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# A neurocomputational model of spinal circuitry for controlling the execution of arm voluntary movements

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**Abstract.** We present a model of the spinal cord in controlling one degree-of-freedom arm movements. The model includes both neural and musculoskeletal functions in an integrated framework. The model has been implemented by an artificial neural network coupled with a computational model of muscle publicly available. The experimental results show that the model is able to regulate the position of the arm and to mediate reflex actions by integrating commands from CNS and signals from proprioceptors.

## 1. Introduction

How voluntary movements of the arm are controlled by the brain is still an open question despite many studies on human movements have been conducted to give an answer to it. In recent years, the scientific community has realized that combining knowledge from behavioural studies, neurophysiological investigations and neural modelling is the right track to understand which processes occur within the central nervous system (CNS) and which is the role of the local circuitries in the spinal cord during the execution of a voluntary movement (Alstermark B. et al., 2007).

The neural structures involved in the control of movement can be roughly separated in four interconnected subsystems: the spinal cord system, the cerebral cortex and brainstem system, the cerebellum and the basal ganglia. Computational models of those systems, as for example (Contreras-Vidal et al., 1997; Stefanovic et al., 2014), are important because they allow to overcome the technical difficulties in monitoring the activity and the interactions of those system during normal tasks, so that physiological studies in human subjects are performed in controlled conditions, i.e. with the subject executes a reduced set of movements. Moreover, they allow to investigate pathways whose activities cannot be explored by other means.

In this study we present a neurocomputational model of the spinal cord and the way the CNS activates such a circuitry for controlling arm's movements.

## 2. The Spinal cord model

The spinal cord subsystem includes the alpha motor neurons, which innervate the skeletal muscle fibers with their axons, and interneurons that are the main targets of the projections coming from the upper centers and the major source of the alpha motor neurons. Moreover, the spinal cord hosts the gamma motor neurons, which innervate intrafusal fibers for keeping the muscle spindle sensitive to stretch.

The spinal cord receives motor commands from the brain motor areas and sensory afferents from spindles and tendon organs. As in part described by (Shadmehr et al., 2005), we hypothesized that, for each muscle, there are five supraspinal signals sent to the spinal cord: *Driving Signal (DS)*, *Length Control Signal (LCS)*, *Force Control Signal (FCS)*, *Gamma Static*, *Gamma Dynamic*.

The *DS* is the motor command used by the central system for selecting the muscle to be activated and for modulating force and velocity of the system.

The *LCS* is a descending input carrying information about the desired value of length for a given muscle and it is compared with the output of the II afferent fibers related to the homonymous muscle. When the output of the II afferent fibers is greater than *LCS* an excitatory synaptic input is sent to the alpha motoneuron and the innervated muscle is shortened.

The *FCS* is a descending input that sets the maximum allowable force that can be generated by the muscle and it is compared with the output of the Ib afferent related to the homonymous muscle. When the signal coming from the Golgi Tendon Organs is greater than *FCS* an inhibitory synaptic input is sent to the alpha motoneuron and the activation of the innervated muscle is reduced.

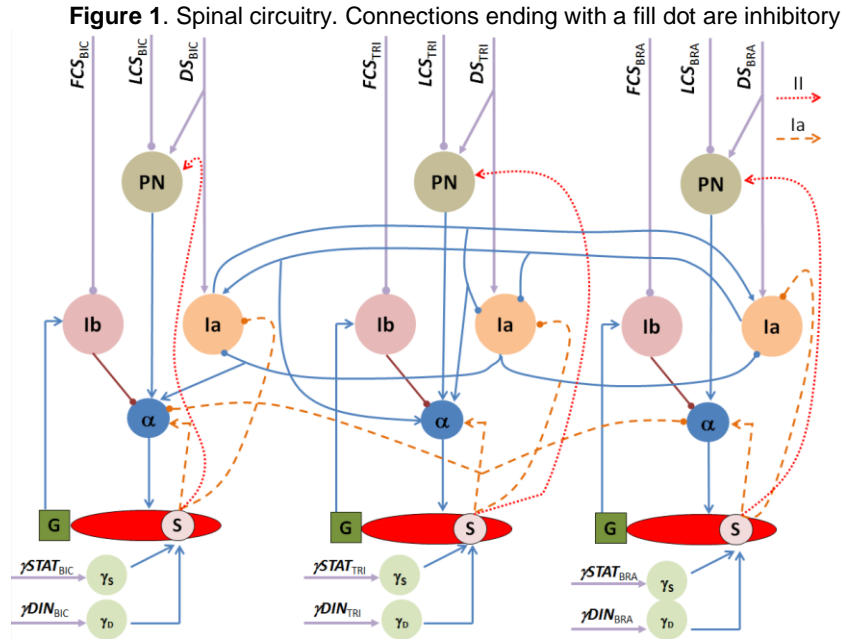
*Gamma Static* is used by the supraspinal system for modulating the output of primary and secondary afferent fibers, while *Gamma Dynamic* is used for modulating the output of the primary afferent fibers.

The spinal networks of the prime-mover muscle and of its synergist and antagonist muscles are interconnected in order to locally regulate the operating point of the system. The interconnections have been partially derived from physiological and anatomical studies (Pierrot-Deseilligny and Burke, 2005) and are reported in Figure 1. In this study, a simple model has been adopted for each neuron, in particular the axonal output is equal to:

$$y = 1/(1 + e^{-a(\sum_i x_i w_i + b)}) \quad (1)$$

where  $x_i$  is the  $i$ -th synaptic input, and  $w_i$  is the related weight that could be positive or negative depending on whether the input was excitatory or inhibitory,  $a$  is the gain and  $b$  is the bias. Given the network in Figure 1, we need to compute 64 parameters in order to define the transfer function of each neuron. To simplify the problem, we hypothesized that each parameter assumes the same value for all the neurons belonging to the same class (i.e. Ib neurons, Ia neurons, etc.), so that the number of unknown parameters dropped to 21. We used a Hill Climber/Steepest Descent algorithm for finding the set of parameters that satisfy the following requirements:

- a relation between the *Driving signal* and the axonal output of the alpha motoneuron as linear as possible;
- if the signal from the Ib afferent fiber is smaller than the *FCS* the axonal output of the Ib inhibitory interneurons must be almost 0, otherwise it must increase with a slope equal to  $1/(1-FCS)$ .



## 2.1 The musculoskeletal model

The musculoskeletal model used in this study is a one degree-of-freedom arm whose motion is restricted to the extension/flexion of the elbow. In fact, the shoulder and the wrist joints are grounded while the elbow joint is modelled as a hinge-like joint. The skeleton is made up of four bones: humerus, ulna, radius and hand. The physical parameters used for the bones are reported in Table 1.

**Table 1** Bones physical parameters

	<i>Mass</i>	<i>Length</i>
Humerus	350 g	28 cm
Ulna	200 g	22 cm
Radius	200 g	23 cm
Hand	500 g	-

The musculoskeletal model includes three muscles: Biceps Short, Brachialis and Triceps Long. We chose to use Virtual Muscle (Cheng et al., 2000; Song et al., 2008) as muscle model, which combines the advantages of phenomenological (Hill-type) and mechanistic (Huxley-type) models. In particular, Virtual Muscle groups a set of phenomenological models, each of which describes the processes involved in muscle contraction. It is needed to specify a set of parameters for each muscle model: the properties of individual fiber type are reported in (Cheng et al., 2000) whereas the morphometric parameters are reported in Table 2.

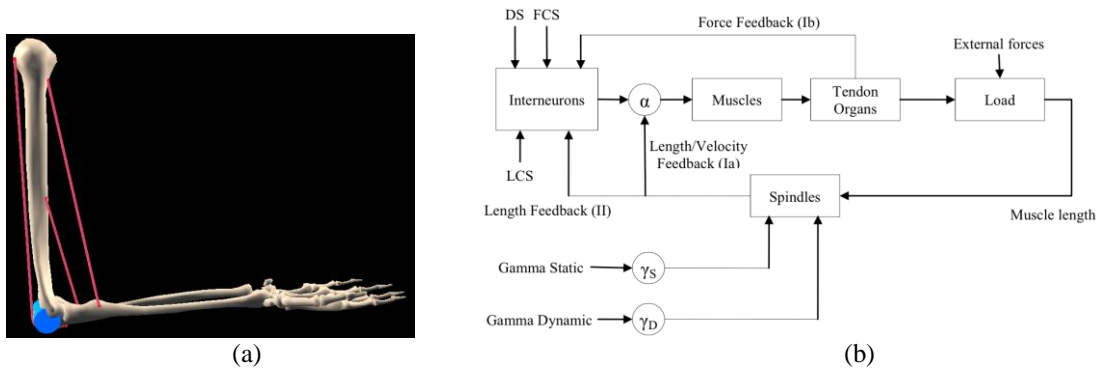
**Table 2** Muscles physical parameters. In the last column S means *Slow* and F means *Fast*

	<i>Opt. Fascicle Len.</i>	<i>Opt. Tendon Len.</i>	<i>Max. Musculotendon Len</i>	<i>Mass</i>	<i>Fibers Type</i>
Biceps	14.75 cm	7.4 cm	32 cm	350 g	40% S., 60% F.
Brachialis	10 cm	3 cm	18 cm	300 g	60% S., 40% F.
Triceps	19.9 cm	9.9 cm	36 cm	500 g	60% S., 40% F.

Force and metabolic energy consumption are estimated by the model in response to neural excitation, muscle length and velocity (Tsianos et al., 2012). Virtual Muscle is equipped with realistic models of spindles (Mileusnic et al., 2006) and Golgi tendon organs (Mileusnic et al., 2006b) that respond, respectively, to muscle stretch and fusimotor control and to muscle tension. The spindle provides information about the rate of muscle length change and muscle length through Ia (primary) afferent fibers, and information about the muscle length through II (secondary) afferent fibers. Golgi tendon organs provide information about the force produced by the muscle during his contraction through Ib afferent.

Eventually, a cylindrical wrapping object is used to model the bony surfaces over which the triceps muscle wrap. It ensures the right calculation and application of the muscle forces produced by the muscle on the skeletal system. The arm model has been developed in the MSMS simulator (Khachani et al., 2008) and it is depicted in Figure 2.a, while Figure 2.b illustrates the connections between the supraspinal systems, the spinal cord, the muscles, the proprioceptors and the environment.

**Figure 2.** : (a) The arm model. Muscles are represented in red, the wrapping object is in blue. (b) The spinal circuitry block diagram



### 3. Experimental results

As validation, we arranged three experiments to verify if the arm movement was appropriate when an external force or a load was applied and if the spinal cord model was able to control the musculoskeletal model for reaching a desired position.

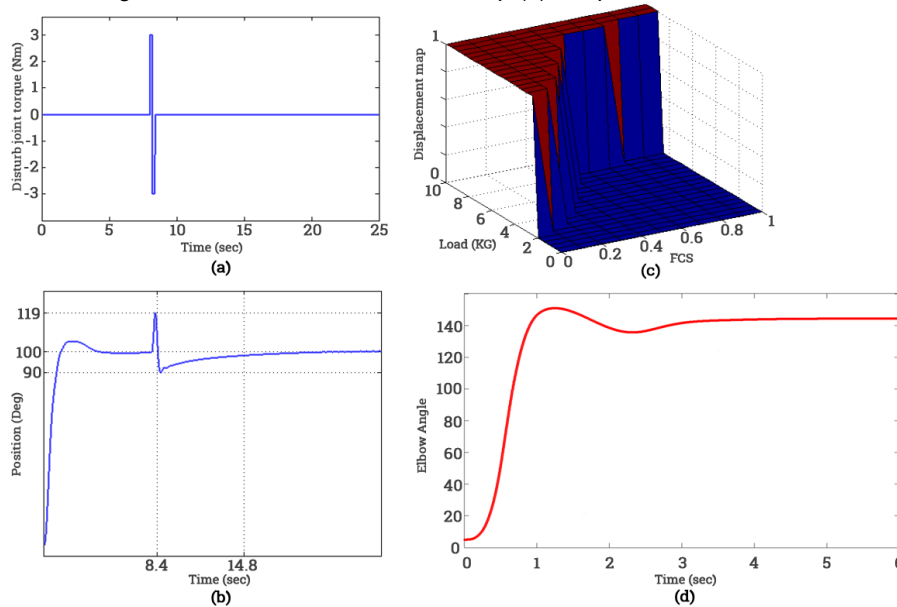
The *first experiment* verified if, without variations of the motor commands sent by CNS, the spinal circuitry was able to keep the position of the arm when the impulsive external force depicted in Figure 3.a was applied. A similar experiment was carried out on deafferented monkeys to evaluate the role of spinal cord in the execution of a movement (Shadmehr et al., 2005). As shown in Figure 3.b, at the beginning the elbow was moved from the initial position  $\theta=5^\circ$  to the desired position  $\theta_D=100^\circ$  and then, after some seconds, the impulsive force was applied. The elbow angle showed an overshoot of  $17.2^\circ$  and an undershoot of  $7.8^\circ$  but after a recovery time equal to 4.8 seconds the desired angle was reached again. The same experiment was performed for different desired positions and the spinal circuitry was always able to keep the position after a mean recovery time equal to 1.19 seconds, a mean overshoot of  $4.2^\circ$  and a mean undershoot of  $3.7^\circ$ . By varying the values of *Gamma Dynamic* signals it was possible to regulate the response of the system (unpublished results).

The aim of the *second experiment* was to verify if the protective mechanism of the Golgi reflex was implemented by the presented spinal circuitry and if it could be modulated by varying *FCS*. The arm was placed at the position  $\theta=100^\circ$  and then the *FCS* value of each muscle and the external weight loaded on the hand were modified. In particular, each muscle received the same *FCS* that was varied from 0 to 1 with a step size of 0.1 while the weight was varied from 0 Kg to 10 Kg with a step size of 0.5 Kg. Given a value for *FCS* and for the weight, we evaluated if the arm kept the initial position or not. In Figure 3.c a displacement map is reported and the displacement was set to 0 if the arm kept the initial position, it was set to 1 otherwise. It resulted that the bigger was the weight the bigger had to be *FCS* for keeping the position of the arm. It follows that *FCS* can be used to regulate the threshold of the Golgi reflex.

Eventually, the aim of the *third experiment* was to verify if it was possible to control the arm in order to reach a desired position in a suitable time. We chose to model each *driving signal* with a square burst for which three parameters had to be specified: the duration  $t$ , the amplitude  $A$  and the steady state value  $E$ . The last two parameters range between 0 and 1 and both modulate the firing frequency of a motor unit. For the sake of simplicity, we hypothesized that each burst had amplitude  $A$  equal to 1, the bursts sent to the agonist muscles had the same duration  $t_{AGONISTS}$ , the steady state value was equal to  $E_{AGONISTS}$  for biceps and brachialis and it was equal to 0 for the triceps because its effect can be taken into account, in first approximation, with the effect of the

gravity. Therefore, the problem was reduced to find the parameters  $E_{AGONISTS}$ ,  $t_{AGONISTS}$ ,  $t_{ANTAGONIST}$  for each direction. For example, the desired position  $\theta_D=140^\circ$  was reached setting  $E_{AGONISTS}=0.40$ ,  $t_{AGONISTS}=0.40$  seconds,  $t_{ANTAGONIST}=0.10$  seconds, as shown in Figure 3.d.

**Figure 3.** (a) External force applied to the arm (b) Position of the arm before and after the external force (c) Effect of the Golgi Reflex when the arm lifts a load up (d) Response of the arm for reaching 140 deg.



#### 4. Conclusions

We have presented a model of human spinal cord that was able to regulate the position of a 1-DOF arm by integrating commands from CNS and signals from proprioceptors. The experimental results confirmed that the presented spinal cord circuitry is able to mediate the same reflex actions showed by the human. Furthermore, the CNS is able to control the arm position by modulating the duration and the amplitude of the driving signals sent to spinal cord circuitry. Nevertheless, as shown in Figure 3.d, a desired arm position is reached in a time that is slower than the time spent by a human to perform the same movement. The slowness of the system is due to the simple scheme adopted to modulate the three driving signals, and therefore, in the future, we will investigate the behaviour of the system when a different time evolution for the five control signals is adopted. Eventually, the realism of the simulated system will be evaluated with other experiments, as for example by verifying that simulated movements show a velocity profile that fits the real one.

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