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Modeling and control of an active knee orthosis using a computational model of the musculoskeletal system

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Abstract. One-third of the stroke survivors remain with some disability, needing assistance to perform the activities of daily life and therapy to recover the lost functions. The robotic rehabilitation is a promissed field in this context improving the effectiveness of the treatment. Many researches have focused on developing human-robot interaction control to ensure user safety and therapy efficiency, but the validation of these controllers often requires contact between humans and robots, which involves cost, time and risk of accidents. This work aims to present a computational model of an ideal active orthosis used to assist the knee movement as a tool for test and validate human-robot interaction controls. Three controllers were applied to make the orthosis move the knee tracking the desired trajectory: a PID controller, an Inverse Dynamics-Based controller, and a Feedback-Feedforward Controller. The model proved to be useful and the controller with the best performance was the Feedback-Feedforward one.

Keywords: Rehabilitation. Human-robot interaction. Exoskeleton. Biomedical Engineering.

1 Introduction

According to the World Health Organization (WHO), stroke is a noncommunicable disease of the cardiovascular type, caused by the suspension of the blood supply to the brain because a bleeding (hemorrhagic stroke) or a clot (ischemic stroke). In 2016, the disease was the second global cause of death (WHO, 2011; WHO, 2018).

Despite of the stroke occurrence is declining in many countries, about 15 million people worldwide suffer a stroke, annually. Of these, 5 million die and another 5 million remains disabled (MACKAY; MENSAH, 2004).

Disabilities resulting from a stroke directly impact the performance of the patient's ability to execute activities of daily living (ADL) such as walking and eating (DIAZ; GIL; SANCHEZ, 2011). Then, the physical therapy, involving rehabilitation, help to treat injuries or impairments and improve the lost functions.

Rehabilitation is defined by the WHO as "a set of measures that assist individuals who experience, or are likely to experience, disability to achieve and maintain optimal functioning in interaction with their environments"(WHO, 2011). In therapy, the patient must repeatedly perform specific movements to cause motor plasticity, recovering the motor skills and minimizing functional deficits.

Traditional rehabilitation therapies, administered by a physiotherapist, are very strenuous, with low reproducibility and less intense, especially for gait rehabilitation, often demanding the attendance of more than three therapists to manually assist the patient's legs and torso. Thus, the use of robots in rehabilitation offers significants advantages over the conventional therapy, such as, realization of more intense and repetitive movements, measurement and storage of patient's data with high reliability, wide range of motion, flexibility and cost reduction of the treatment (HUANG; KRAKAUER, 2009; DIAZ; GIL; SANCHEZ, 2011; IBARRA; SIQUEIRA, 2014; ANDROWIS et al., 2018).

The interaction between humans and robots require a high degree of security and reliability, furthermore, the rehabilitation robots should to attend the *Assist-as-Needed Paradigm* that is to help the patient to reach the pre-definite training objectives only when necessary (JUTINICO et al., 2017).

Currently, many researches have focused on the development of human-robot interaction controls, however, to test, validate, and apply such controls, real robots and human involvement are required, which involves costs, time and risk of accidents.

The objective of this work was to develop a computational model of an active orthosis applied to the right knee of a subject and to use such a model to develop, tune and apply three types of controllers to perform a desired movement without the need to involve humans and robots.

The development of a computational model of the patient-robot assembly is desirable, since the financial, time and energy costs, as well as the risk of damage, are reduced. Such model presents as a tool to develop, tune, test and validate new types of interaction control between patients and robots, as well as, test e analyze rehabilitation exercises.

2 Bibliographic Review

The first human-robot interaction control was he Impedance Control, introduced by Hogan (1985). This control was initially proposed to guarantee interaction between humans and industrial manipulators, however, over the years it has been widely used in the robotic rehabilitation area where it is the basis to development of interaction controls between assistive robots and patients.

Sousa et al. (2016) developed a musculoskeletal platform using OpenSim integrated to MATLAB to develop and simulate control strategies. They used this platform to compare performance of four types of controllers applied to Functional Electrical Stimulation Cycling (FES Cycling). To simulate the controllers, a musculoskeletal model was used having the muscular excitation as control signal in order to perform a movement of pedal a bike. In this case, no type of orthosis was used, and the control with better performance was the proportional-integral.

Durandau et al. (2016) used computational musculoskeletal model from OpenSim, scaled to specific subjects, in order acquire muscle kinematics information to realize an EMG-driven models of human-machine interaction. This technique was experimentally applied to a individual wearing the H2 exoskeleton in a real-time mode.

An Adaptive Impedance Controller was developed by Peña (2017), where the robot's stiffness is varied according to the patient's stiffness. This controller was applied to a active knee orthosis, and the stiffness of the user and the reference torque was determined using the neuromusculoskeletal computational model Gait 2392 of the OpenSim. In this case, the computational model did not include the active orthosis and was used only to determine the parameters of torque and stiffness, not to simulate the control.

A knee exoskeleton based on the four-bar linkage was designed by Khamar & Edrisi (2018) to assist patients strengthen their shank muscles. A backstepping sliding control (BSC) combined with a nonlinear disturbance observer (NDO) was used to make the exoskeleton track the desired position trajectory. To validate the controller, simulations were performed in MATLAB and OpenSim, using a computational model of the exoskeleton coupled to a knee model. OpenSim was also used to estimate the knee torque required to perform the motion, comparing it with the torque produced by the proposed controller, presenting an difference less than 1N.m.

A control strategy based on kinetic motor primitives was develop by Nunes, Santos & Siqueira (2018). The musculoskeletal model Gait 2392 of the OpenSim was scaled to a subject specific and used to compute te joint torques necessary to perform a desired movement. Then, motor primitives were calculated using Principal Component Analysis (PCA). Finally the robot torques necessary to assist the patient was determined based on the weight of the motor primitives. The controller was applied to a knee exoskeleton and the experimental results showed that this method is efficient to recovery the movement profile of the patient.

Other applications of musculoskeletal computational models include: evaluation of muscle driven forward dynamics simulations (WALTER; PANDY, 2017; KIA; STYLIANOU; GUESS, 2014; KOEHLE; HULL,), estimation of joint moments and muscle forces (MOISSENET; CHÈZE; DUMAS, 2014; SHAO et al., ; SETH; PANDY, 2007; LLOYD; BESIER, 2003), analyze of the influence of the exoskeleton on the motor primitives of healthy subjects walking (NUNES et al., 2017) and analysis of the joint stiffness (PANCHAL; SANJEEVI; VASHISTA, 2018).

3 Methodology

This section describes the technologies and procedures to perform this project.

3.1 OpenSim

OpenSim [1] is an open-source and freely available platform for modeling, simulation and analyzing of the neuromusculoskeletal movement developed in 2007 by Delp et al. (2007).

The computational modeling and simulation provided by the OpenSim allows the researchers and clinicians to understand the mechanisms that are the base of movement disorders and design effective treatments in the area of rehabilitation medicine.

In this work, the OpenSim was used to calculate the torques required to perform a movement, and later integrated to MATLAB to simulate the controls of the active orthosis. For this, a default subject musculoskeletal model from OpenSim was used.

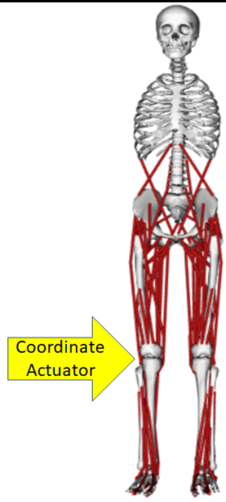

Figure 1: Gait 2392 Model. The red lines are the musculotendon actuators. The yellow arrow indicates the location of the actuator that represents the active orthosis.

3.2 Musculoskeletal Model

A three-dimensional biomechanical model from OpenSim, Gait 2392 Model, was used to simulate the musculoskeletal system of a subject that is about 1.8 m tall and weighs 75.16 kilograms (Fig. 1). The model has rigid bodies to represent the bones and 92 musculotendon actuators to represent 76 muscles in the lower limbs.

To produce the torques at the joints (hip, knee and ankle) the muscles, which are based on Thelen, Anderson & Delp (2003) model, are activated and contract, moving the limb. In this work, an coordinate actuator (an OpenSim actuator that is attached to a movable joint) representing an active orthosis was coupled to the right knee in order to replace the muscles responsible for the generation of torque of extension and flexion of this joint.

3.3 Active Orthosis Model

The virtual model of the active orthosis is a coordinate actuator that should flex and extend the right knee, applying a torque in the joint causing an angular displacement in order to move the leg according to a position reference.

The transfer function of the orthosis is give by:

$$\tau = u \cdot \tau_{optm} \tag{1}$$

where τ_{optm} is the maximum torque (optimal torque) that the actuator can apply (in this case, 250 N.m) and u is the control signal that varies between -1 and 1.

The transfer function above represents a general and ideal model of actuators which may be of the most varied types (e.g. DC motor coupled to a Series Elastic Actuator).

3.4 Inverse Dynamics Tool

Through a kinematics that describe a movement (e. g. position, velocity and acceleration), and perhaps external loads applied to the model (e.g. ground reaction forces), is possible to determinate the joint torques responsible for the given movement, using the inverse dynamics.

The classical mechanics equations of motion can be expressed by

$$M(q)\ddot{q} + C(q,\dot{q}) + G(q) = \tau \tag{2}$$

where $M(q)\ddot{q}$ is the inertia matrix, $C(q,\dot{q})$ is the vector of Coriolis and centrifugal forces, $G(q)$ is the vector of the gravitational forces and τ is the generalized torques (i.e. joint torques).

The generalized positions, velocities and accelerations determine the motion of the model, and the inverse dynamics uses the know motion and parameters of the model to determine the unknown generalized torques, solving the equation (2).

[1] http://opensim.stanford.edu

In this work, the inverse dynamics was calculated using the Inverse Dynamics Tool of the OpenSim (Fig. 2). External forces were considered null.

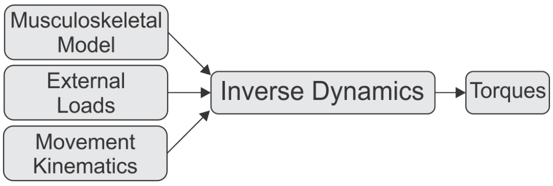

Figure 2: Inputs and outputs of the Inverse Dynamics Tool of the OpenSim.

3.5 Proportional-Integral-Derivative Controller

At first step, the PID controller (Fig. 3) was used to determine the control signal u that causes the orthosis to produce the torque needed to move the knee joint.

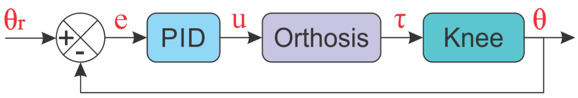

Figure 3: PID Controller utilized. θ_r is the angular reference, e is the position error, u is the control signal, τ is the torque of the orthosis and θ is the real angular position of the knee.

The control signal u is calculated as

$$u = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{3}$$

where $e(t)$ is the position error: $e(t) = \theta_r(t) - \theta(t)$. For this case, the best gains are $K_p = 0.125$, $K_i = 0.115$ and $K_d = 0.105$.

The reference input θ_r is a ramp that varies from -90 to 0 degrees in an interval of 10 seconds (Fig. 4). The torque (output of orthosis) is determined by the equation (1).

3.6 Inverse Dynamics-Based Controller

In the Inverse Dynamics-Based controller (IDB), the torque is calculated by the Inverse Dynamics Tool of the OpenSim that solves the equation (2) for the desired movement. This method makes it possible to compute the torque in an off-line way, based only on the desired movement and system dynamics, different from the PID control that is based on the error.

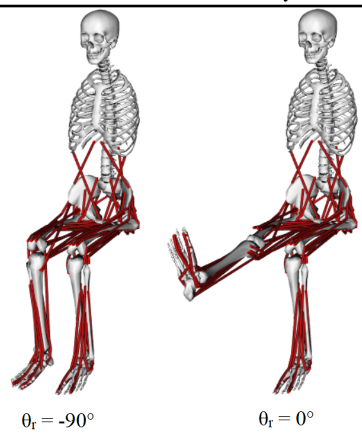

Figure 4: Initial ($\theta_r = -90°$) and final ($\theta_r = 0°$) angular position of the knee.

For our tests, a open-loop IDB controller (Fig. 5) was used to execute the movement described in the section 3.5.

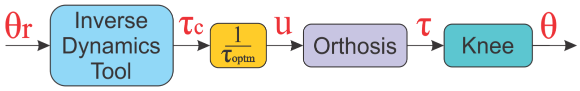

Figure 5: Inverse Dynamics-Based Controller. τ_c is the torque computed through inverse dynamics.

3.7 Feedforward-Feedback Controller

The Inverse Dynamics-Based controller presents low robustness, being little immune to noise and disturbances. In addition, the open-loop causes trajectory tracking errors not to be detected and eliminated.

To solve these issues, a controller with a feedforward loop based on reverse dynamics and a feedback PID loop was designed and applied. Thus, a total torque composed of a torque computed by the Inverse Dynamics Tool and a torque based on the position error was obtained.

The PID gains are $K_p = 0.125$, $K_i = 0.115$ and $K_d = 0.105$.

In this paper, the Feedforward-Feedback controller control will be referred to as IDB+PID controller.

3.8 Tests Description

To perform the tests, a integration routine of the model states was written in MATLAB. The model states are

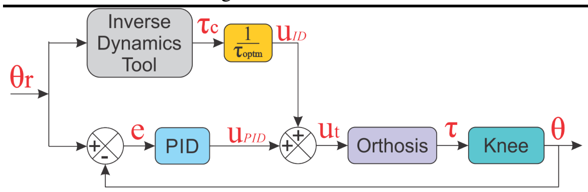

Figure 6: Feedforward-Feedback Controller. u_ID is the torque computed through inverse dynamics, u_{PID} the one determined by the PID control and u_t the total torque ($u_t = u_{ID} + u_{PID}$).

the kinematics of the model, the fiber length and the muscles activation.

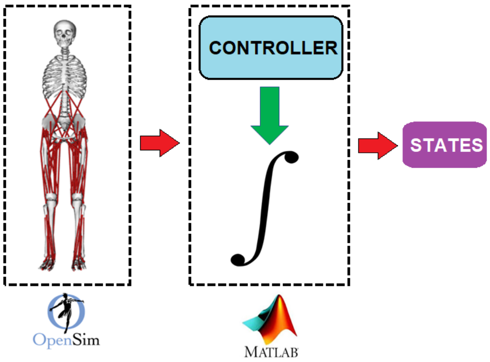

Figure 7: Algorithm flowchart of the tests performed. In the MATLAB, a integration routine determines the states of the musculoskeletal model.

Three tests were performed, one for each type of controller: PID, IDB, IDB+PID. The reference input was a ramp, described by the equation:

$$\theta_r = 9t - 90 \qquad 0 \leq t \leq 10 \tag{4}$$

4 Results and discussion

In this section, we present the results obtained from the set of tests performed to evaluate the fidelity of the active knee orthosis model employed and the effectiveness of the controllers.

The fidelity of the orthosis model is characterized by the ability of the model to perform the desired movement, thereby developing the required torque. In addition, the modeled orthosis should be able to replace all the muscles involved in knee movement, without prejudice to the execution of flexion and extension.

It is possible to notice that the orthosis model shows such fidelity, since the movement was completely executed, as shown in Figure 8.

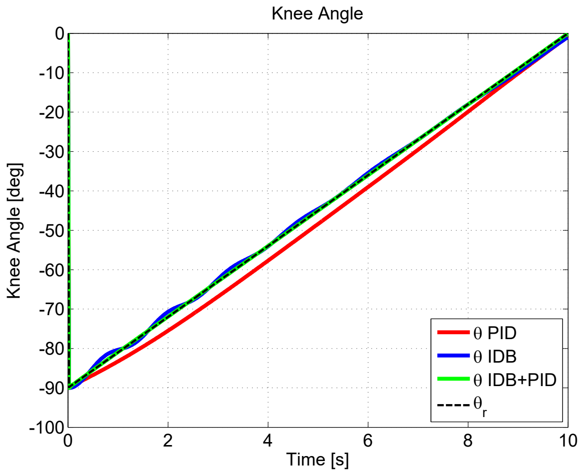

Figure 8: Angular position of the knee joint. The movement was completely executed by the orthosis, no muscles was involved.The position generated by the IDB+PID controller is relatively close to the reference, the one produced by the IDB controller shows some oscillation and that one yielded by the PID has a considerable track deviation.

The efficacy of the controllers is assessed by analyzing the trajectory tracking error (i.e. the position error). According to Figure 8, the controller that allows the smallest position errors was the IDB+PID, while the PID controller presented the highest tracking errors. This can be verified by analyzing Figure 9 which shows the variation of the position error along the execution time of the movement, and Table 1 which presents the maximum, minimum and RMS errors for each type of controller.

Table 1: Error analyze of each test. The minimum and maximum values refers to the absolute value of the errors. The IDB + PID controller presented the lowest error values, confirming its performance over the other controllers. The PID controller had the worst performance.

Error [degrees]	PID	IDB	IDB+PID
Minimum	0.000	0.000	0.000
Maximum	3.843	1.527	0.225
RMS	2.809	0.619	0.045

In relation to the torque applied to the joint, the PID controller induced the production of lower torque values over time (Fig. 10), making the knee position

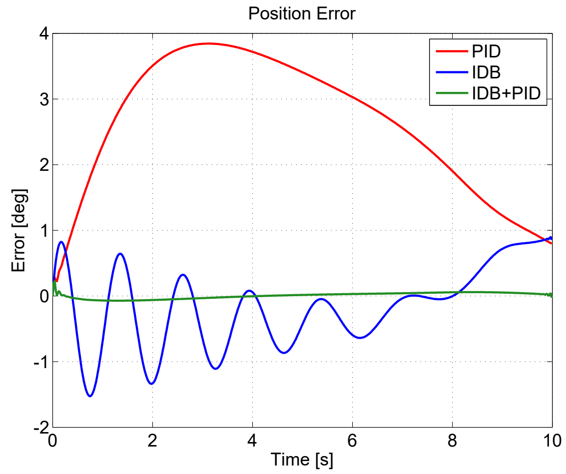

Figure 9: Position error of the knee joint. The PID controller presents the largest deviation error over time, while the IDB controller presents errors that oscillate around zero with increasing amplitude at the end of the movement, the IDB + PID controller presents the smallest errors over time, indicating that the trajectory followed by the knee was very close to the reference, making it the best controller among the three used.

always lower than the reference value (Fig. 8).

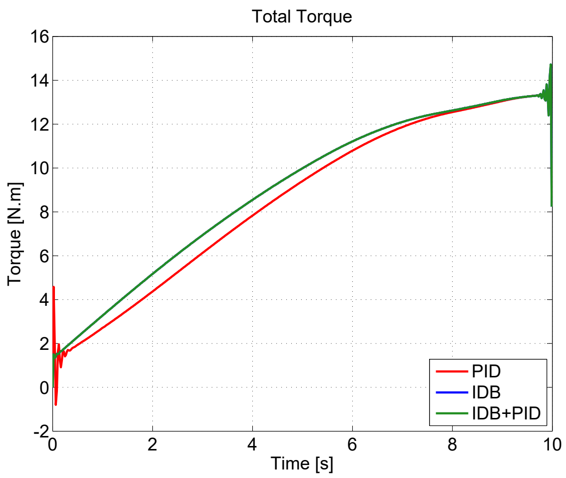

Figure 10: Torque applied by the orthosis to the right knee joint. The RMS values for each controller are: PID = 9.4230, IDB = 9.7402 and IDB+PID = 9.7190 N.m.

The torques produced by IDB and IDB+PID have approximate values, but the last one have a noise at begin and end of movement, due to the feedback loop. In the IDP+PID controller, as the plant model (i.e. the musculoskeletal model) is imperfect, the computed torque by the inverse dynamics does not produces the correct movement, so position errors appear and are eliminated by the feedback torque. Finally, the controller that presents best performance is the IDB+PID.

The simulation algorithm presented here is very close to that developed by Sousa et al. (2016), however in this work the musculoskeletal model has an active orthosis coupled and the controllers are applied on this orthosis, not on the muscles.

Khamar & Edrisi (2018) simulated only feedback controllers, while in this work was simulated feedback and feedforward controllers, by other hand, she included disturbance in her simulation, which was not done here.

Peña (2017) and Nunes, Santos & Siqueira (2018) used musculoskeletal models in their works to design and tune the interaction drivers proposed by them, however, such models did not contain the controlled exoskeletons nor were simulations performed. The musculoskeletal model with active coupled orthosis, introduced in this work, allows such controls to be simulated and configured for a specific subject.

5 Conclusion

In this paper, a computational model of an active knee orthosis was showed and three position controllers was tested: a feedback PID controller, a open-loop controller based on inverse dynamics of the musculoskeletal model and a feedforward-feedback controller that integrate the last ones. The controls proved to be able to extend the patient's knee, according to a reference trajectory, and are therefore applicable to the rehabilitation of knee movements. The controller with the best performance was the feedforward-feedback one.

The musculoskeletal model with coupled orthosis presented here is useful for the development of new interaction controls as well as the simulation of the controls proposed in the literature that are only tested experimentally, allowing them to be compared and adapted to specific cases.

For the next steps:

- Include active orthosis in the hip and ankle.
- Simulate and compare another controllers presented in the literature.
- Simulate the gait of a specific subject.

- To develop an interaction control law to aid in the recovery of gait pattern of hemiparetic patients.

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