

# The Neural Control of Limb Movement

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Current theoretical research on nonlinear intelligent multi-input multi-output (MIMO) control systems is hampered by the lack of working engineered examples of such systems. Biological control systems include many examples of such systems that perform very well. This paper reviews work done by the authors and their colleagues on a sub-class of such biological control systems, those that control locomotion in humans and cats. Optimal control theory is used to explain how these control systems work. This leads to a suggestion as to how these controllers are organized and operate. Finally, research is proposed that might further elaborate and detail these suggestions.

## Controlling Limb Movement

There has recently been a great deal of interest among controls researchers in the design and theory of nonlinear multi-input multi-output (MIMO) intelligent control systems. One of the best ways to begin the design of any device is with a detailed knowledge of a similar design that works well. It is only necessary to look in a mirror to see an example of a very satisfactory nonlinear intelligent MIMO control system.

Humans and other living creatures contain many such systems. Well known examples include the systems that control heartbeat, body temperature, body weight (arguably an example of an ineffective controller), and eye movement: The emphasis in this article is on another

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example, the control of limb movement as it is done by humans and cats. There are three primary reasons for this emphasis:

1. Limb movement is important to humans, animals, and many kinds of robots.
2. Limb movement more clearly involves intelligence, at least in its initiation, than the other examples cited.
3. There is a large amount of experimental data and many experimental techniques for studying limb movement.

The research described here is not primarily motivated by the desire to learn about control systems. Knowledge about controls is a useful by-product of work aimed at understanding the neural control of limb movement. The major goal of such research is to provide improved self-sufficiency to individuals having motor control difficulties, such as those with spinal cord injuries and cerebral palsy.

The work described here is primarily that of the authors and their collaborators. A brief survey of important prior work in neurophysiology is included; however, much useful and important work will not be mentioned because it is not relevant to the specific examples in this paper. The examples include descriptions of work done by us and our collaborators on specific movement tasks, jumping, pedaling a bicycle, maintaining posture, and walking. Some suggestions for further research are also presented.

## Biological Context

The neuromuscular systems of mammalian limbs are an obvious choice for a biological analog of MIMO control because they contain many independently controllable actuators (muscles), many independent sensors that correspond generally to typical state variables (proprioceptors), and a linkage among the components (skeleton) that

is complex but analytically tractable. Locomotor behaviors are an obvious choice for applying optimal control techniques because they often suggest simple performance criteria such as speed (the bicycling task described later), height (the jumping task), or efficiency and stability (the walking/standing task). However, the controllers of biological systems (central nervous system) are not a single black box but rather a multiplicity of parallel and serial stages, each working on a very different part of the problem, yet often with no clearly definable hierarchy. If these are simply lumped into a single box, one loses most of the insights that should be sought. Experimental investigations of the individual stages have led to a number of historically important insights.

#### *Regulation of Individual Actuators*

Everyone is familiar with the clinical testing of the knee-jerk reflex, in which a tap to the patellar ligament activates the stretch receptors of the quadriceps muscles, which in turn excite the motoneurons of the same muscles as part of a length-feedback servocontroller. In many (but not all) muscles, this connection is the single most powerful connection known; furthermore, its gain is modulated as a part of many voluntary motor behaviors and may become pathologically large or small as a result of different neurological disorders. These observations led Liddell and Sherrington [1] and many others to focus on the servocontrol of individual muscles as a fundamental building block of the central nervous system CNS hierarchy. This view was reinforced by the subsequent discovery that the motoneurons controlling each muscle included a subset devoted to intricate modulations of the sensitivity of the stretch receptors (the gamma motoneurons controlling the fusimotor muscle fibers of the muscle spindles; for review see [2]) and by the identification of specific interneurons that relayed negative feedback from strain receptors in the musculotendinous junctions, the Golgi tendon organs (for control implications, see [3]). These circuits suggested a control scheme in which open loop control from a higher center is assisted by servoloops around each actuator that serve to "linearize" the otherwise messy, intrinsic mechanical properties of muscles.

#### *Central Pattern Generator (CPG)*

Sherrington and others also studied extensively certain cutaneous reflexes in which single stimuli resulted in widespread excitation and inhibition of various muscles in the limb [4]. Sherrington suggested that the interplay between the cutaneous and proprioceptive reflexes and the mechanics of the limb could result in complete cycles of behavior such as locomotion; surprisingly normal walking movements of the legs can be elicited in decerebrate and even spinal quadrupeds. This would seem to imply that the open-loop controller might be quite simple, perhaps just the on-off center that was subsequently identified in the brainstem (mesencephalic locomotor region; (MLR) [5]). However, the existence of a fairly sophisticated and autonomous CPG was clearly established by the phenomenon of "fictive" locomotion, in which the muscles are paralyzed or the dorsal (sensory) roots are cut (hence the limb produces no phasic sensory feedback) but the motoneurons are still being excited to produce locomotor-like rhythmic sequences of electrical output [6].

#### *Intersegmental Mechanics and Control*

While Western neuroscience concentrated on a reductionist approach to the circuitry of the CPG and the clinical reflexes, Nicolas Bernstein in Russia produced a pioneering inverse dynamic analysis of human locomotion ([7] — translated from articles appearing in the

1930s) that suggested the inadequacy of regulating individual muscles. He noted the complex and widespread effects that tension in a single muscle would have on the trajectory of the linked segments that make up the skeleton, arguing that substantial amounts of feedback would be needed to achieve stability and that this feedback could not be limited to the servocontrol of individual muscles by their own proprioceptors. Unfortunately, this work was not well known in the West until long after its initial appearance; furthermore, mathematical and computational tools for describing and modeling distributed controllers were primitive to nonexistent until relatively recently and remain inaccessible to many experimentalists with limited backgrounds in mathematics and engineering. The biomechanical approach to understanding sensorimotor control has become more compelling in light of recent discoveries of widespread convergence and divergence in the interneuronal circuitry between the sensors and the actuators (for review, see [8]). While it is still true that homonymous feedback (between proprioceptors and motoneurons in one and the same muscle) is often stronger than in other individual circuits, it is also true that there are many more heteronymous than homonymous circuits and that, in aggregate, they provide the majority of the total feedback component of control.

#### *Adaptive Control and Neural Networks*

One scheme for distributed computation and control that has periodically captured the imagination of neuroscientists is the neural network, a descendant of the perceptron introduced by Donald Hebb [9] as a model of cognition (which is also a MIMO problem). While it is not the purpose of this paper to consider the neural mechanisms for computing the optimal controllers discussed here, it is also not possible to categorize control schemes without some consideration of how they might be combined into hierarchical systems concerned with specifying the desired trajectory and evaluating the actual performance. Many of the model optimal controllers considered to date are MIMO in the sense of having many actuators and many state variables but they run open-loop in real time; furthermore, their optimization criteria are unidimensional, involving either a single sensor or a single estimate derived from a fixed subset of sensors. Others require some real-time feedback (e.g., triggering of phase transitions in jumping and walking), but these are again unidimensional, even binary state transitions. In contrast, we have also begun to examine MIMO feedback regulators. This raises questions about the relationship between such feedback regulators and the open-loop component of control required to account for phenomena such as fictive locomotion and the initiation of voluntary behaviors (see [10]). In particular, if both the controller and the regulator are adaptive control systems and both receive sensory feedback and produce motor output (directly or indirectly), how can their functions be kept distinct? This is the biological analog of the "team problem" that has been the subject of extensive analysis by control theorists. Unfortunately, the solution that is actually embodied in the CNS is not compatible with the team conclusion that all input and all output should be routed to a single, central decision-making center. Biological control is known to be distributed among anatomically distinct neural structures; lesions of individual structures produce very different failure modes, not a general deterioration of function. Furthermore, the fact that biological systems evolve gradually (rather than being designed top-down) imposes a formal requirement for such modularity [11]. Fig. 5 shows one possible scheme for maintaining modularity in a MIMO system with multiple loops of adaptive control. However, the scope of this problem has yet to be examined seriously.

One compelling reason for accelerated research into the control of neuromusculoskeletal systems is the application of neural prosthetic interfaces such as FNS for the restoration of motor control in patients with spinal cord injury, stroke, cerebral palsy and other disorders of the higher levels of the CNS (e.g., [12]). Most such patients have intact motoneurons, muscles, proprioceptors and even lower spinal reflex circuits that have been deprived of their command signals from upper motor centers. Electrical stimulation of peripheral nerves can reanimate their paralyzed limbs and, to a more limited extent, electrical recording can detect sensory feedback from the periphery and residual command signals from the CNS. Nothing is likely to provide as compelling a test of the adequacy of neuromuscular control theories as the prospect of trying to get real muscles to perform real tasks for a patient whose rehabilitation depends on the exercise.

### **Using Optimal Control Theory to Study Control**

The basis of all the research reported in this section is the belief that optimal control theory is a useful tool for the study of the neurophysiological control of limb movement. That is not to say either that animals use optimal control theory to decide how to control their limbs or that the controls they use are optimal with respect to some obvious performance measure. Instead, optimal control theory is used to state and solve precisely specified mathematical problems. The solutions are then compared with the controls actually used by animals and humans. The differences between the two provide quantitative information about the actual control system, insight into both control theory and neuromotor control, and suggest changes in the optimal control model that ought to improve the match between experiment and theory. This process is reiterated until the experimental data are not sufficiently accurate or detailed to refute the theoretical model.

The word "insight" was used in the previous paragraph to suggest creative thinking rather than simple agreement or disagreement between model and data. It is important for both biologists and control engineers to remember that the control systems that have been invented to date are almost certainly a meager subset of all possible types of control and even of all control methods used in biological systems. Thus, the study of biological systems should not be confined to testing whether their performance is compatible with control schemes invented to date but must include detailed examination of their inner workings to discover new types of control. Thus, it is important to perform more than superficial comparisons of emergent behavior in search of agreement between model and organism. What is needed are insightful searches for incompatibilities between the properties and behaviors of the components of the model and their analogues in the organism. Fortunately, there is a wealth of data about the detailed connections and working of the neural circuitry involved in animal behavior.

#### *Maximum Height Jumping*

The work summarized in this article began with a study of maximal height jumps as performed by humans and cats. Note that the task, jump as high as possible, is slightly artificial. However, it is certainly within the repertoire of behaviors of humans and cats. Furthermore, the task defines a precise and unambiguous performance measure, making it particularly amenable to analysis by means of optimal control theory.

There were believed to be several advantages to beginning with a study of maximal height jumps. There were experimental advantages to

the fact that both humans and cats performed the task. In contrast to walking, the task was not periodic. Thus, the CPG for jumping could not simply be a clock. Because it was conjectured that the optimal control was bang-bang, feedback would be used only to adjust the timing of the controls if at all. Because perturbations during the behavior were believed to be small it was conjectured that feedback stabilization could be safely ignored.

The results of this study have been documented in a series of papers [13]-[17]. Only the most important highlights will be repeated here. First, the dynamics of muscle and tendon are extremely important in specifying the motor control system. As suggested earlier by Hatze [18] good models of musculotendon dynamics are crucial to the analytic study of neurophysiological control of movement. Models of the jumper that ignore muscle and tendon dynamics produce maximal height jumps that are very different from those produced by humans and cats. Second, the maximal height jump is not the result of a bang-bang control even though the Hamiltonian is monotone in the controls and the controls are bounded. The optimal control is singular in regions where the foot is flat on the ground. Third, there is a period from the instant the heel leaves the ground to the instant of lift-off during which the optimal control is bang-bang. Coordination is very important in this period. Small changes in the timing of the controls convert a maximal height jump into a collapse. The singular and bang-bang regions are qualitatively supported by experimental results.

The experimental data do show a substantial deviation from the optimal control model. All the experimental subjects turn off their extensor muscles shortly before lift-off. The optimal control model indicates that they should not do this. It is known that joints contain sensors of joint angle and that this information is fed back and used to prevent damage to the joint. Presumably, this is the cause of the discrepancy. This is a good example of the complexity of neurophysiological controls. The feedback from the joint sensors, while certainly present, would be too late to prevent injury if a human jumper tried to perform a mathematically optimal jump. The feedback presumably is used to learn not to hyperextend the joints. Once this is learned the feedback is no longer necessary to prevent injury.

#### *Maximum Speed Pedaling*

Although work is continuing on maximal height jumps, the recent emphasis has been on humans pedaling a stationary bicycle at maximum speed. This is a task that is much closer to walking, arguably the most important locomotor task, than is jumping. As with maximal height jumps, perturbations are likely to be small so feedback stabilization can be ignored. However, the performance measure and task definition are not as unambiguous as the maximal height jump.

#### *Simplified Model*

In the interest of obtaining a good understanding of the fundamentals of the maximum speed pedaling problem, a greatly simplified version was studied first [19]. This pedaling problem was based on the geometric situation shown in Fig. 1. Assuming that the pedaler remains seated, a little bookkeeping shows that this dynamical system has only three degrees of freedom. Writing the equations of motion is somewhat complicated by the constraints imposed by the bicycle seat and crank. A further simplification to the geometry was incorporated into this preliminary study. The ankles were assumed coincident with the ends of the crank. This eliminates the feet, pedals, and ankle controls from the problem. The result is a pedaling problem with only one degree of

freedom. One could argue that such a model is a not unreasonable approximation to pedaling a bicycle. Many cyclists maintain their feet at a constant angle to the horizontal as they pedal. The lever arm between the ankle and the end of the crank is generally small. However, the real reason for the assumption is to simplify the mathematics.

Two additional simplifications were also introduced. The controls were assumed to be ideal torque generators at the knees and hips. That is, there are four controllers and they have the form:

$$u_{i\min} \leq u_i(t) \leq u_{i\max}, \quad i = kl, hl, kr, hr \quad (1)$$

$u_i(\cdot)$  is piecewise continuous

and  $k$  denotes knee,  $h$  denotes hip,  $l$  denotes left, and  $r$  denotes right.

As we said earlier, using this crude a muscle model guarantees that the analytical results will not match experimental results very well. The goal here is insight and a more accurate muscle model would obscure the underlying mechanics. Finally, the performance criterion was changed slightly. Maximizing the speed is somewhat ambiguous because the angular velocity varies throughout the pedal cycle. It is much clearer to minimize the time required to complete one full crank cycle which is presumably the general goal of a sprinting racer.

The performance measure is clearly artificial. It is very difficult and somewhat unnatural to minimize the time to complete a single crank rotation from a standing start. A more natural problem is to minimize the time required for some number of crank cycles. However, the time required for the computer solution increases rapidly with each additional crank cycle. Also, subjects tire very rapidly when working at maximal effort. Thus, the choice of one pedal cycle is experimentally and analytically convenient, but attention must be paid to the initial and final conditions, as discussed below.

With these simplifications the optimal control model takes the form

Choose  $u_i(t)$ ,  $i = kr, hl, hr, hl$

$$\text{to minimize } \int_0^T dt \quad (2)$$

$$\text{subject to the constraints that } \theta(T) = \theta(0) + 2\pi \quad (3)$$

and

$$\begin{aligned} [I(\theta) + I(\theta + \pi)] \ddot{\theta} = & [B(\theta) + B(\theta + \pi)] \dot{\theta}^2 + g[h\theta + h(\theta + \pi)] + l_k(\theta)u_{kl}(t) \\ & + l_k(\theta + \pi)u_{kr}(t) + l_h(\theta)u_{hl}(t) + l_h(\theta + \pi)u_{hr}(t) \\ & + T_0(\theta, \dot{\theta}) \end{aligned} \quad (4)$$

where

$g$  = acceleration due to gravity

$\theta$  = crank angle

$I(\theta)$  denotes the inertia of the left leg

$B(\theta)$ ,  $h(\theta)$  and  $l_i(\theta)$  are functions of  $\theta$

$T_0(\theta, \dot{\theta})$  is the drag.

See [19] for details.

To complete the specification of the problem it is necessary to specify any additional constraints. One possibility is to apply no additional constraints. This models a situation where the cyclist is accelerating. A second possibility is to constrain all angular velocities to be periodic of

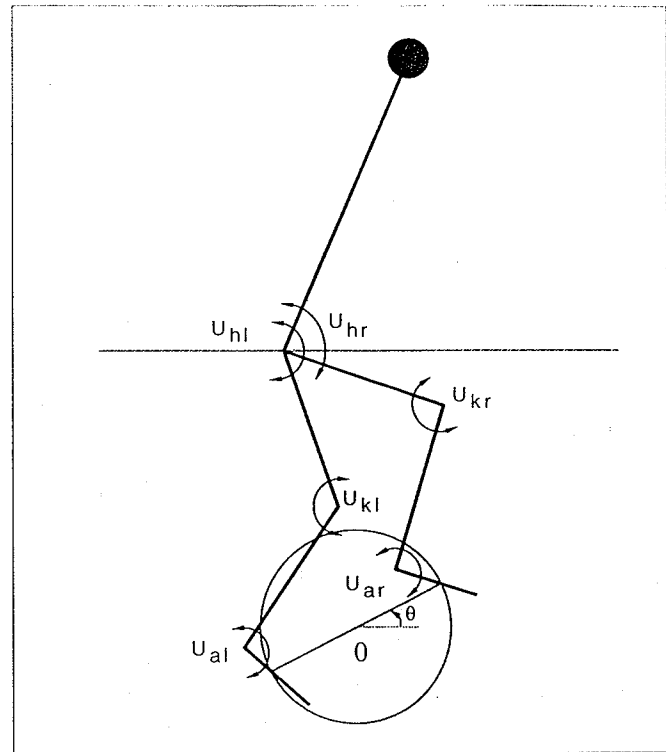


Fig. 1. Model of a human pedaling a bicycle. The hips are assumed to be fixed to the seat and the feet are assumed to be fixed to the pedals. The resulting dynamical system has three degrees of freedom.

period  $T$  and all angles, not just  $\theta$ , to satisfy  $\alpha(T) = \theta(0) + 2\pi$ . This corresponds to the situation where the cyclist is pedaling in periodic steady state.

These problems can be solved quite neatly when the initial angular velocity of the crank is greater than zero and the drag is constant. Constant drag is physically reasonable for a stationary bicycle. The experiment is safer if the cyclist does not start from  $\omega = 0$ . Rewriting (4) in state space form gives

$$\begin{aligned} \dot{\theta} &= \omega \\ \dot{\omega} &= a(\theta)\omega^2 + b(\theta) + l(\theta)u(t) \end{aligned}$$

Letting  $x = \omega^2/2$  gives

$$\frac{dx}{d\theta} = a(\theta)x + b(\theta) + l(\theta)u(t) \quad (5)$$

and the performance measure becomes

$$\text{minimize } \int_0^{2\pi} \frac{d\theta}{\sqrt{x}} \quad (6)$$

This new scalar version of the minimum time to complete one cycle pedaling problem has a largely analytic feedback solution [19]. It is not surprising that the controls switch every  $\pi$  rad. The switches correspond to the sign reversals in the  $l_i(\theta)$ . The  $l_i(\theta)$  reverse sign at maximum and minimum leg extension.

Admittedly, this is just a proof that the obvious answer is correct. However, it is useful to have a proof that the optimal control, in the absence of muscle dynamics and with the other simplifications of the

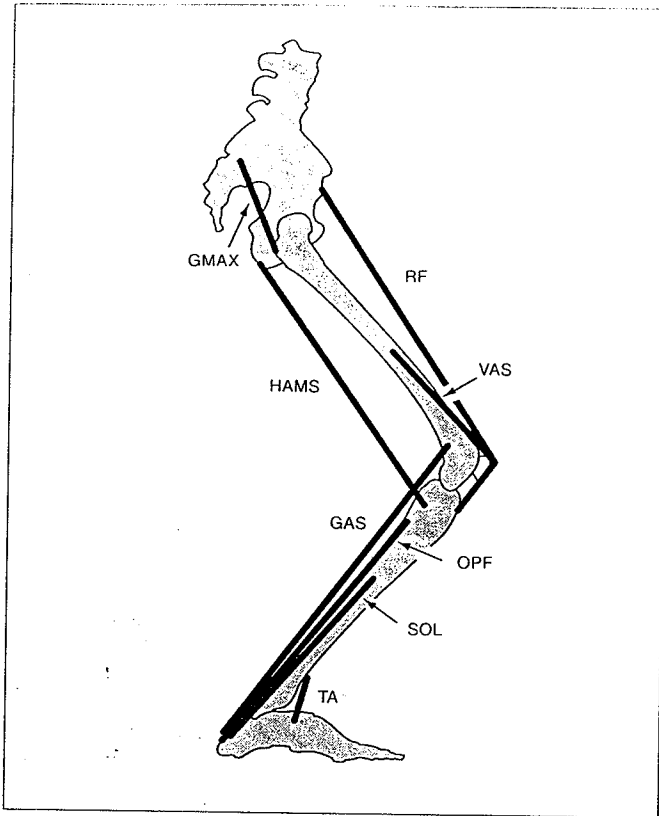


Fig. 2. Schematic representation of the musculoskeletal model for the vertical jump. Symbols appearing in the diagram are: soleus (SOL), gastrocnemius (GAS), other plantar flexors (OPF), tibialis anterior (TA), vasti (VAS), rectus femoris (RF), hamstrings (HAMS), and gluteus maximus (GMAX). GMAX is not included in our pedaling model. Adductor magnus (AM), a roughly parallel muscle, is included. (Redrawn with modifications from [17]).

model, switches at maximum and minimum leg extension. Because humans do not switch their muscle activations in the way this model predicts, attention is focused on what causes the discrepancy. One might argue that this difference between experiment and model is primarily due to the feet which are, after all, excluded from the above model. A new model, including feet and muscle dynamics, was developed to assess the contribution of each to the controls that minimize the time for one pedal cycle.

#### More Realistic Model

The new model is based on the geometry of Fig. 1. Since this model has three degrees of freedom there are six states resulting from the constrained skeletal mechanics. There are actually about 33 muscles activating each leg. There is some ambiguity about the number because anatomically distinguishable muscles may not be functionally distinct and vice versa. Because pedaling is confined primarily to the sagittal plane, it is reasonable to ignore muscles and muscle action outside this plane. Muscles that have substantially similar effects in the sagittal plane such as medial and lateral gastrocnemius can then be lumped into a single "muscle." The result is eight muscles moving each leg. They are shown in Fig. 2 with one exception. The pedaling model does not include GMAX. Adductor magnus (AM), a similar hip exten-

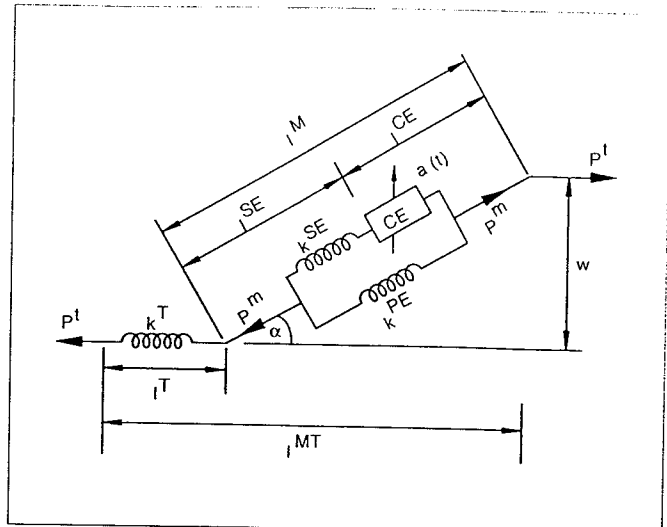


Fig. 3. Schematic representation of the musculotendon model. Note that:  $l^{MT} = l^T + l^M \cos \alpha$ ;  $l^M = l^{SE} + l^{CE}$ ;  $l_0^M \sin \alpha_0 = l^M \sin \alpha = W = \text{const}$ ;  $P^T = P^M \cos \alpha$ ; where  $l^{MT}$  is the length of the musculotendon actuator,  $l^M$  and  $l^T$  are the lengths of muscle and tendon respectively;  $l^{SE}$  and  $l^{CE}$  are the lengths of the series-elastic and contractile elements;  $P^M$  and  $P^T$  are muscle and tendon forces;  $\alpha$  is the pennation angle of muscle;  $k^T$  is tendon stiffness;  $k^{SE}$  and  $k^{PE}$  are the stiffness of the series-elastic (SE) and parallel-elastic (PE) elements; CE and MT denote the contractile element and musculotendon actuator, respectively;  $W$  (a constant) represents muscle thickness;  $l_0^M$ ,  $\alpha_0$  are the fiber length and pennation angle at which peak isometric force is developed; and  $a(t)$  designates activation of the contractile element. (Redrawn with modifications from [21]).

sor, is included. AM originates near HAMS on the hip and inserts on the thigh.

The knee, hip, and ankle torques that drive the skeletal model are then functions of the muscle forces and moment arms. The moment arms are easily computed from the known muscle attachments and the skeletal geometry. That is

$$\underline{u}(t) = \underline{M}(\theta) \underline{p}(t) \quad (7)$$

where

$\underline{u}(t)$  is the six-vector of joint torques

$\theta(t)$  is the three-vector of angles that specify the geometry

$\underline{M}(\theta)$  is the  $6 \times 16$  matrix of muscle moment arms

$\underline{p}(t)$  is the 16 vector of muscle forces.

The details of  $\underline{M}(\theta)$  and the individual muscles can be found in [17] and [20]. The actual numerical values were based on measurements of experimental subjects where possible and on the literature where direct measurement was not possible.

Fig. 3 shows a standard mechanical model for muscle. The essential features of this model are:

a) The series spring ( $k^T$ ) stores energy between the muscle and the limb.

b) The parallel elastic element ( $k^{PE}$ ) and the contractile element (CE) are nonlinear.

c) After some calculation and assumptions regarding the force-length and force-velocity characteristics of muscle the model in Fig. 3 can be described mathematically as

$$\dot{p}^T = f \left[ p^T, p^{MT}, v^{MT}, a(t) \right], \quad a_{\min} \leq a(t) \leq 1 \quad (8)$$

$$\dot{a} = g(a(t)) + h(a(t), u(t)), \quad 0 \leq u(t) \leq 1 \quad (9)$$

See Fig. 3 for notation.

Detailed derivations and discussions of this model can be found in [21]. These details are not particularly important. Any reasonable model of muscle results in an optimal control model of the minimum time pedaling problem in which the Hamiltonian is in  $u$ .

The control,  $u(t)$ , is a model for the neuronal excitation of muscle. This excitation is actually accomplished by trains of similar looking pulses on a large number of neurons. Control is actually accomplished by adjusting the pulse rate on each neuron and the number of neurons carrying pulses. Hatze [18] has used two control inputs to describe this. It is more common to use only one input since the recruitment of additional neurons is very highly correlated to pulse rate and desired force. The rectified, smoothed EMG signal is qualitatively similar to the  $u(t)$  in this paper.

Research is currently proceeding on the solution to the three degree of freedom minimum time to complete one crank cycle pedaling problem. To simplify and speed up the computation of the optimal controls and to separate the role of the ankles and muscle dynamics in specifying control switch times, the ankle trajectory was constrained to follow an experimentally determined path. This reduced the optimal control problem to a one degree of freedom problem that was reasonably tractable.

The optimal solution for this simplified minimum time to complete one cycle optimal control problem, when the cyclist starts from rest, is shown in Fig. 4 as a function of crank angle. The initial crank angle is  $+15^\circ$  measured counter-clockwise from the forward horizontal (the usual  $x$ -axis) and the angular velocity of the crank is zero. The direction of motion is clockwise. The time required to complete  $360^\circ$  of rotation is 0.82 s. This is slower than our experimental subjects; suggesting that the glutei muscles should be added to our model. Notice that only TA, an ankle flexor, is active initially in the left leg. At the start the left leg should pull up on the pedal. The right leg, which is pushing down, has most of its muscles active. Only TA, RF, and HAMS are inactive. It is not surprising that TA is inactive. When the leg is in this configuration it is basically a leg lifter (anatomically, an ankle dorsiflexor). RF and HAMS are two-joint muscles. Anatomically, RF flexes the hip and extends the knee while HAMS extends the hip and flexes the knee. Notice in Fig. 4 that HAMS is excited almost immediately after pedaling is initiated. A plausible explanation for this is that at crank angles between roughly  $0^\circ$  and  $-100^\circ$  the leg is in a position in which HAMS acts primarily as a hip extensor. Similarly, the activation pattern of RF suggests it is being used primarily as a knee extensor, in parallel with VAS.

The activation pattern for VAS is somewhat surprising. As an anatomical knee extensor one would expect the left leg VAS to be active at crank angles from  $-90^\circ$  until almost  $-270^\circ$  and the right leg VAS to be active at all other crank angles. The most likely explanation for the excitation pattern for VAS in Fig. 4 consists of two parts. First, there is a lag of approximately 30 ms between the onset of excitation and the peak in muscle force. Thus, the onset of excitation will be earlier than would be expected from considerations of force or torque alone. This is why the left VAS is first excited at  $-50^\circ$  rather than  $-90^\circ$  and the right at  $-230^\circ$ .

Second, muscles continue to produce force for quite some time after excitation ceases. For example, the right VAS continues to produce force for the first 300 ms of the pedaling task even though it is only excited at the very beginning. This long lag in turning off the force means that

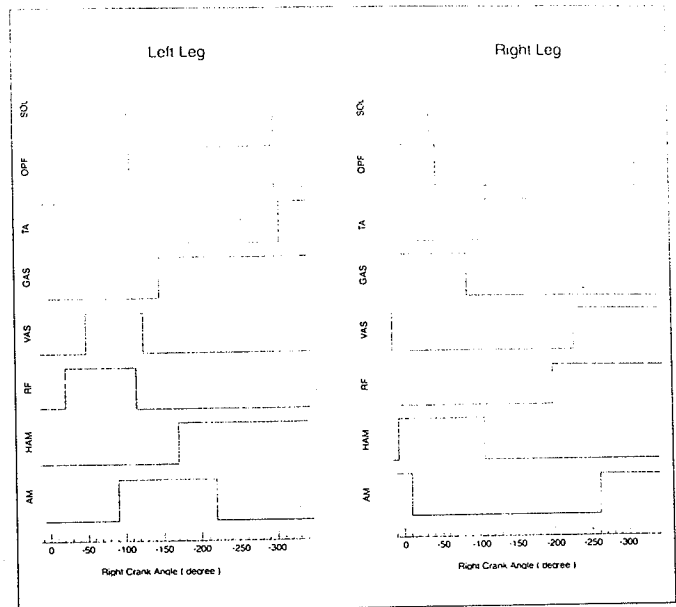


Fig. 4. Computed, optimal muscle excitation (approximately equivalent to rectified, smoothed EMG) for completing one cycle of the crank of a stationary bicycle in minimum time. The problem begins with the crank stationary at  $+15^\circ$  from the horizontal. The crank is driven counter-clockwise so the right leg is maximally extended at approximately  $-90^\circ$  and the left leg at  $-270^\circ$ . The time to complete the cycle is 0.82 s.

the excitation of VAS must cease well before the limb reaches full extension in order to avoid VAS force acting to oppose the upstroke.

The fact that the model predicts this surprising behavior for the vasti (VAS) is very encouraging. The experimental data from human bicyclists shows the same surprising on-off pattern for the vasti.

Notice that writing the optimal control as a function of crank angle, a simple trick to the control engineer, has interesting implications to the biologist. The proprioceptors provide the information needed to estimate crank angle. Thus, a feedback control with crank angle as the feedback signal is biologically feasible. The complex timing relationships among the muscles involved in pedaling need not be stored in the brain and supplied to the limb muscles. Instead, the timing may be an emergent property of a feedback controller based on crank angle.

#### Current Research on Pedaling

It would be very desirable to solve the full three degree of freedom pedaling problem. To do so requires development of an algorithm to compute optimal controls when they are singular. This is one of two high priority current research tasks on pedaling.

The other high priority pedaling problem is the solution of optimal control problems that correspond to novel pedaling tasks. Dr. Felix Zajac and his staff have built a stationary bicycle in which the relation between the pedals can be more or less arbitrary. For example, it can be arranged that the left leg must pedal clockwise and the right leg counter-clockwise. Suppose experimental subjects perform the novel tasks of pedaling as fast as possible when their legs must pedal in opposite directions differently from the mathematically optimal solution. This would be evidence for hard-wiring of certain coordination patterns.

The major difficulty in solving the optimal control problems that correspond to novel pedaling tasks is finding a control  $u(t)$  that actually causes the crank to rotate  $360^\circ$  and that can be used as an initial guess

at the optimal control. It is then easy to successively improve the control until at least a local optimum is reached. Devising algorithms for generating these initial controls is the main focus of the attempt to solve novel pedaling problems at the present time. It is hoped that this research can be used to shed light on how novel tasks are learned as well as on built-in muscular synergies.

As will be seen below, this problem of piecing together simple movements to form complex ones is very important to a nascent theory of motor control. A natural way to form an initial control for pedaling is to combine a control for extending the leg with a control for retracting the leg. If one can find a smooth transition from extension to retraction and vice-versa then one has an initial control for turning the crank. Thus far, efforts to create an algorithm that will do this in a way that provides an initial control that can then be optimized have failed. It appears to be difficult to make a smooth transition from extension to retraction.

#### Feedback Regulation of Posture

The work described above is essentially limited by the analysis technique to open-loop aspects of the controller. The focus is on the optimal neuronal excitation and the resulting trajectories and not on how the neuronal excitation is actually generated by the brain, spinal cord and proprioceptors. Because the means whereby the control signals are produced are not addressed, it is not possible to address directly the effects of external perturbations, internal inaccuracies in realizing desired inputs, or measurement uncertainties (errors and noise). The work described below was specifically designed to address both of these issues. How is the control signal actually generated? How are proprioceptors (physiological sensors) utilized?

One of the starting points for this investigation of feedback controls was the realization that there were proprioceptors for every state variable in a reasonable model of the limb. Thus, a state feedback controller seemed to be at least plausible. Perhaps the simplest motor control problem in which to study the use of feedback is the regulation of posture. The objective is clear and simple. Stay close to a desired posture. Furthermore, although it is quite clear that the regulator of posture in humans and cats is nonlinear, a linear model is reasonable for small perturbations.

The above arguments suggest the linear quadratic regulator (LQR) or  $H_\infty$  with state feedback as theoretical tools for studying small perturbations of static, standing posture. Such a study, using the LQR, was performed and the details reported in [22]. One of the results of this study was a suggested purpose for the Renshaw cells. These cells sense and feed back motoneuronal output. Such feedback is needed in an LQR-based regulator but is not even useful in most of the other neural control schemes that have been proposed.

The main questions addressed in that study were the mathematical modeling of the various proprioceptors and the choice of weights in the quadratic performance measure. It was found that a particular choice for the weights gave fairly good agreement to experimental data on posture regulation by cats. A more interesting test would be to compare the feedback gains predicted by the model to the number of proprioceptors in particular portions of the limb and to the strength of interneuronal connections between particular proprioceptors and effector neurons. Large numbers of proprioceptors are generally believed to mean high measurement resolution is needed while many connections imply that large feedback gains are at least possible. Small numbers where the LQR predicts high gain would refute the theoretical model.

The results of the LQR based study of the regulation of posture were promising enough to motivate an attempt to extend them to walking. Admittedly, the attempt is somewhat procrustean. Make the neuronal control of walking fit an LQR model. However, the result is plausible and, it is hoped, refutable.

The basic idea is a common one in controller design. Break the control of walking into two parts. Design a feedforward controller to generate a nominal control signal and a nominal trajectory. Then design a closed-loop LQR to keep the actual trajectory close to the nominal. The design of the LQR is standard [23]. Because it is based on linearization about a trajectory the linearized dynamics are time-varying. Because the trajectory is periodic the linearized dynamics are also periodic. The weights in the quadratic performance criterion can be adjusted to reflect very different performance goals for the leg in the stance phase and the leg in the swing phase of walking (some preliminary results were reported in [10]).

There are several objections to the scheme outlined above. First, if the performance of the controller is the only issue then a single, centralized omniscient controller will always be at least as good as the modular controller described above and will usually be better. Second, the nominal control and trajectory must be changeable by feedback from the periphery. The mesencephalic cat and fictive locomotion results demonstrate this biologically. From an engineering viewpoint the need to make substantial changes in the nominal control in response to perturbations is obvious. Third, it is unreasonable to expect the brain to store complete nominal controls and nominal trajectories for even the variety of walks much less for the full repertoire of movements. Worse, the brain would have to store the complete set of time-varying feedback gain matrices for all of these movements.

The obvious response to the first objection is that the biological evidence strongly suggests modularity. Furthermore, modularity has two important advantages over a single unified controller. A modular controller is more likely to continue to function, albeit at reduced performance, in the event of damage. In addition, evolution favors modularity because it is much more likely that an already well-adapted creature can become better adapted by improving some module than by some global change (see [11] for a detailed version of this argument).

#### Modular Neuromotor Control Scheme

A possible answer to objections two and three is shown in Fig. 5. The nominal control, nominal state trajectory, and the time-varying feedback gains are all generated in the CPG and Temporal Mediator. Both of these modules receive peripheral feedback that can change their outputs. The CPG has the responsibility for overall timing. It is where the frequency of the step cycle is generated. Peripheral feedback can modulate this overall frequency. The temporal mediator generates the detailed timing. For example, it is the TM that sets the relative duration of the stance phase. Feedback from the periphery can cause changes in the stance phase of a limb without changing the frequency of the step cycle.

Of course, the problem of storage remains unless one assumes that the entire output of both CPG and TM is the result of peripheral feedback. The proposal here is that the brain supplies *constant gains* to spinal cord circuits, in particular the CPG and TM, which act analogously to an analog computer to generate the time-varying signals needed by the sensorimotor apparatus.

To see how this might work, consider Fig. 6.

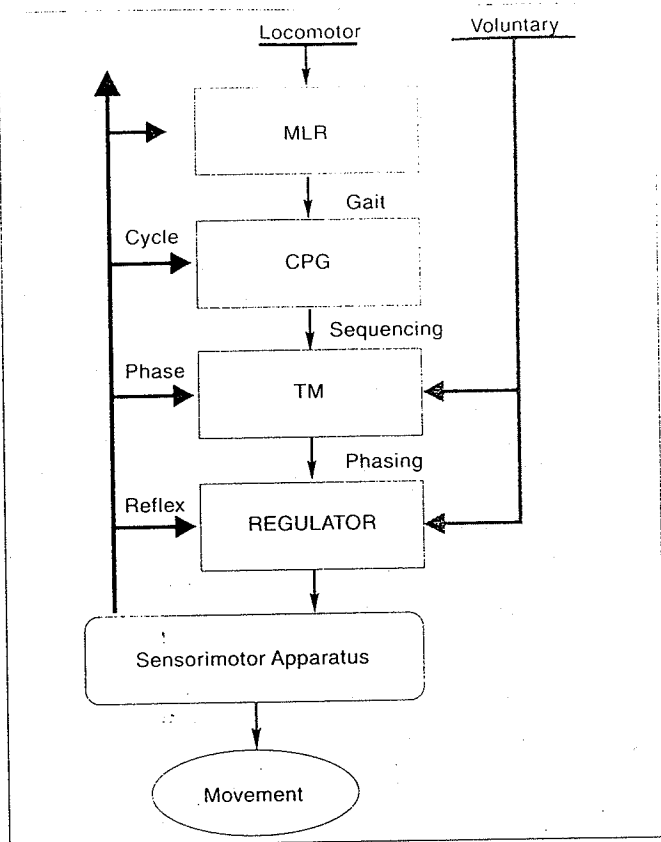


Fig. 5. Schematic control system for locomotion, starting with mesencephalic locomotor region (MLR), central pattern generator (CPG), temporal mediator (TM), and interneuronal regulator controlling the activation of multiple muscle groups in the limb. (Redrawn and modified from [10]).

Suppose the brain supplies the three constants  $\alpha_c$ ,  $\beta_c$ ,  $\gamma_c$  to the little analog computer shown. In the absence of peripheral feedback ( $\alpha_p(t)=0$ ),  $y(t)$  will be sinusoidal with frequency  $\sqrt{\alpha_c}$ . Assuming that  $\alpha_p(t) \geq 0$ , peripheral feedback can only increase the frequency. The effect of peripheral feedback on  $y(t)$  can be large but it must be smooth. That is, jumps in  $\alpha_p(t)$  are integrated twice before they appear at the output. This model of the CPG is obviously oversimplified. In particular, the periodic trajectory is stable but not asymptotically stable and there is no provision for properly adjusting force. But, look at the aspects of the available data that it fits. The memory requirement is very modest. Three constants generate a large family of time signals. This combination of constants from the brain and peripheral feedback to modulate some of these gains could produce both the mesencephalic cat and fictive locomotion results.

This proposal improves on an earlier and somewhat related suggestion by Albus [24] who proposed a hierarchical scheme for motor control in which very coarse information was supplied by the brain and refined by successive modules. However, the higher levels in his scheme had to supply parameters such as velocity. Because velocity is actually time varying, his model did not avoid the problem of storing complicated time signals. The individual modules in his proposal are also different from those proposed here.

It should be noted that an analog computer consisting of nothing but integrators, summers, and gains can generate any continuous function

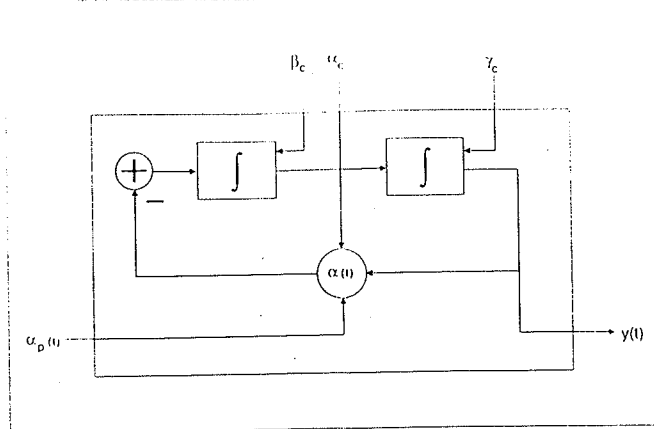


Fig. 6. A plausible, albeit oversimplified, analog computer model of the CPG. Note that  $\alpha_c$ ,  $\beta_c$ ,  $\gamma_c$  are constants supplied by higher centers,  $\alpha_p(t)$  is supplied by feedback from the periphery (e.g., from proprioceptors),  $\alpha(t) = \alpha_c + \alpha_p(t)$ , and  $y(t)$  is the output from the CPG (periodic if  $\alpha_p(t)$  is constant).

on a finite interval. This is a trivial consequence of Weierstrasse's Theorem [25]. All of these elements can be created by simple neural circuits. Artificial neural networks, and presumably real ones, are good at storing numbers, i.e., coefficients. Thus, the proposal seems to have some promise.

There are two serious problems with this simple scheme for motor control. The first is that neurons have very limited dynamic range. That is, the individual components of the analog computer saturate for small signal levels. Albus argues that the actual signal is encoded in the limited signals of a large number of neurons. This is plausible but these are still difficulties. Bernstein [25, p. 67] proved that the coefficients  $a_0, a_1, \dots, a_n$  of a polynomial of degree  $n$ ,  $P(t) = a_0 + a_1 t + \dots + a_n t^n$ , bounded in absolute value by 1 on the interval  $[0, 1]$  are exactly bounded as

$$|a_0| \leq 1; |a_1| \leq 2n^2; \dots |a_k| \leq 2^{2k} \frac{n(n+k-1)!}{(n-k)!(2k)!}; \dots |a_n| \leq 2^{2n-1}$$

Thus, the range of the required gains (the  $a_i$ ) can be extremely large. This can make the internal signals large as well.

The second problem can be illustrated by a more detailed discussion of walking. There is much more to walking than just creating a periodic nominal control and stabilizing the trajectory to keep it close to the nominal. For example, it is necessary to start walking and stop walking. It is also necessary to accelerate or decelerate both volitionally and in response to changes in terrain. A scheme that purports to explain how walking is controlled by the brain and spinal cord must say how these are accomplished.

All of the walking tasks described in the previous paragraph could be accomplished by modulating the three parameters in the analog computer. However, the modulating signals that the brain or some higher region of the spinal cord must supply would have to be time-varying. These can, in principle, be generated by constant gains supplied to yet another analog computer but the number of gains and the size and complexity of the computer is starting to look very big. Furthermore, walking is just one element of the repertoire of volitional movements.

Neither problem seems insurmountable. Clever synthesis procedures could presumably avoid the limited range problems, perhaps in



combination with some form of coding. For example, 3 gains, 2 integrators, and feedback produce  $y(t)=A\cos(\omega t+\theta)$  even though a polynomial synthesizer of this signal requires an infinity of integrators and coefficients. The problems associated with the size and complexity of the movement repertoire need investigation. Given that the same set of coefficients from the brain can evoke a set of movements because of different peripheral feedback the number of distinct movements that the brain must store explicitly may be relatively modest.

Needless to say, much more work needs to be done before the above suggestions can be called a theory. The fact that the ideas are plausible is encouraging. However, it is important that the ideas be sharpened until predictions that are not just plausible but that are actually testable can be made.

### Suggestions for Further Research

There are three areas of further research that are believed to be of particular interest to specialists in systems and control. The first is the extension of the models to three space dimensions. Humans and animals move in three dimensions so two dimensional models usually involve some distortions. For example, it is obvious that many groups of muscles that are functionally equivalent insofar as motions that are constrained to two dimensions are easily separated by their function in three dimensions. Modeling limb movement in three dimensions presents some challenges. It is difficult to write the equations of motion of a multi-segment limb in three dimensions by hand. Fortunately, computer software to generate such equations is now available (e.g., SD/FAST from Symbolic Dynamics Inc.). Similarly, other hardware and software is making it feasible to collect 3D data from animals and humans as they locomote. Finally, the computer graphics needed to display both experimental and analytical results in forms that support the development of intuition are now affordable.

The second area of controls research deals with the issues raised at the end of the previous section. Can the suggestion that complex movements are produced by a combination of gain settings (constants) from the brain and feedback from the periphery be made precise enough to be experimentally tested? In particular, schemes for coping with the limited range of neuronal signals must be devised. The initiation and termination of movements must be explained. If complex movements are created by piecing together building-block movements then the mechanism for combining the components must be describable. This last problem is a more complicated version of the problem of operating a gain scheduled controller across the-schedule boundaries.

The third area of controls research is in nonlinear intelligent MIMO control theory. Although most of this article emphasizes the study of neurophysiological control problems as a means to learn about nonlinear intelligent MIMO control theory, it is clear that, as always, theory and practice advance hand in hand. The questions that were asked in this article were deeply dependent on the available theory. The methods that were used to analyze the experimental data were from control theory. It is hoped that this paper will encourage control theorists to think about nonlinear intelligent MIMO control theory in ways that are compatible with what is known about the neurophysiological examples of such controllers.

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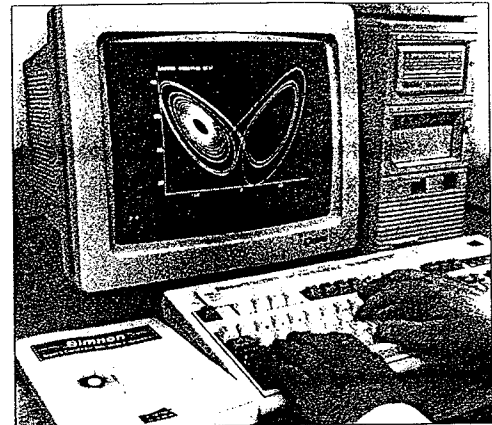


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