

# Control of a Virtual Leg via EMG Signals from Four Thigh Muscles

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**Abstract.** The work presented in this paper is our first step toward the development of an exoskeleton for human gait support. The device we foresee should be suitable for assisting walking in paralyzed subjects and should be based on myoelectrical muscular signals (EMGs) as a communication channel between the human and the machine. This paper concentrates on the design of a biomechanical model of the human lower extremity. The system predicts subject's intentions from the analysis of his/her electromyographical activity. Our model takes into account three main factors. Firstly, the main muscles spanning the knee articulation. Secondly, the gravity affecting the leg during its movement. Finally, it considers the limits within which the leg swings. Furthermore, it is capable of estimating several knee parameters such as joint moment, angular acceleration, angular velocity, and angular position. In order to have a visual feedback of the predicted movements we have implemented a three-dimensional graphical simulation of a human leg which moves in response to the commands computed by the model.

**Keywords.** EMG signals, human knee, exoskeleton, simulation

## Introduction

Several research projects are currently focused on the development of devices to support human movements and although the results are promising none of the proposed solutions provide an effective control system for such machines [2,7,9,11,13]. This work represents our initial effort toward the realization of a wearable robotic device (exoskeleton) to assist people who are denoted by a limited control of their lower limbs during basic but pivotal motion tasks such as sitting on a chair, standing up, staying erect, starting and stopping walking. Although those tasks might seem quite simple, they are actually essential for an effective rehabilitation process as they provide a first level of autonomy to the patient. The device we want to develop will be endowed with a control system capable of understanding the subject's intentions through the analysis of myoelectrical signals (EMG signals) and defining a proper level of actuation to independently move the robotic orthosis for assisting injured patients.

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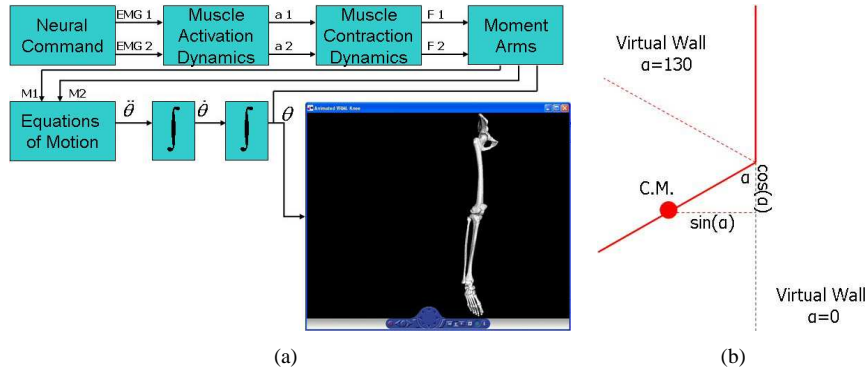
We decided to focus our efforts on the development of supporting devices for the human leg because of the lack of research regarding such machines compared with the advancements on upper extremity exoskeletons. While the latter have been studied for more than ten years, only recently particular attention has been put on lower extremity exoskeletons and human gait support despite the potentially large number of consumers for such machines [7,9,11,13]. As a matter of facts, every year a number of people are suffering neuropathologies affecting the lower limbs. Additionally, the amount of aged people is supposed to increase by the 2030 with a ratio estimated to be the 20% of the EU population [8].

From the beginning of our work we started a tight cooperation with the Department of Rehabilitation at Sant'Antonio Hospital in Padua, Italy. This allowed to clearly define patients' needs as well as to understand how individual thigh muscles are activated to generate joint moments and movements, and how they allow coordinated knee torques [12]. Only a proper model of the relations between EMG signals and the associated movements will yield to the design of an effective robotic exoskeleton suitable for supporting neurologically injured patients or aged people [2,6,7].

Hereafter, we will firstly motivate our choices regarding the knee features we decided to take into consideration (section 1). Then, we will describe the structure of a biomechanical model of the human leg (sections 2 and 3) with the purpose of recognizing the subject's intentions (we considered to be the number of flexo-extension movements) by performing an analysis of the electromyographical activity. Finally, we will present the implementation of a three-dimensional graphical simulation of a human lower extremity which moves in response to the prerecorded EMGs (section 4). The comparison between the number of varying knee flexo-extensions and the number of simulated ones allowed a validation of the model (sections 4 and 5).

## 1. Preliminary Remarks

We have chosen to concentrate on the knee as it plays a significant role in the human motion. We will only consider the knee torsion movement as it is the main task performed by the knee articulation. We neglected any modeling of the knee rotation as its contribution is not significant to the whole set of possible movements carried out by a subject [6]. In order to improve our previous work based on a simplified version of the virtual knee accounting for only two muscles [14], we now present a new model incorporating four thigh muscles. This extension is motivated by the partial unreliability of the previous model. The only extensor muscle we selected was, in fact, the rectus femoris which is mainly active during low force movements only. Therefore, whenever the subject performs higher force extensions the predicted movement might be imprecise [7]. The inclusion of only one flexor muscle could lead to rather accurate simulations when pure knee flexion motion tasks are studied. Nevertheless, for more complex movements the inclusion of additional flexor muscles is recommended [7]. The selected muscles with their *Physiological Cross-sectional Area* (PCA) [15] are the following ones: *rectus femoris* (8%), *vastus lateralis* (20%), *semitendinosus* (3%), and *biceps femoris* (10%). They cover a total of 41% of the cross-sectional area of all thigh muscles. The remaining area is occupied by the vastus medialis (15%), the semimembranosus (10%), the vastus intermedius (13%), the gastrocnemius (19%), the sartorius (1%), and the gracilis (1%) [7]. While the lat-



**Figure 1.** (a) Forward Dynamics Approach and Graphical Interface. (b) Virtual leg modeled as a rigid swinging body.

ter two are negligible due to their small force output, the gastrocnemius has not been recorded because it spans both knee and ankle articulations and it is not possible to relate its activity to the knee without considering also the ankle. The vastus intermedius is not recordable using surface electrodes [6]. Since we want to define the smallest set of muscles that assure correct simulations of the flexo-extension movement regardless of the amount of force involvement, we decided to leave out any contribution of the vastus medialis and semimembranosus and verify whether this simplification compromised the model accuracy (sections 4 and 5). Finally, we have used a forward dynamic approach in the study of the human movement (fig. 1a). This choice has been encouraged by the results in Buchanan *et al.* [3]. A detailed description of the phases involved in the control of the virtual knee will be provided in the following sections.

## 2. EMG Interpretation

### 2.1. Signal Acquisition and Muscle Activation

A raw EMG signal is a voltage that can be both positive and negative and changes as the neural command calls for increased or decreased muscular effort. It is quite difficult to compare the absolute magnitude of an EMG signal from different muscles because the magnitudes of the signals can vary depending on many factors (e.g. gain of the amplifiers, the types of electrodes, etc.) [3]. In order to use the EMG signals in a neuromusculoskeletal model, we first need to normalize them into a specific range (between 0 and 1) so that we can eventually compare them one with another. The signal resulting from the processing stage is a value that is called *muscle activation* and is meant to describe the process that makes the electrical activity to spread across the muscle causing its activation. Hereafter we will present the steps we adopted to perform this transformation which have been inspired by the Buchanan *et al.*'s study [3].

The acquisition stage comprises the sampling and the processing of the EMG signals while the subject executes flexions and extensions of his leg. The signals have been sampled at 1 kHz while the BIOPAC MP35 data acquisition unit was connected to a personal computer. During the acquisition stage the signals have been amplified (differen-

tial amplifier, gain of  $1000\frac{V}{V}$ ) on both channels and successively bandpass filtered from 20 to 450 Hz [5]. Successively, the resulting signals have been full wave rectified and normalized via software to approximate the *activation* of the muscle,  $a(t)$ .

## 2.2. Muscle Force

We expressed the muscular force as a function of the muscular activation,  $a(t)$ , previously computed:

$$f_i(t) = \frac{1}{T} \int_{t-T}^t |a_i(t)| dt \quad (1)$$

where  $T$  is a temporal window specifying the dimension of the interval during which the calculation of every sample is executed. The index  $i$  has been introduced to identify which muscle, the force and the activation refer to. Equation (1) is a very rough approximation of the muscular force. However, we do not want to perform a careful clinical analysis of the muscles behavior. We just want to understand the time interval during which the muscles are active along with the intensity of contraction. Refer to section 4 to see how our approximations did not negatively affect the simulation phase.

## 2.3. Driving the Virtual Knee

Once all the muscle forces are calculated, we can compute the corresponding contribution to the joint moment. This requires knowledge of the muscle moment arms. According to the results of Herzog *et al* [10] they can be valuated as follow:  $r_i(\theta) = b_0 + b_1 \cdot \theta + b_2 \cdot \theta^2 + b_3 \cdot \theta^3 + b_4 \cdot \theta^4$ , where  $\theta$  is the knee joint angle expressed in degrees, while  $b_0, b_1, b_2, b_3, b_4$  are coefficients related to the  $i$ -th muscle. The corresponding joint moment  $M$  can now be estimated:

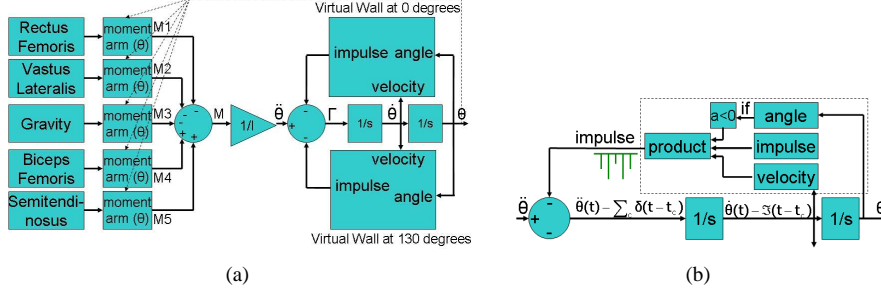
$$M(\theta, t) = \sum_{i=1}^m (r_i(\theta) \cdot f_i(t)). \quad (2)$$

The muscle force  $f_i(t)$  is obtained from Equation 1. The joint moment, in turn, will cause the movements. The knee angular acceleration and the related command signal are calculated directly from the computed joint moment as explained in the following section.

## 3. The Biomechanical Model

The human lower extremity has been modeled as a rigid body swinging between  $0^\circ$  and  $130^\circ$  (fig. 1b). Our software simulates the action of the gravity affecting the rigid body during its movement, the action of the extensor and flexor muscle forces as well as some contact forces that limit the range within which the leg moves (see section 3.1). The anthropometric data for modeling the rigid body are defined in [4] and represent average values. We considered a center of mass of the rigid body placed at 21.65 cm from the knee joint and with a weigh of 3.8 Kg.

Figure 2a shows the structure of the biomechanical model which predicts the angular position from the subject electromyograms. In the first stage the muscular forces,

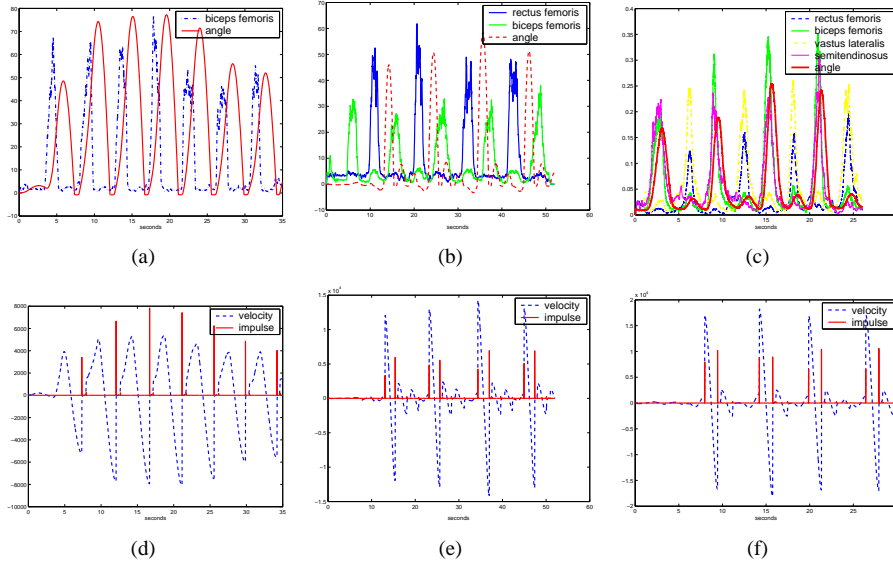


**Figure 2.** (a) Biomechanical Model Structure. (b) Virtual Wall placed at  $\alpha = 0^\circ$  (in the outlined square).

along with the gravity, are coupled with their respective moment arms (according to the equation 2). The net knee joint moment,  $M$ , is then combined with the inertial coefficient and the resulting acceleration  $\ddot{\theta}$  is composed with the action of the Virtual Walls (Section 3.1) placed at  $\alpha = 0^\circ$  and at  $\alpha = 130^\circ$ . The resulting signal is integrated twice to obtain the angular position  $\theta$  used as a command signal for the virtual knee (see fig. 2a and 2b).

### 3.1. The Virtual Walls

The Virtual Walls generate impulsive forces for the purpose of stopping the motion of the leg before it reaches undesired positions. These forces are required only in the correspondence of the temporal instants in which  $\alpha$  gets equal to  $0^\circ$  or to  $130^\circ$  (*critical instants*). These limits to the motion simulate: (1) the natural restriction affecting the knee torsion that prevents it to be further extended once the shank is aligned to the thigh (this is what happens in a healthy human knee), (2) the restriction of motion caused by an hypothetical exoskeleton worn by a subject that impedes the leg to be further flexed beyond a certain threshold ( $130^\circ$  in our specific case). Hereafter we will concentrate on the description of the wall placed at  $\alpha = 0^\circ$  (fig. 2b) as the wall at  $\alpha = 130^\circ$  behaves in a similar manner. The virtual wall constantly checks the knee angle and as soon as it gets negative ( $\alpha < 0^\circ$ ) an unitary impulse is generated and multiplied by the scalar value of the velocity at which the leg swings (see fig. 2b). As this process always takes place when the leg reaches undesired positions, we obtain a sequence of impulses centered on the correspondence of critical instants. Each impulse has an area that is equal to the value of the velocity the leg assumed in each critical instant. This impulse train is the output of the virtual wall (see fig. 2b). In order to stop the motion of the leg we now need to set to zero the velocity that the leg assumes at every critical instant. To achieve this we first subtract the resulting impulse train from the acceleration signal,  $\ddot{\theta}(t)$ . Then, we integrate the resulting signal:  $\Gamma(t) = \ddot{\theta}(t) - \sum_c \delta(t - t_c)$ , where  $\delta(t - t_c)$  is an impulse centered on the critical instant  $t_c$ .  $\Gamma(t)$  is now integrated as follows:  $\int_{t_{start}}^{t_{stop}} \Gamma(t) dt = \dot{\theta}(t) - \sum_c \mathfrak{S}(t - t_c)$  where  $t_{start}$  and  $t_{stop}$  indicate, respectively, the starting and stopping time of the simulation, while  $\sum_c \mathfrak{S}(t - t_c)$  is a step train (resulting from the integration of the impulse train) whose steps are centered on the critical instants. The result is that the velocity signal  $\dot{\theta}(t)$  is set to zero by the action of the integrated impulse train exactly in the correspondence of the critical instants (see fig. 3).



**Figure 3.** Graphs (a), (b) and (c) show the muscle force contractions overlying the computed control signals. Graphs (d),(e) and (f) show that the velocity is set to zero by impulsive forces at the critical instants.

## 4. Experimental Evaluation

### 4.1. Simulated Graphical Environment

To graphically see the behaviour of our model we implemented a virtual leg (fig. 1) driven by EMG signals. The original 3D image representing the lower extremity has been developed at the Department of Anatomy of the Université Libre de Bruxelles (ULB) and it is anatomically correct [1]. By using the *Data Manager* program, also developed at the ULB, we exported every single part of the 3D knee to the VRML format [1]. A VRML program has been written to integrate all the exported parts into a single virtual leg that can be controlled via EMG signals. We chose to adopt VRML for the rendering phase because it makes the communication between the MATLAB Simulink biomechanical model and the virtual knee easier to setup.

### 4.2. Experimental Results

To verify the accuracy of our simulator in predicting the human movement, we performed three tests. The testing phase is based on the gradual addition of muscles to the model for the purpose of observing changes in the system behavior depending on the number of included muscles. All the tests required the subject to stand up right and to flex and extend his leg several times. The computed command signal (angular position) and the number of knee torsions reproduced by the virtual knee have been compared with the actual subject's muscle contractions. The number of simulated torsions has been intended as the only assessing parameter. For the purpose of this work any validation of the computed angle has been neglected as we were only interested in recognizing the patient's intentions that in our case were expressed by the number of flexo-extensions.

In the first test we only considered the flexor muscle activity (biceps femoris). Figure 3a shows that after every muscle contraction (blue line) the biomechanical model generated an appropriate command signal (red line) which made the virtual knee to correctly reproduce all the seven torsions originally performed by the subject. In the second test we recorded the rectus femoris extensor muscle as well as the biceps femoris flexor muscle activity (fig. 3b, green and blue lines respectively). Figure 3b shows that after each couple of extensor and flexor muscle contractions, the biomechanical model generated an appropriate command signal (red line) that simulated all the four torsions originally performed by the subject. The third test was done by recording all the four muscles electrical activity. Four torsions have been performed by the subject and, as well as in the previous experiments, all the four flexo-extensions were correctly reproduced (see fig. 3c). However, likewise the second test, some undesired oscillations in between torsions had taken place due to *cross-talk* interferences between the recorded electromyograms. As the number of selected muscles increases, the amount of cross-talk interferences grows too. This behaviour can be adjusted by improving the processing stage of the EMG signals. Figures 3d, 3e and 3f show the behavior of the virtual walls previously described. More precisely, it is possible to see that, for each test, the angular velocity had been set to zero in the correspondence of every critical instant by the generation of impulsive forces.

## 5. Conclusions

This paper presented a study on the control of a virtual knee based on the analysis of biological signals. We developed a new *four-muscles-based model* that extends our previous one which was based on two muscles only [14]. This extension was motivated by two reasons. Firstly, to assure accurate predictions of flexo-extension movements regardless of the actual force involvement. Secondly, to allow a future study on more complex movements, such as sitting on a chair or standing up. Those movements would require a higher force involvement compared to the knee flexo-extension. Moreover, they could not be properly modeled by using EMG signals recorded from one extensor and one flexor muscle only [3,7]. The tests we carried out (section 4) were aimed at estimating the accuracy of our *four-muscles-based model* in recognising the flexo-extensions performed by the subject. Experimental results demonstrated two facts. First of all, our current model correctly recognised all subject's movements despite some cross-talk interferences. Second of all, a biomechanical model based on two extensors and two flexor muscles allows to carefully simulate the flexo-extension movement with no need of including the vastus medialis and the semimembranosus. This addition would eventually complicate the model without offering valuable improvements.

## 6. Future Work

Although the results derived from our experiments are quite satisfactory, the inclusion of a *geometry model* that takes into account the *force-length* relationship of muscles would significantly improve the accuracy of the model for future research on dynamic movements. Several studies show that the *EMG-to-force* relationship strongly depends

on the muscle's fibers length indeed. A non-inclusion of it may lead to predictions off by 50% or more, depending on the joint angle [3,7]. We also intend to make our model both portable and able to run in real-time. Moreover, we would like to make use of angle sensors in order to properly compare the predicted angle with the one of the subject's knee.

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