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EMG-DRIVEN HUMAN-EXOSKELETON INTERACTION MODEL FOR KNEE FLEXION AND EXTENSION REHABILITATION

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Abstract. *The use of computational models is extremely important for robotic rehabilitation, as it allows the simulation of its dynamic behavior before building the device represented by the model, ensuring its safe performance, an essential feature for the use of the instrument in physical therapy treatments. Using this approach of dynamic systems modeling, this work aims to present and simulate a human-exoskeleton interaction model for knee flexion and extension equipped with an active orthosis, estimating its the human torque having EMG signals as inputs. The importance of this work is the development and analysis of a biomechanical model that takes into account biological aspects of the human being, based on the EMG signals, instead of considering a human body as a multibody system subject only to torques, which is, in its nature, purely mechanical. In order to develop biomechanical relationships, the EMG signals are converted into muscle activations and then torques exerted by the muscles. These require an interaction model, developed in OpenSim software, to obtain the angular positions of the system during movement. Finally, the accuracy of the EMG signal method is compared with another more traditional method, that of Inverse Dynamics, and with experimental data collected by sensors. The use of active EMG signals is effective in estimating the dynamic behavior of the movement, but the torque values derived from the Inverse Dynamics are more realistic.*

Keywords: *human-robot interaction, OpenSim, wearable robots.*

1. INTRODUCTION

It is estimated that around 15 million people suffer strokes annually worldwide. Of these, five million remain with some motor disability and need physical therapy to regain movement in their upper or lower limbs (WHO, 2011, 2018). In this aspect, traditional therapies, although successful, are slow, impacting the lives of patients who need their movements to perform some kind of work, or even lowering the self-esteem of these people because they do not see advances so quickly.

In order to enhance these physiotherapy treatments, robotic devices for rehabilitation have been widely developed, called exoskeletons (Vinoj *et al.*, 2019; dos Santos *et al.*, 2017b; Young and Ferris, 2017; Huo *et al.*, 2016). Thus, the use of this technology enables a faster recovery for the patient and, consequently, provides a better quality of life for them, allowing them return to their daily activities as soon as possible. In addition, the exoskeleton also requires less effort from the physiotherapist and can even reduce the number of these professionals per patient, as tasks that were previously performed by them could be then carried out by the robotic device. Additionally, exoskeletons can also collect data about the individual movement for a better diagnosis of their motor disability, which increases the possibilities of how these robots can enhance rehabilitation therapy treatments (Huang and Krakauer, 2009; Diaz *et al.*, 2011; Ibarra and Siqueira, 2014; Androwis *et al.*, 2018).

However, in order to build reliable exoskeletons, it is important to develop both a model and a simulation that computationally reproduce its behavior, before starting to build the device. Obtaining mathematical and computational models is paramount for engineering, as it allows one to understand the relationships between the physical quantities of an object of study and to estimate the behavior of a physical system, before it is tested, so that it does not cause possible damage to people environment and devices involved. Avoiding these damage is very relevant, specifically, in bioengineering, in which the human being and the physical system constantly interact, bringing risks to people if the interaction is not well planned. Furthermore, prior knowledge of a system and its impacts increases the effectiveness of health treatments. Several works have resorted to modeling and simulation with a focus on the development of controls and movement analysis, but there is a lack of work that proposes the development of EMG-driven human-exoskeleton interaction models. (Peña *et al.*, 2019; de Sousa *et al.*, 2019; de Sousa, 2018; de Sousa *et al.*, 2016; Khamar and Edrisi, 2018; Ghannadi *et al.*, 2017;

Delp *et al.*, 2007)

In this work, is presented the development and analysis of an EMG-driven human-exoskeleton interaction model for knee flexion and extension and whose purpose is to increase the biomechanical understanding of the neuromusculoskeletal system, providing relationships between EMG signals and human torques from a user equipped with an active orthosis. To verify the effectiveness of the EMG signal method, its results are compared with those obtained by the Inverse Dynamics method and with the experimental data.

Two hypotheses are proposed: (1) the results obtained by the method of EMG signals present behavior consistent with the experimental data, being able to describe the dynamic behavior of the system. (2) the torques and angular positions of the knee obtained by the method of EMG signals are closer to the experimental ones than those acquired by the Inverse Dynamics method.

2. METHODOLOGY

In this section we present the materials and methods used in the development of this work. First a subject performed a physical experiment as showed in the Experimental Procedure section, then the data collected from this experiment where used to prepare the EMG-driven human-exoskeleton interaction model. Such model was used to determine the human torques by two methods: Inverse Dynamics-based and EMG-based, and then used to carry out Forward Dynamics simulations. Finally we present how the analysis of the results obtained was made.

2.1 Experimental Procedure

To perform the experimental procedure, a health subject, male, 29-year-old with 1.77 m height and 84 kg mass, wearing an active knee orthosis, performed, in a seated position, movements of flexion and extension of the right knee. The desired and performed trajectories were showed to the subject through a graphical interface, so that he could perform the movement as close as possible to the desired one.

The EMG signals of five muscles of the subject were measured using a Trigno™Wireless EMG system (Delsys Inc., Natick, MA, USA), during the experimental procedure. The muscles whose EMG signal was measure are: the flexors semitendinosus (SM) and biceps femoris (BF) and the extensors vastus lateralis (VL), vastus medialis (VM) and rectus femoris (RF).

In this work the active knee orthosis is constituted by the knee module of the exoskeleton ExoTAO. The ExoTAO is a modular lower limb exoskeleton with six free and independent joint developed by (dos Santos *et al.*, 2017b) able to perform sagittal movements (Fig. 1a). The knee module has a series elastic actuator (SEA) designed by (dos Santos *et al.*, 2017a) that was used to measure the knee angular position and the torque exerted by the orthosis actuator.

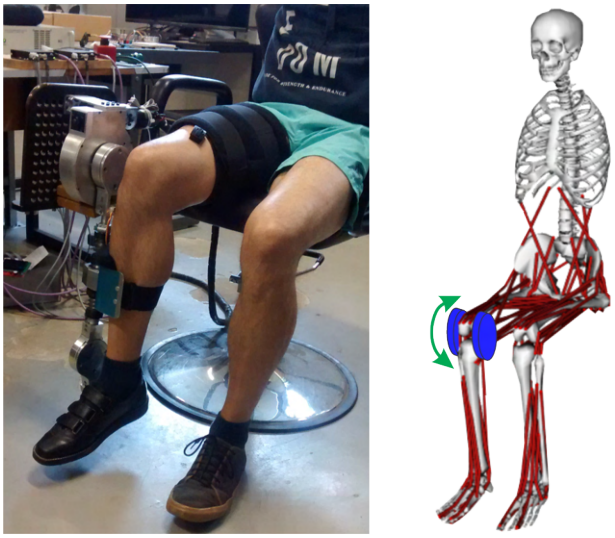

Figure 1. (a) A user wearing only the knee joint of the ExoTao, (b) the correspondent human-robot model (red lines denote the musculotendon actuators, the blue disc represents the robot actuator and the green arrow indicates the sagittal direction of the movements).

During the experimental procedure the active orthosis was controlled by an impedance control described by Eq. (1)

$$\tau_R = K_R(\theta^d - \theta) - B_R\dot{\theta} \tag{1}$$

Where τ_R is the torque exerted by the orthosis, K_R is the stiffness coefficient and B_R is the damping parameter. The reference trajectory and the one performed by the user are θ^d and θ, respectively. The angular velocity of the joint is $\dot{\theta}$.

This experimental procedure was divide in two phases:

- **Phase I:** The orthosis behaved as active-assistive, helping the user to perform the desired movement. For this, both the desired trajectory of the user and the orthosis were the same.
- **Phase II:** The orthosis behaved as active-resistive, opposing to the movement performed by the user. For this, the desired trajectory of the orthosis was shifted of 180 degrees in relation to the desired trajectory of the user.

2.2 Human-exoskeleton Interaction Model

A computational model of the subject wearing the active orthosis was developed in order to emulate the interaction between them (Fig. 1b). With this model was possible to estimate the human torque and carry out Forward Dynamics simulations.

The interaction model was developed using the human neuromusculoskeletal model *gait2392* that is a three-dimensional, 23 degree-of-freedom model of the human lower limbs with 92 musculotendon actuators representing the 76 muscles in the lower extremities and torso, developed by Delp *et al.* (1990) and provided through OpenSim Delp *et al.* (2007). A coordinate actuator was added to the right knee of the neuromusculoskeletal model in order to simulate the actuator of the orthosis used by the subject during the experimental procedures. Such actuator is ideal, that is, without response delay and losses. The joint axes of the robot and user are considered collinear.

In this work, the model is referred to as EMG-driven due to its ability to deal with muscle activations and related quantities, obtained by measuring EMG signals. In order to fit the anthropometry of the model to the one of the user, we used the *Scale Tool* from OpenSim.

2.3 Human Torque Determination

Knowing the torque that the patient is performing during the rehabilitation movement is extremely useful, as it allows the development of more efficient human-robot interaction controls, in addition to providing quantitative data for a prognosis. However, direct measurement of human torque is not possible, so it needs to be determined by indirect means. In this work we used two methods to determine the human torque: Inverse Dynamics-based and EMG-based.

The Inverse Dynamics method consists of determining the torques necessary for a given mechanical system to perform a pre-defined kinematics. Thus, having the generalized positions, velocities and accelerations, the physical characteristics (mass and moment of inertia) of the human-exoskeleton system and the external forces, it is possible to estimate the torque exerted by the user, solving the equation below.

$$\tau_{ID} = M(q)\ddot{q} + C(q,\dot{q}) + G(q) + F_{ext} \tag{2}$$

Where N is the number of degrees of freedom, $q, \dot{q}, \ddot{q} \in R^N$ are the vectors of generalized positions, velocities, and accelerations, respectively, $M(q) \in R^{NxN}$ is the system mass matrix, $C(q,\dot{q}) \in R^N$ is the vector of Coriolis and centrifugal force, $G(q) \in R^N$ is the vector of gravitational forces, F_{ext} is the external forces (in this case, the torque applied by the orthosis) and τ_{ID} is the human torque.

When determining human torque using Inverse Dynamics, only its mechanical characteristics (kinematics, mass and moment of inertia) are considered, not taking into account its biological characteristics (muscle activation, muscle-tendon fiber length), so that the subject is seen only as a multibody mechanical system, as it occurs in the determination of the Inverse Dynamics of robots.

In order to determine the human torque, taking into account the biological characteristics, we based on the work from Peña *et al.* (2019) and used the EMG signals as well as the biomechanical features provided by the interaction model.

First the EMG signal was filtered and processed as described in Peña *et al.* (2019), then the muscular activation was determined using the Equation (3).

$$a(u) = \frac{e^{AuR^{-1}} - 1}{e^A - 1} \tag{3}$$

Where u is the processed EMG signal, $-3 \leq A < 0$ is a nonlinear shape factor and R is the maximum voluntary isometric contraction.

The active and passive forces of the muscles were determined according to the Equations (4) and (5), respectively.

$$F_A^m = f_A(\tilde{l}^m).f_V(\dot{\tilde{l}}^m).F_0^m.a(u) \tag{4}$$

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

Where $f_A(\tilde{l}^m)$ is the normalized active force-length function $f_V(\dot{\tilde{l}}^m)$ is the normalized force-velocity function, $f_P(\tilde{l}^m)$ is the normalized passive force-length function and F_0^m is the maximum isometric force.

The fore provided by the muscular unit is then determined by

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

Where α is a scale factor and ϕ is the pennation angle (the angle between the muscle orientation and the tendon fibers).

Finally, the joint torque is determined as

$$\tau_{EMG} = |\sum_{i=1}^{n} F_i^{mt} r_i| - |\sum_{i=1}^{m} F_j^{mt} r_j| \tag{7}$$

Where n is the number of flexors, m is the number of extensors and r are the moment arms.

The moment arms, tendon fiber length, pennation angle, maximum isometric force were determined using the interaction model scaled to the subject.

2.4 Forward Dynamics-based Simulation

After executing the experimental procedure, and having the human torque determined, Forward Dynamics-based simulations were carried out, in order to verify if the interaction model can perform the same movement that the subject did during the experiment.

Unlike Inverse Dynamics, Forward Dynamics determines the generalized kinematics of the model when subjected to the influence of forces and torques. It is accomplished by solving the Equation (8) in order to determine the generalized acceleration and then numerically integrating it to obtain the generalized velocity and position.

$$\ddot{q} = M(q)^{-1}[\tau + C(q,\dot{q}) + G(q) + F_{ext}] \tag{8}$$

Where $\tau \in R^N$ is the vector of joint torques (the others components of the equation are the same of the Equation (2)).

A illustration of the workflow performed in this work is depicted in the Figure 2, showing how the variables measured during the physical experiment were used to prepare and carry out the simulations.

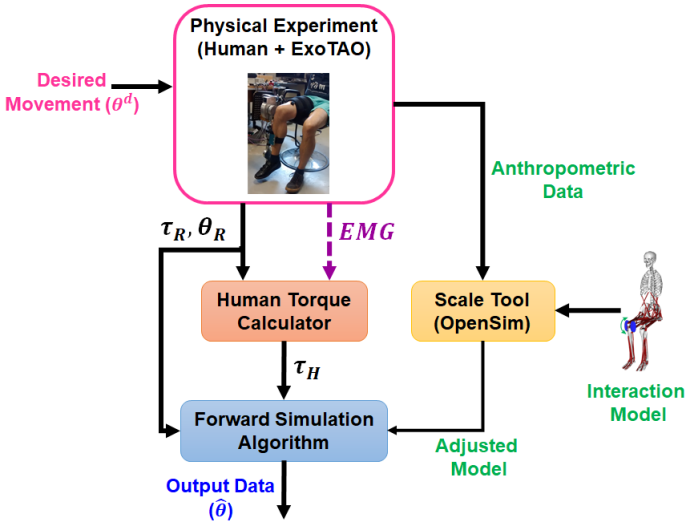

Figure 2. Flowchart of the procedures performed, related to the physical experiment, model scaling, determination of human torque and Forward Dynamics-based simulations.

In Figure 2, the θ^d is the reference movement that the subject should have followed during the physical experiment. The θ_R is the movement actually performed by the user and τ_R is the torque applied by the orthosis.

The **Scale Tool** block fits the interaction model to the anthropometry of the subject that performed the physical experiment, so that the model has the same mass, height, moments of inertia and, consequently, muscle parameters as the person.

The **Human Torque Calculator** block represents the step of to determine the torques exerted by the subject. As discussed in Section 2.3 two methods were used to determine human torque: Inverse Dynamics-based and EMG-based. So, τ_H in the output of this block can represent τ_{ID} or τ_{EMG}, according to the method used.

The **Forward Simulation Algorithm** uses the variable from the previous blocks and solve the Equation (8), determining $\hat{\theta}$, which is the movement performed by the interaction model fitted to the subject in question. It is expected that, with the interaction model having the same anthropometry as the subject who performed the physical experiment, the movement determined by the simulation is as close as possible to that performed by the subject, that is: $\hat{\theta} \approx \theta_R$.

All simulations were carried out on a computer with Intel®Core™i7-8750H 2.20 GHz processor, 8.00 GB of RAM, 128 MB dedicated video card, Windows 10 Home Single Language 64 bits. The OpenSim version 3.3 and the MATLAB R2015a were the platforms where the simulations took place.

2.5 Analysis

In order to evaluate the effectiveness of the proposed model, we compared the torques obtained by the processes mentioned in Section2.3as well as the simulated movement obtained from the application of each human torque.

As mentioned above, the model will perform well if the human torques used make the model closely follow the movement performed by the subject during the physical experiment (i.e. $\hat{\theta} \approx \theta_R$).

3. RESULTS

The muscular activation obtained through the measured EMG signals and the Equation (3) are depicted in the Figure 3. As expected, the extensors were more activated as they had to produce more force to overcome the gravity. Furthermore, during Phase II the muscles demanded greater activation than in Phase I, as they needed to exert more force to overcome the resistance imposed by the orthosis. The antagonists (flexors during the extension and extensors during the flexion) also were activated during the motion, in order to provide stability to the knee and control to the movement.

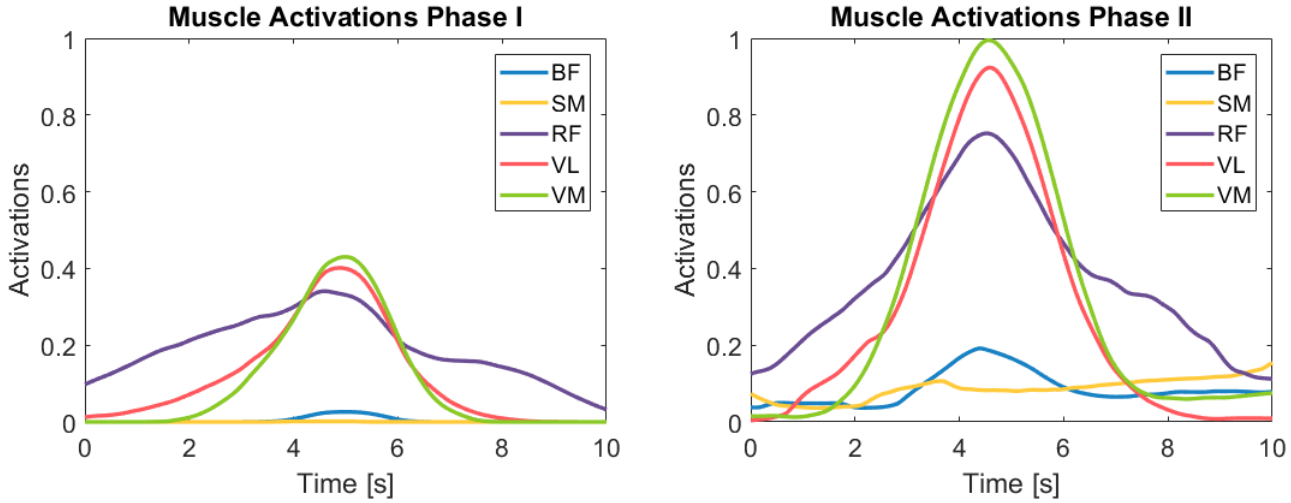

Figure 3. Muscle activations determined from the EMG signals measured in the Phase I (a) and Phase II (b). The muscles whose EMG signal was measure are: the flexors semitendinosus (SM) and biceps femoris (BF) and the extensors vastus lateralis (VL), vastus medialis (VM) and rectus femoris (RF).

The torques applied to the knee are shown in the Figure 4. In Figure 4 (a) (Phase I) it is possible to see that the torque exerted by the orthosis is low, since the robot is operating as active-assistive and the user is a healthy subject, who did not need auxiliary torque. In Figure 4 (b) (Phase II) the human torque is great than the one of the Phase I, since the robot is operating as active-resistive and the subject need to perform more torque to accomplish the desired movement.

The torque determined by EMG-based method (τ_{EMG}) is close to the one determined by the Inverse Dynamics-based method (τ_{ID}), in Phase I, but differs reasonably in Phase II. However, τ_{EMG} showed an increase from phase I to phase II, as expected and as happened with the activations, which shows consistency of the EMG-based method.

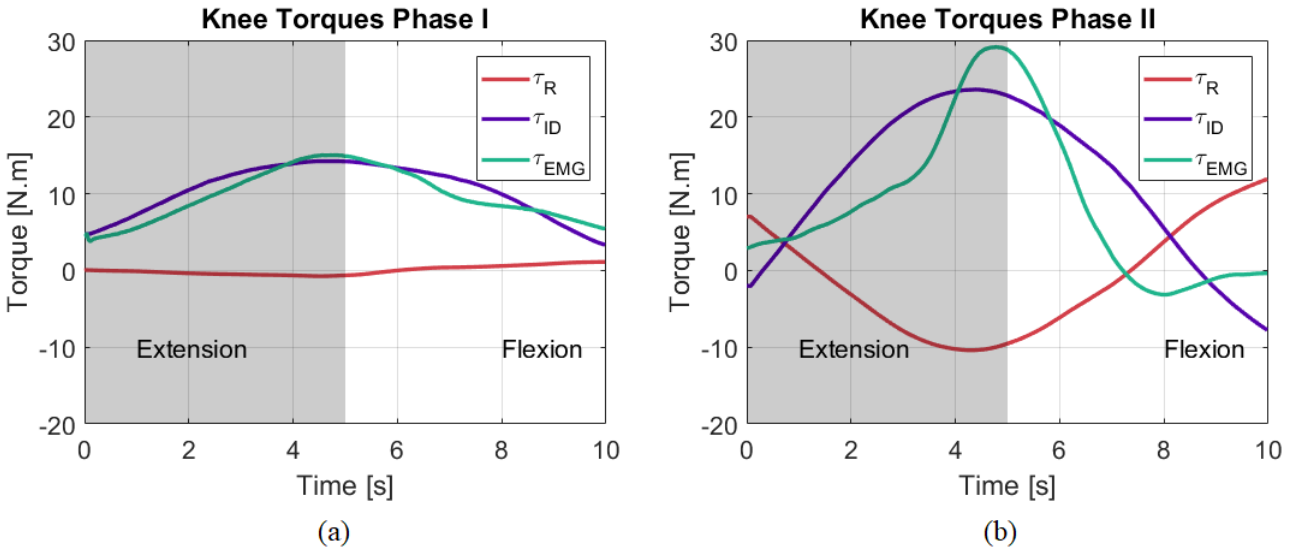

Figure 4. Knee torques involved in Phase I (a) and Phase II (b). τ_R is the orthosis torque, τ_{ID} is the human torque determined through the Inverse Dynamics and τ_{EMG} is the human torque determined through the measured EMG signals.

Figures 5(a) and 6(a) presents a comparison between the movement performed by the interaction model and the one performed by the user during the physical experiment. It is possible to notice that when using the torque determined by the Inverse Dynamics-based method (τ_{ID}) the interaction model track the reference better than when using the torque determined by the EMG-base method (τ_{EMG}), this can be confirmed by analyzing the Figures 5(b) and 6(b).

Despite of the tracking errors, the shape of the curve of the movement performed by the model is close to the shape of the curve of torques, what can be seen comparing the Figures 5(a), 6(a) and 4. This proves that the approach is coherent, the model is feasible and capable of helping to determine human torques based on EMG measurements, as well as simulating movements using such torques.

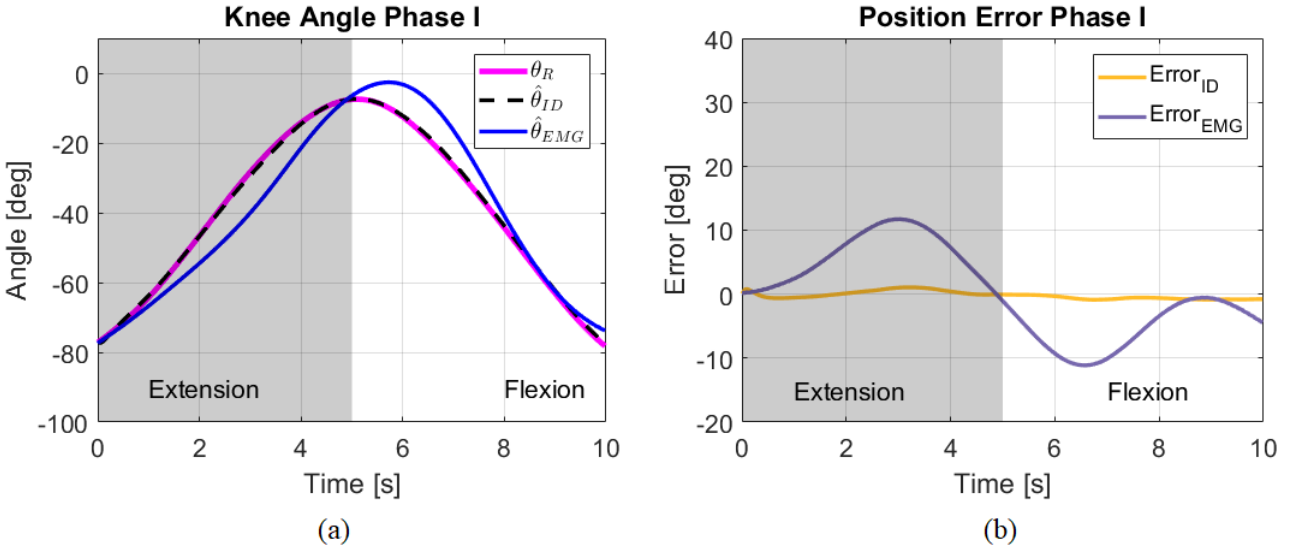

Figure 5. Knee angular position (a) and error related to the reference (b) to the Phase I. The index ID and EMG means that the human torques involved are from the Inverse Dynamic-based and EMG-based methods, respectively.

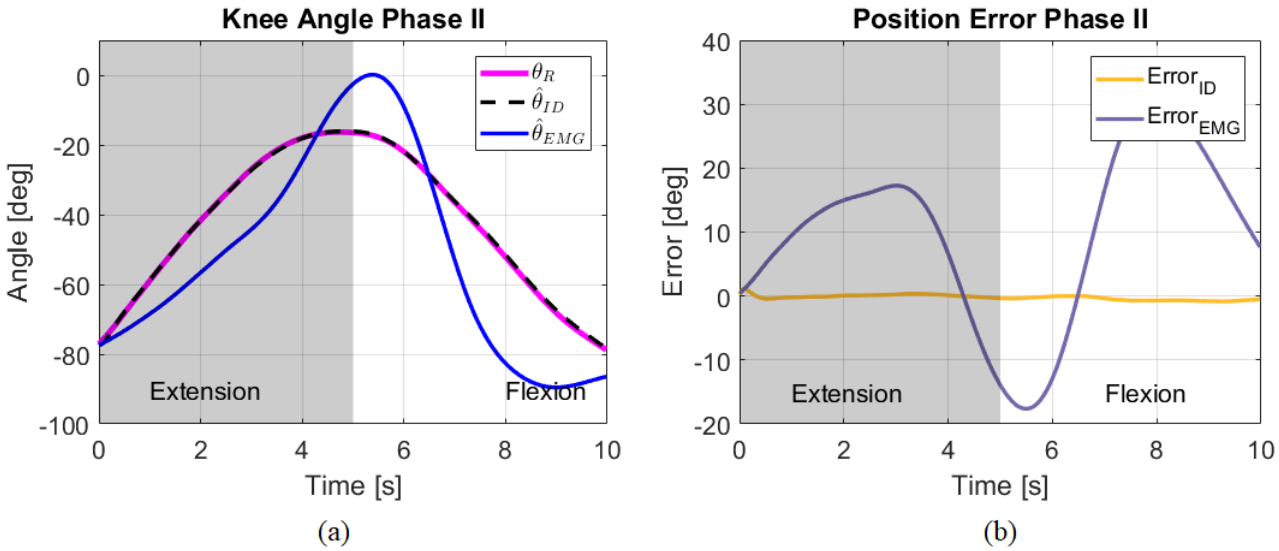

Figure 6. Knee angular position (a) and error related to the reference (b) to the Phase II. The index ID and EMG means that the human torques involved are from the Inverse Dynamic-based and EMG-based methods, respectively.

Although the model did not perform the movement with EMG-based human torques as well as compared to Inverse Dynamics-based ones, it is possible to affirm that the approach is coherent and useful, and may offer a tool for biomechanical analysis of interactions between humans and rehabilitation robots.

The fact that only a few muscles were considered as well as the problem of muscle redundancy and parametric uncertainty contributed to τ_{EMG} not being as accurate as τ_{ID}. Furthermore, the motion simulations with the model were performed using an algorithm based on Forward Dynamics, which simply solves the inverse of the problem that determines τ_{ID}. This contributes to the movement being less imprecise with τ_{ID} than with τ_{EMG}.

4. CONCLUSIONS

In this work, we presented the development and analysis of a flexion and extension model of the human knee equipped with an exoskeleton. The dynamic behavior of the model was simulated using EMG signals.

Analyzing the results of the simulations, it can be stated that the method based on EMG signals produces a response coherent with the experimental data, that is, it shows the instants at which the user makes greater or lesser effort, in addition to indicating when when flexion or extension occurs, confirming the first hypothesis.

However, the Inverse Dynamics method presented values closer to the experimental data. This is more evident in the case where the exoskeleton exerted a torque contrary to the movement of the user, negating the second hypothesis. This fact can be justified for two reasons: surface electromyography does not capture EMG signals from all muscles, but only from the most external ones; the Direct Dynamics method, used to generate the final results of the angular positions of the system, has a great affinity with the Inverse Dynamics, as one is the inverse of the other, unlike the method based on EMG signals.

For future work, in order to make the method based on EMG signals even more promising, signals that represent the entire muscle activity of the user should be measured.

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