

Towards a Hierarchical Neuromuscular Control Model with Reflex-based Spinal Control

- Study with a Simple Running Model

Seungmoon Song

Robotics Institute, Carnegie Mellon University
smsong@cs.cmu.edu

Abstract. Humans can generate diverse locomotion behaviors through the hierarchical control of the supraspinal and the spinal systems, where the spinal control is often assumed to consist of central pattern generators and reflexes. It has been demonstrated through simulation that human walking and running can be generated with control models where the central pattern generator is controlled in a hierarchical structure. However, no reflex control model in such framework has been proposed. Here we propose that locomotion behaviors can be controlled by a hierarchical control structure where the supraspinal system modulates reflexes with simple signals. We demonstrate in physics simulation that a simple neuromuscular model with a hierarchical reflex control can regulate running speed and height on unknown terrains with height differences of $\pm 10cm$.

1 Introduction

Humans exhibit agile locomotion behaviors such as altering the locomotion speed and jumping over obstacles as needed. It is widely recognized that such behaviors are realized through a hierarchical control structure consisting of the supraspinal and the spinal control layer [1]. Spinal locomotion of decerebrated cats [2] and other vertebrates [3, 4] demonstrates that large part of the control of normal locomotion is conducted in the spinal cord. To intentionally control locomotion behaviors based on environmental cues, it is necessary to modulate the spinal control through the supraspinal system. Therefore, understanding the mechanism of the spinal control and how it interacts with the supraspinal control is essential for explaining how legged locomotion is governed in biological systems.

Different types of human neuromuscular control models have demonstrated stable bipedal locomotion in physics simulation [5–8]. In a previous study, we have shown with a 3D human neuromuscular model that a reflex-based spinal control can generate diverse locomotion behaviors, including walking and running, slope and stair negotiation, and deliberate obstacle avoidance [8]. Each behavior has been generated with different set of spinal control parameters, leaving unexplained how the different sets can be stored and selected by the supraspinal system. In this study, we explore a simple solution of building a lookup table by mapping, in prior, all relevant states and control parameter sets. To this end,

we investigate a simple hierarchical neuromuscular control model, which consists of a spinal control layer with a single reflex pathway and a supraspinal control layer with a lookup table of spinal control parameters (Sec. 2). The model can regulate running speed and height on unknown terrains with height differences of ± 10 cm (Sec. 3). The implications of the proposed approach and its alternatives are discussed (Sec. 4).

2 The Simple Neuromuscular Running Model

2.1 Musculoskeletal System

The mechanical model is a 2D planar system which consists of a 80 kg point mass, which is the center of mass (COM), and a 1-meter-long massless leg as proposed in [9] (Fig. 1-a). The leg has two segments with equal lengths l_S , where the upper segment freely rotates around the COM and the lower segment connects to the upper segment by a revolute knee joint. The virtual leg is defined as a line connecting the COM and the foot (the distal edge of the lower segment); the leg length l_{leg} is defined as the distance between the foot and the point mass, and the leg angle or the angle of attack α is defined as the orientation of the virtual leg in the inertial frame.

The system dynamics alters between flight and stance phases. During flight, the COM undergoes a ballistic fall due to gravity g . During stance, the foot is assumed as a free revolute joint on the ground, and the knee joint is actuated by a knee extensor muscle resulting in a leg force along the virtual leg F_{leg} . The transition from flight to stance occurs if the foot touches the ground, and enters flight if the virtual leg extends to its nominal length l_F . In summary, the COM dynamics is determined as

$$\begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix} = \frac{|F_{leg}|}{m} \begin{bmatrix} -\cos(\alpha) \\ \sin(\alpha) \end{bmatrix} - \begin{bmatrix} 0 \\ g \end{bmatrix} \quad (1)$$

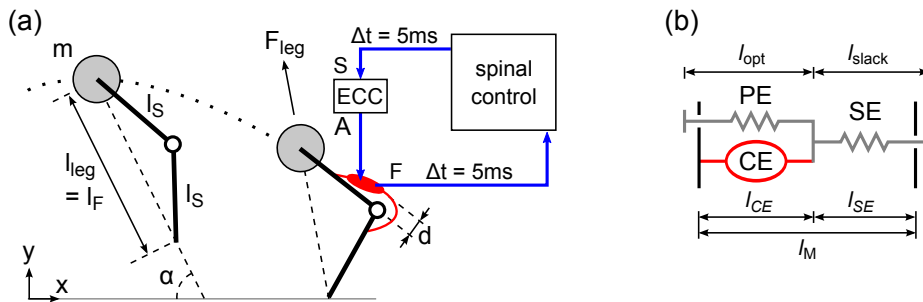


Fig. 1. The simple neuromuscular running model. (a) The mechanical system consists of a point mass and a segmented massless leg. (b) The knee extensor is modeled as a Hill-type muscle.

Table 1. Model parameters.

| | | | | | |
|-------------|--------|-----------------|------------------------|------------|---------------------------|
| m | 80 kg | g | 9.81 ms^{-1} | l_S | 0.5 m |
| d | 0.04 m | φ_{ref} | 120° | l_{ref} | 0.5 m |
| F_{max} | 15 kN | l_{opt} | 0.1 m | v_{max} | $12 l_{opt}\text{s}^{-1}$ |
| l_{slack} | 0.4 m | τ_{ECC} | 0.01 s | Δt | 0.005 s |

where during flight $|F_{leg}|$ is zero, and during stance it is

$$|F_{leg}| = \frac{d}{\sqrt{l_S^2 - \left(\frac{l_{leg}}{2}\right)^2}} F_M \quad (2)$$

given the muscle force F_M , and the moment arm of the muscle d .

The knee extensor is modeled as a Hill-type muscle-tendon model (Fig. 1-b). The muscle model consists of a contractile element (CE), a series elasticity (SE), and a parallel elasticity (PE), which together defines the muscle force $F_M = F_{SE} = F_{CE} + F_{PE}$. SE and PE are passive elements which exert force when stretched over their reference length l_{slack} and l_{opt} , respectively. CE actively contracts proportional to the muscle activation A as $F_{CE} = AF_{max} f_l(l_{CE}) f_v(v_{CE})$, where F_{max} is the maximum isometric force which is a constant, while $f_l(l_{CE})$ and $f_v(v_{CE})$ are the force-length and force-velocity relationship of CE, each defined based on optimum length l_{opt} and maximum contraction velocity v_{max} , respectively. The details of how F_{SE} , F_{PE} , $f_l(l_{CE})$, and $f_v(v_{CE})$ are calculated are described in [9, 7].

We model two sources of signal delays in the spinal reflex control loop: excitation-contraction coupling and neural transmission delays. The excitation-contraction coupling is modeled by a 10 ms first-order delay as $\tau \dot{A} = S - A$, where S is muscle stimulation or the output of the neural controller, which has a value between 0 and 1. Based on observations in human physiology [10], we model the one way transmission delays between the spinal cord and the knee extensor as $\Delta t = 5$ ms, i.e. the close loop reflex delay is 10 ms. No transmission delay between the spinal and supraspinal control system is modeled, since it uses anticipatable sensory data for control.

The model is implemented in MATLAB Simulink (R2013a), and use ode45 solver. All the parameters used in the model are summarized in Table 1.

2.2 Neural Control

We set the control goal as to regulate the mechanical energy of the system in both horizontal and vertical axes. This can be formulated as to track the forward velocity and height of COM at apexes $[\dot{x}, y]_{apex}$ (we drop the subscript $_{apex}$ in the remainder of this paper). Given such control goal, the neural controller is hierarchically structured consisting of the supraspinal and the spinal control layer (Fig. 2). The spinal control is modeled as a local reflex pathway generating muscle stimulation during stance. The supraspinal controller modulates the

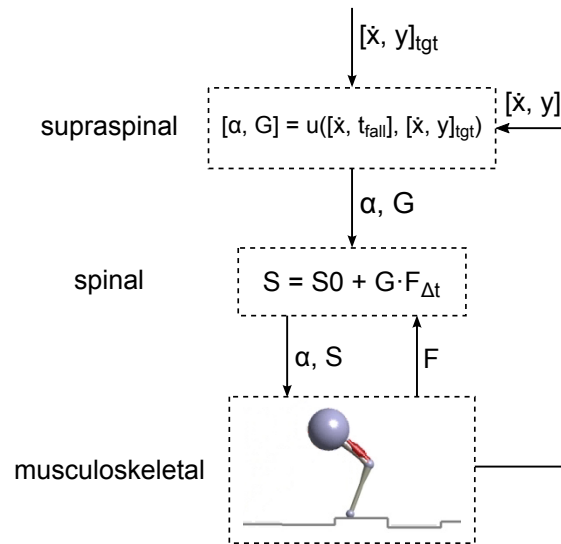


Fig. 2. Hierarchical control model. The controller consists of a supraspinal and a spinal control layer. The spinal control is modeled as a reflex pathway which directly interacts with the musculoskeletal system. The supraspinal control takes the system state and control goal as inputs and modulates the spinal control by commanding the reflex gains.

spinal control gains to achieve the control goal. During flight, the leg length l_{leg} is fixed at a constant $l_F = 0.99$ m, and perfectly follows the angle of attack α commanded from the supraspinal system.

2.3 Spinal Reflex Layer

The spinal control for the knee extensor during stance is defined as a positive force feedback, adopted from [9]. Positive force feedback has been proposed as an effective control for realizing compliant stance leg behavior, which is widely recognized as the basic stance leg behavior of locomotion [11, 12]. Positive force feedback generates muscle stimulation for the knee extensor S as

$$S = S_0 + GF_{\Delta t} \quad (3)$$

where S_0 and G are parameters given from the supraspinal system, and $F_{\Delta t}$ is muscle force data delayed by 10 ms modeling the closed loop reflex delay. As stance begins, muscle activation A is set to S_0 motivated by the so-called stance preparation, which stiffens the leg before making contact in human locomotion [13].

2.4 Supraspinal Control Layer

Our focus on the supraspinal control is to devise a controller that appropriately modulates the reflex pathway, rather than proposing a specific model in a bi-

ological form. More specifically, for the supraspinal control, we formulate the problem as to derive a function which takes control states and goals as input and outputs the corresponding control gains of the spinal controller such as

$$[\alpha, G, S_0] = u_0([\dot{x}, y], [\dot{x}, y]_{tgt}) \quad (4)$$

which can be a lookup table. The table can be constructed by inverting the apex return map $[\dot{x}, y]_{i+1} = M([\dot{x}, y]_i, [\alpha, G, S_0])$, where the subscript $i+1$ indicates the next apex of i . We further modify the control so that 1) the number of output matches the number of control states, and 2) the model can negotiate rough terrain without knowing it in prior. We derive such control in three steps.

First, we build the full return map $[\dot{x}, y]_{i+1} = M([\dot{x}, y]_i, [\alpha, G, S_0])$ by simulating the spinal-musculoskeletal model. The range and resolution of the indexes are $\dot{x} = 0 : 0.2 : 10 \text{ ms}^{-1}$, $y = 0.8 : 0.01 : 1.1 \text{ m}$, $\alpha = 40^\circ : 1^\circ : 110^\circ$, $G = 0 : 0.2 : 10 F_{max}$, and $S_0 = 0.01, 0.02 : 0.02 : 0.3$. Since there are two states and three control variables, we explore if we can drop a control variable without reducing much of the control capability. As a rough estimate of the control capability, we considered the area in the state space where fixed points exist. In Fig. 3, the area in the state space where fixed point exists with any S_0 are marked in gray, and the area with $S_0 = 0.01, 0.1, 0.2, 0.3$ are marked in black in each subplots. It shows that fixed points found with $S_0 = 0.01$ covers over 70% of that found with $0.01 \leq S_0 \leq 0.3$, and it reduces as S_0 increases. Therefore, we choose to keep S_0 as a constant value 0.01.

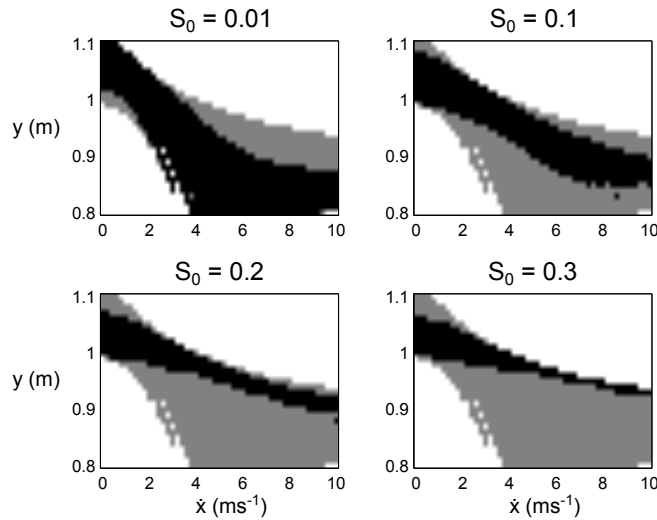


Fig. 3. Fixed points. The graph shows the state space, where the gray area (which is a super set of the black areas) indicates where fixed points exist with the spinal control of $0.01 \leq S_0 \leq 0.3$. Black areas of each graph shows the fixed points for $S_0 = 0.01, 0.1, 0.2$, and 0.3 , respectively.

The second step is to invert the return map and derive the control table

$$[\alpha, G] = u|_{S_0=0.01}([\dot{x}, y], [\dot{x}, y]_{tgt}). \quad (5)$$

For this, we discretize $[\dot{x}, y]_{i+1}$ into $[\dot{x}, y]_{tgt}$ with multilinear interpolation.

When the model touches the ground, the previous apex height relative to the ground height can be calculated as

$$y = \frac{1}{2}gt_{fall}^2 + l_F \sin(\alpha) \quad (6)$$

where falling time t_{fall} is the time passed since the previous apex [14]. Using this property, controller Eq. 5 can be converted to a version that continuously updates the output $[\alpha, G]$ during flight based on the falling time, so that whenever the model touches the ground the output is set to the correct values. Therefore, the final controller

$$[\alpha, G] = u([\dot{x}, t_{fall}], [\dot{x}, y]_{tgt}) \quad (7)$$

blindly adapts to unknown terrains.

For cases when $[\dot{x}, y]_{tgt}$ is not reachable at one step, we define control priorities as

$$p1 : \operatorname{argmin}_u |y_{i+1} - y_{tgt}| \quad (8)$$

$$p2 : \operatorname{argmin}_u |\dot{x}_{i+1} - \dot{x}_{tgt}| \quad (9)$$

where $p1$ has higher priority than $p2$. In other words, the controller tries to achieve apex height goal $y_{i+1} \approx y_{tgt}$ close as possible, then target speed, because maintaining apex height is more important in surviving (or not falling down) on rough terrains.

In summary, the supraspinal control is devised as a four dimensional lookup table where each element contains values for $[\alpha, G]$. At flight, forward velocity is constant which specifies a three dimensional subspace. Target states $[\dot{x}, y]_{tgt}$ together with the constraints Eq. 8 and 9 only leaves t_{fall} undetermined. As falling from apex., t_{fall} is tracked and the corresponding $[\alpha, G]$ values are commanded to the spinal reflex control.

3 Results

The performance of the control on rough terrains should be evaluated with statistical methods, since individual trials depend on the pattern of terrains. We leave quantifying the performance as future work, and here note that, for most trials ($\geq 90\%$), the model could control the COM states on terrains with maximum height differences of ± 10 cm (Fig. 4).

Theoretically, on flat ground, the proposed hierarchical controller can control the apex states at least within the black area shown in Fig. 3. However, simulation results show that the model cannot accelerate over 7 ms^{-1} . This is because we discretized target states at Eq. 5, which means the minimum acceleration the model can make is $\Delta 0.2 \text{ ms}^{-1} \text{ apex}^{-1}$. Under 7 ms^{-1} , the model can reach any state in about $5 \sim 10$ steps.

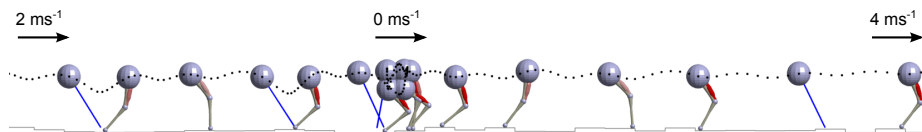


Fig. 4. Blind running on unknown terrain. The model can control the running speed and height on unknown terrains. The model starts at 2 ms^{-1} , decelerates to 0 ms^{-1} , and accelerates to 4 ms^{-1} . The height differences of the ground is between $\pm 10 \text{ cm}$. The black dots trace the COM trajectory with 50 ms intervals, and the snapshots of the model is taken every 500 ms , where the blue line indicates the virtual leg during swing.

4 Discussion

We proposed a hierarchical control for running, where the supraspinal system modulates the spinal reflex gains. With the controller a simple musculoskeletal system can blindly run on rough terrains with height differences of $\pm 10 \text{ cm}$. Such result suggests that the reflex network in the spinal cord can be modulated by simple signals from the supraspinal system, and such modulation might be enough to generate diverse locomotion behaviors. In the presented work, the supraspinal control is devised as a lookup table. Whether the supraspinal system of humans operates as a lookup table is unclear. However, it is clear that a lookup table style control has limitations in the aspect of generalization. For instance, to apply such control for walking, we need to construct the table in prior independent from what we already have for running. On the other hand, if one can identify the relationship between the control outputs and the inputs of the running control table [15], then it can be tested if that relationship is applicable to new scenarios. In addition, the lookup table approach is susceptible to the so-called curse of dimensionality. Humans have much more states and spinal control parameters than the simple model. For example, the 3D human model in our previous study has about 50 states and 80 spinal control parameters [8]. To approximate the mapping for such high dimensional system, we can resort to machine learning techniques, such as value iteration and policy iteration. Such techniques have been applied in controlling simulation legged characters [16].

References

1. Orlovskii, G.N., Deliagina, T., Grillner, S.: Neuronal control of locomotion: from mollusc to man. Oxford University Press (1999)
2. Shik, M., Severin, F., Orlovskii, G.: Control of walking and running by means of electric stimulation of the midbrain. *Biofizika* **11**(4) (1965) 659–666
3. Grillner, S., Georgopoulos, A., Jordan, L., et al.: Selection and initiation of motor behavior. *Neurons, networks, and motor behavior* (1997) 3–19
4. Cabelguen, J.M., Bourcier-Lucas, C., Dubuc, R.: Bimodal locomotion elicited by electrical stimulation of the midbrain in the salamander *notophthalmus viridescens*. *The Journal of neuroscience* **23**(6) (2003) 2434–2439

5. Taga, G., Yamaguchi, Y., Shimizu, H.: Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment. *Biological cybernetics* **65**(3) (1991) 147–159
6. Ogihara, N., Yamazaki, N.: Generation of human bipedal locomotion by a biomimetic neuro-musculo-skeletal model. *Biological cybernetics* **84**(1) (2001) 1–11
7. Geyer, H., Herr, H.: A muscle-reflex model that encodes principles of legged mechanics produces human walking dynamics and muscle activities. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on* **18**(3) (2010) 263–273
8. Song, S., Geyer, H.: A neural circuitry that emphasizes spinal feedback generates diverse behaviours of human locomotion. *The Journal of physiology* (2015)
9. Geyer, H., Seyfarth, A., Blickhan, R.: Positive force feedback in bouncing gaits? *Proceedings of the Royal Society of London. Series B: Biological Sciences* **270**(1529) (2003) 2173–2183
10. Knikou, M., Rymer, W.Z.: Effects of changes in hip joint angle on h-reflex excitability in humans. *Experimental brain research* **143**(2) (2002) 149–159
11. Blickhan, R.: The spring-mass model for running and hopping. *Journal of biomechanics* **22**(11) (1989) 1217–1227
12. Geyer, H., Seyfarth, A., Blickhan, R.: Compliant leg behaviour explains basic dynamics of walking and running. *Proceedings of the Royal Society B: Biological Sciences* **273**(1603) (2006) 2861–2867
13. Perry, J., Burnfield, J.M.: *Gait analysis: normal and pathological function*. 2nd edn. SLACK Incorporated (2010)
14. Seyfarth, A., Geyer, H.: Natural control of spring-like running optimized self-stabilization. In: *Proceedings of the Fifth International Conference on Climbing and Walking Robots*. Professional Engineering Publishing Limited. (2002) 81–85
15. Song, S., Geyer, H.: Regulating speed in a neuromuscular human running model. In: *Humanoid Robots (Humanoids), 2015 15th IEEE-RAS International Conference on, IEEE* (2015) accepted.
16. Coros, S., Beaudoin, P., van de Panne, M.: Robust task-based control policies for physics-based characters. *ACM Trans. Graph. (Proc. SIGGRAPH Asia)* **28**(5) (2009) Article 170