

# Modeling motor control with a spinal cord

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## Abstract

This paper revisits the essential role of the spinal cord in motor control and compare it with the current motor control models, mainly inverse model controllers, put forward in the literature. As a first step in that direction, we suggest that a simple spinal reflex controller may suffice to reproduce some of the observed human behaviors and to replicate some results obtained by an inverse model control strategy.

## 1 Introduction

Patients who suffer from severe sensory neuropathy cannot sense their position nor detect motion of their joints, since input from muscle spindles and Golgi tendon organs is not present. It has been shown that those patients are still capable to learn to achieve complex movement solely using external feedback. In fact, movements are highly sensitive to perturbations. This finding has brought many researchers to the conclusion that motor control is mainly achieved by the higher brain centers. In this context, the role of the spinal cord is typically reduced to an error correction mechanism (noise filter). The motor control achieved by the higher brain centers is then thought to rely on a learned model of the environment dynamics [1, 2, 3, 4, 5, 6, 7, 8] used to predict the system behavior [3, 5, 6, 9, 8] and derive a control law, often corresponding to an inverse model dynamics, which is applied open-loop [2, 1, 4, 10, 11, 12, 13]. The step-and-hold movement observed in [5, 11, 14, 15, 16] is also advanced as an argument in favor of such an open-loop control strategy. Following this view, the movement would be readjusted intermittently to introduce some necessary feedback when the control is not sufficiently accurate for various reasons such as an unexpected perturbation.

Nevertheless, experiments have shown that animals with a spinal cord transection maintain the ability to execute complex movement, such as walking on a treadmill [17, 18]. This behavior occurred even though the spinal cord was disconnected from brain inputs. This suggests that the spinal cord is capable on its own, through proprioceptive feedback, to direct complex movement patterns. We investigate how such abilities from the spinal cord could benefit the motor control system.

In this paper, we describe a reaching movement experiment based on a six-muscle human arm model attached to a robot manipulandum [5]. Using this model and a spinal reflex approach, preliminary results suggest that the intermittent behavior observed in human in presence of a perturbing force field can be reproduced. Section 2 review the essential characteristics of the spinal cord and its role within the overall motor control system. Section 3 compare the results obtained by an inverse model controller and a simple spinal cord controller and is followed by a short conclusion in section 4.

## 2 The spinal cord

There is a general tendency to present the movement control as directly achieved solely by higher brain centers and therefore neglecting the potential role of the spinal cord [1, 2, 19, 3, 4, 5, 6, 7, 8]. In this view, the brain would implement a model-based control, often in a form of a model inverse with state prediction to compensate for sensory delays. The spinal cord is then viewed as a noise filter used mainly to compensate for modeling error.

Based on the physiological architecture, we attend to give a general picture of the motor control system while suggesting a more complete role to the spinal cord.

A simplified diagram of the motor control system is given in figure 1, adapted from [17] (Note that the sensory information is not presented in this diagram, yet is many and present in most blocks).

Although other brain areas are involved in the motor control, this picture should suffice to give a general view of its functional organization.

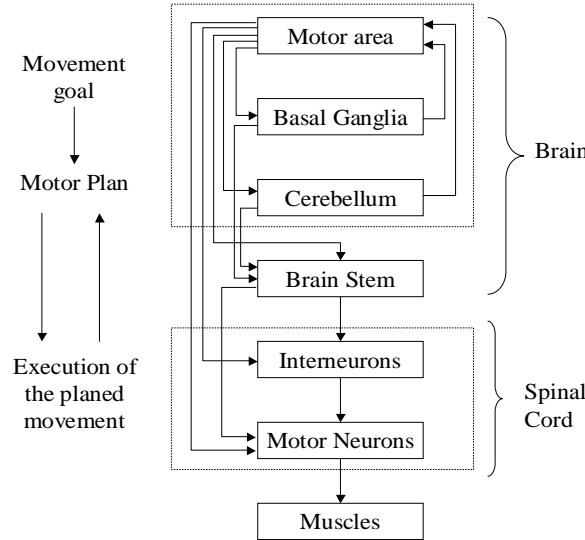


Figure 1: General architecture of the efferent motor control system.

The diagram presents the motor control system organized hierarchically but not in a rigid top-down/bottom-up fashion since most of the areas involved affect many areas below, with the cortical motor area acting directly onto most blocks. However, we can distinguish three main sections: the motor area-basal ganglia-cerebellum, the brain stem and the spinal cord. The role of these structures is as follow. The cortical motor area, the basal ganglia and the cerebellum are acting recursively on each other to achieve the cognitive part of the motor control involving decision making, movement planning, learning, supervision and refining of the movements. The cerebellum and basal ganglia do not act directly on the spinal cord neurons but indirectly through the brain stem. Hence, they do not have a direct motor control influence except for some refining (postural and smoothness) of the movement. The brain stem is an integrating motor component as it receives brain motor areas (cerebral and cerebellum) and most sensory inputs and then connects directly to interneurons and motor neurons of the spinal cord. The spinal cord is in charge of executing the planned movement. The interneurons integrate proprioceptive and descending inputs to perform complex movements i.e. movements resulting from a rhythmic coordination of sub-movements. The networks of spinal neurons responsible for such movement are called the central pattern generators (CPGs). At the end of the control chain there is the motor unit constituted by the alpha-motor neuron and the muscle fibers it connects to.

The above description is a sort of open-loop top-down view of the motor control system that tells us very little on how precisely the control is achieved. The robustness of the motor control systems indicates that it must rely heavily on sensory information. It is the sensory information that are processed by each block of the control hierarchy that would indicate the role of those blocks. Below, we focus on the spinal cord since it can be generating complex movements.

There are various feedback reflexes (sensor-actuator loop neuronal circuits) embedded in the spinal cord. An interesting one is the stretch reflex. This is a mono-synaptic pathway between the alpha-motor neuron and the spindle receptors located within the muscle. This loop can close very rapidly on the order of ms. There are two receptors within the spindle fibers, the Ia primary afferent responding mainly to increase in muscle length (muscle length velocity) and the II secondary afferent, responding to muscle length. The motor neurons receiving inputs from descending pathways, from interneurons or directly though the brain, it is possible to modify their comportment according to basic desired motor goals such as desired muscle length and lengthening. Hence, the muscle spindle-alpha motor neuron loop with the descending inputs can be seen as a feedback loop regulating muscle length and lengthening as desired. In control theory such a control law is referred to as a proportional and derivative controller, a PD (not PID, i.e. with no integral term).

Another interesting component of this reflex is the gamma motor neuron which is co-activated by the alpha motor neuron. This feedback component is necessary at first glance to ensure that the muscle spindle change its length following the muscle length change. This is to avoid that the muscle spindle

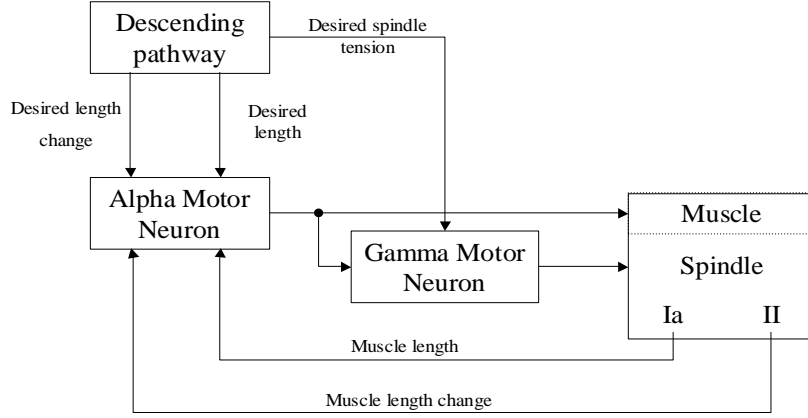


Figure 2: Block diagram of the spinal reflex.

becomes slack and thus stop responding correctly to the muscle activity. The gamma motor neuron receives also descending inputs that will influence the sensitivity of the muscle spindle making it an active sensor [20]. By modifying the spindle sensitivity one can adapt the response dynamic of the stretch reflex (indirectly the gains of the feedback loop) to the type of movements to perform. Note that a sort of look-up table strategy could be used to store the spindle sensitivity parameters (the stretch reflex gains) appropriate to a certain context.

Given the above components of the stretch reflex, the alpha motor neuron output (the input to the muscle fiber)  $u(t)$  can be expressed as follow :

$$u(t) = K_p(l_d - l(t)) - K_d \frac{dl(t)}{dt} \quad (1)$$

where  $K_p$  is the proportional gain,  $l_d$  is the desired muscle length to reach,  $l(t)$  is the muscle length at time  $t$ ,  $K_d$  is the derivative gain and  $dl(t)$  is the derivative of the muscle length at every time  $t$ .

In summary, the extended stretch reflex (with descending efferents) is a fast and adaptive feedback control mechanism which possesses all characteristics to achieve basic movements primitives. The spatio-temporal superposition of this movement primitives would be achieved by CPGs. As a result a vast number of movements could be fashioned by impulses conveyed by supraspinal pathways [19, 9, 7, 8, 21, 22, 23].

To summarize, the production of movements would involved hierarchically the whole central nervous system in which the spinal cord would play a crucial role using proprioceptive feedback [7, 8, 22].

### 3 A six-muscle human arm example

This section aims at comparing the results obtained by an inverse model controller to a simple old fashion spinal cord controller.

The control problem, borrowed from [10], is a simulation of the experiment used to train human subjects to perform reaching movements constrained to the horizontal plane by the connection of the subject hand to a robot manipulandum (see Fig. 3). Two different situations are considered: in Expt.1 the hand is moving in a null force field (no perturbing forces) and in Expt.2 the hand is moving in a velocity dependent force field. The force field pushes away the hand with a force corresponding to three time the amplitude of the velocity. During Expt.1 the subjects are tested after sufficient practice in the null force field (thus assuming that they have acquired a model of the robot manipulandum under this circumstance). In Expt.2 the subjects learn a model of the force field B1 and then is tested in another force field B2. The force fields B1 and B2 are velocity dependent force fields which push away the hand with a force corresponding to three time the amplitude of the velocity. The difference is that B2 pushes away the hand in the opposite direction to B1.

The simulations are using a six-muscle two-joint planar human arm model attached to the model

of the robot manipulandum. The full set of equations describing this model is given in [10]. The muscles produce passive force via zero-delay stiffness and viscosity mechanical response, and active force in response to the six control inputs. The spinal stretch reflex provides added stiffness and viscosity but at time delay of 30ms. The state of the arm  $\theta$ , the two joint angles and velocity, is made available to the controller after a delay of 120 ms. The motor commands have a delay of 60ms from the controller to the generation of a measurable force in the muscle. The model used during the simulations of Expt.1 is disturbance free and during Expt.2 the model includes the field B1 and the control is tested in field B2.

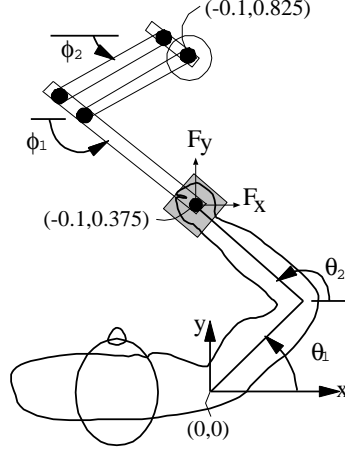


Figure 3: The human arm attached to the robotic manipulandum

Both Expt.1 and Expt.2 consist in moving the human hand from the spatial coordinate  $[x; y] = [-0.1; 0.4750]$  to a set point  $r = [x; y] = [-0.1; 0.3750]$  in about 0.5 seconds. A desired system trajectory satisfying a minimum jerk trajectory was fed to the inverse model to generate the control (see [10] for the description of the inverse model controller). However, no desired trajectory was specified for the spinal controller. The Euler method was used for the integration of the system model. The integration step was 0.004 seconds. The simulations were run for 1.5 seconds each.

The spinal controller has been implemented in its simplest form since we have considered a simple co-activation of the antagonist muscles as described in [10]. Given this co-activation only 6 control gains, instead of 12, had to be chosen to specify the spinal controller (three  $K_p$  gains proportional to muscle length and three derivative gains  $K_d$  as described in Eq. 1). The derivative gains were chosen to be ten times smaller than the proportional ones since in that case the hand velocity profile correspond to the one observed in humans. To compensate for the muscles differences, the proportional gains were chosen from elbow to fore arm to be  $[-1.25; -0.7; -1.45]$

The spatial trajectory obtained by the inverse model controller, a typical subject and the spinal controller are respectively depicted from left to right in Figure 4. The results obtained during Expt.1 (null field) and Expt.2 (force field) are depicted respectively in the top and bottom rows.

We see that during Expt.1 the inverse model and the spinal controller are doing a similar and perfect control of the human arm model. These results are comparable to the performance of the typical subject. More importantly we see that the movements follow a quasi straight line. The velocity associated with the three results are all exhibiting a similar bell shape which reflect a minimum jerk trajectory (not shown). This shows in the spinal control case, for which no desired trajectory was specified but only the final set point, that there is no need for specifying a desired system response to obtained a minimum jerk trajectory. This is an important result as there is no evidence that a desired trajectory is generated by the brain.

During Expt.2 we also see that both the spinal controller and the inverse model controller behave similarly, exhibiting the movement discontinuities observed in the typical human subject.

## 4 Conclusion

The aim of this paper was to bring back the projector on the spinal cord which tends to be forgotten in the motor control models which are currently proposed in the literature. After recalling the main

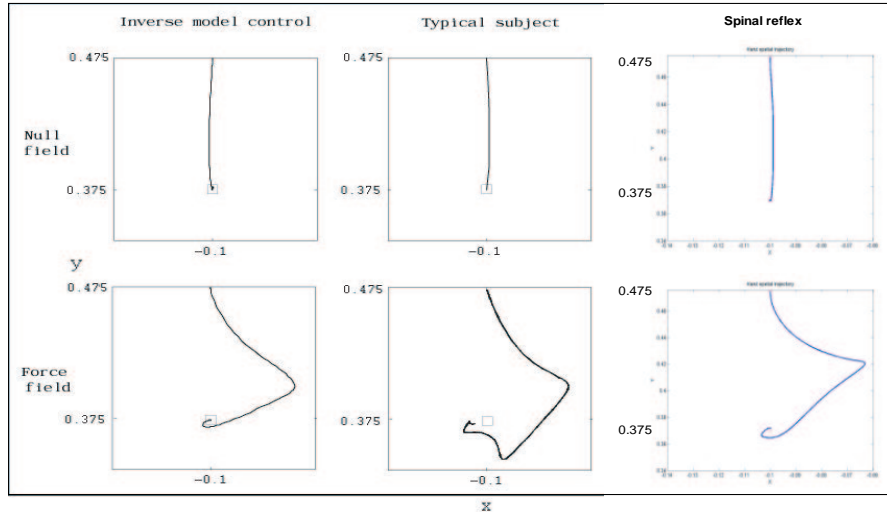


Figure 4: The spatial trajectory obtained by the inverse model controller, a typical subject and the spinal reflex controller are respectively depicted from left to right. The results obtained during Expt.1 (null field) and Expt.2 (force field) are shown in the top and bottom rows respectively.

properties of the spinal cord, we have compared results obtained by an inverse model controller (the very trend in motor control models), by a typical human subject and by a spinal controller during a reaching movement task. We have shown that the spinal control (in fact, a crude stretch reflex control) suffices to reproduce observed human behaviors and to replicate some results obtained by the inverse model controller. It remains to be seen how a complete motor control model with such a spinal control will compare with the inverse model controller, but the simplicity and biological plausibility are appealing.

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