical interface shown in Figure 5 becomes visible. The data is inserted by clicking the button *Add Data*. Figure 5 also shows the position and applied torque, obtained in a given experiment with the orthosis.

The next step corresponds to the inverse dynamics calculation of patient/exoskeleton system, aiming to calculate the torque generated by the patient based on the data of position and applied torque obtained from robotic system. By clicking the button *Inverse Dynamic Tool*, the environment uses the OpenSim library to perform the necessary calculations. Figure 6 shows the results obtained.

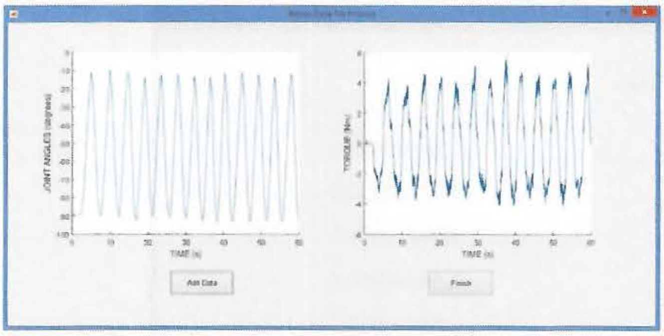

Figure 5. Graphical interface for robot data insertion. In the left, the joint angle, and in the right, the applied toque.

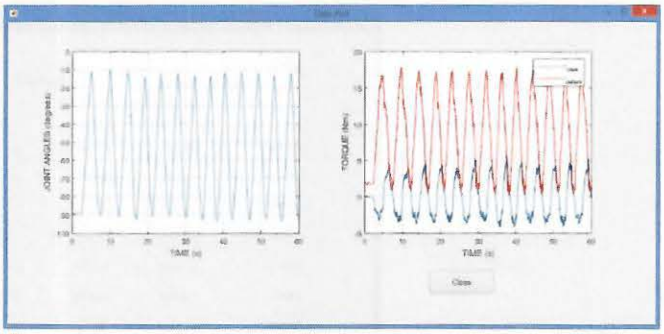

Figure 6. Inverse dynamics results. The joint angle is presented at the left and the resultant torques, i.e robot (blue) and patient (red).

The EMG data are inserted through the button *EMG Pre Process Data*. The graphical interface shown in Figure 7 becomes visible. Similarly, the data is inserted by clicking the button *Add Data*. Figure 7 also shows the raw (left) and processed (right) EMG signals from the same experiment of Figure 6.

After inserting the robot and EMG data, and calculating the estimated torque of the patient, the next step is the optimization process (button *Optimization*), where the musculoskeletal model parameters are adjusted using the procedure proposed by (Jauregui et al.) or the NN is trained. Figure 8 shows the result of the optimization process.

The optimized parameters of the musculoskeletal model or the resulting NN-based model can be evaluated in another data set of the same subject. For accomplish this evaluation, the user must enter the robot data (*Robot Data Pre Process*), perform the inverse dynamics (*Inverse Dynamic Tool*), and enter the corresponding EMG data (*EMG Pre Process Data*). After the inclusion of new data, just click the button *Evaluation* (Figure 8 shows the results).

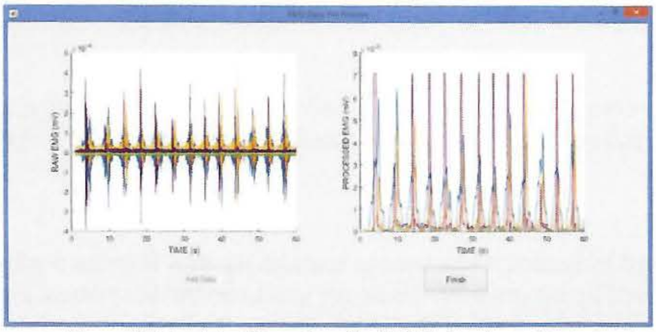

Figure 7. Graphical interface for EMG data insertion.

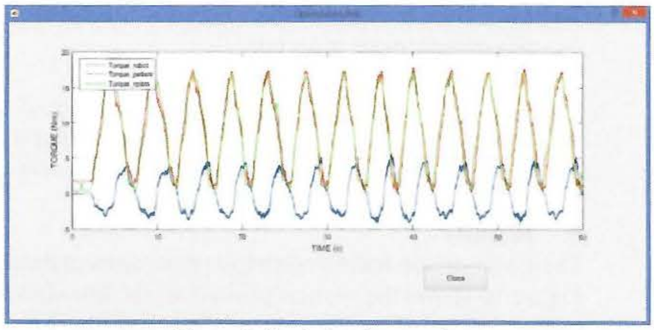

Figure 8. Optimization results.

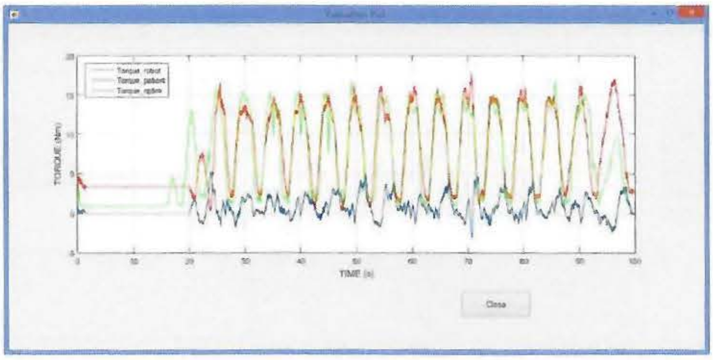

Figure 9. Evaluation results

5. User-exoskeleton interaction database

A database was created containing the robot and EMG data obtained from the embodiment of a protocol for studies of the interaction between the user and the exoskeleton.

The protocol consists in the realization of a series of movements with the user wearing the active knee orthosis and acting both actively and passively. The desired trajectory for the orthosis correspond to a sinusoidal signal with 8 seconds of period and amplitude ranging from -90° a -0°. A graphical user interface shows the desired trajectory and the current position of the orthosis, so that the user is asked to follow it as close as possible during his/her active phase. The desired stiffness of the orthosis is defined as 0 Nm/rad, 30 Nm/rad, or 60 Nm/rad.

Table 1. Evaluation protocol.

Phase	**User**	**Robot Stiffness** k_r
1	Passive	0
2	Passive	30
3	Passive	60
4	Active	60
5	Active	30
6	Active	0
7	Active	0 + 180° phase shift
8	Active	30 + 180° phase shift
9	Active	60 + 180° phase shift

The evaluation protocol (Table 1) defines nine phases of interaction between the user and the exoskeleton, each one with 5 cycles of sinusoidal trajectory[3]:

During phases 7, 8, and 9, the desired trajectory of the orthosis is defined with a 180° phase shift with relation to the desired trajectory shown to the user at the graphical interface. That is, the robot imposes an opposite force to that one performed by the user, characterizing a resistive exercise.

6. Results

The EMG-driven torque estimation environment described in Section 4 was used to evaluate the data from the 5 subjects. Figure 10 shows the angular position of the knee (measured by the orthosis) the torque generated by the orthosis, and the patient estimated torque (obtained through the inverse dynamics tool of OpenSim) for the 9 phases of the protocol, considering the data of Subject 1, trial 1.

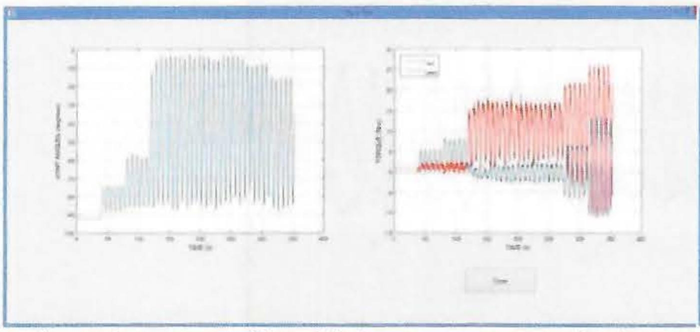

Figure 10. Angular position of the knee, torque generated by the orthosis and user estimation torque.

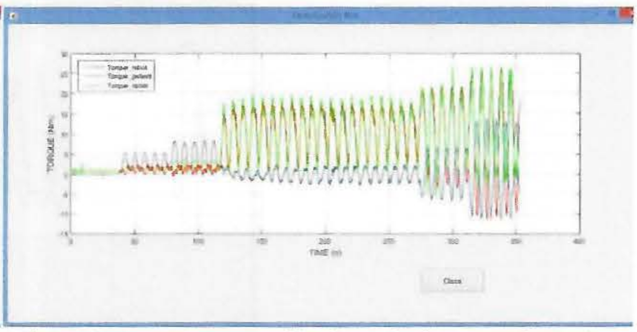

Figure 11. Torque generated by the orthosis, user estimated torque (OpenSim), and user estimated torque (EMG).

Figure 11 shows the torque generated by the orthosis, the user estimated torque from OpenSim and the torque estimated through EMG-driven NN-based model. Note that during the frist three phases (from 0 s to 120 s), the user is passive and his estimated torque is low. During the next 4 phases (from 120 s to 280 s), where the user is active and the orthosis follows the same desired trajectory defined to the user, the user estimated torque predominates. During the last two phases, where the desired trajectory of the orthosis is defined with a 180° phase shift, both the user and robot torques increase proportionally to the stiffness defined to the orthosis.

7. Conclusions

Two EMG-driven models of patient torque estimation for robot-aided rehabilitation is presented. Both the simplified musculoskeletal model and the NN-based approaches are efficient to estimate the user torque when compared with the torque generated by the inverse dynamics tool of the OpenSim software, considering a scaled musculoskeletal model. Both approaches are also suitable to be implemented in an online adaptive control strategy of adjusting the robot assistance as the one presented by (Pena et al.). The NN solution has the advantage of decreasing the number of parameters to be optimized. The EMG-driven Torque Estimation of Environment and the database with data from 5 healthy subjects are made available for further analyses of user-exoskeleton interaction.

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[3] The data obtained from five healthy volunteers (two sequences of the protocol each) along with the Matlab script files of the EMG-driven Torque Estimation of Environment are available in the link: https://www.dropbox.com/s/y7sxzoa9g2nd3og/Database\-EMG.zip?dl=0.

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