OPTIMIZATION OF FEEDFORWARD AND FEEDBACK CONTROL DURING WALKING

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INTRODUCTION

We used a simple walking model to study how feedforward (FF) and feedback (FB) control can be optimally combined to produce steady walking motions. We interpret combined FF and FB control in terms of an internal model that is updated by sensory information. The theory of state estimation suggests there is an optimal balance of FF and FB control for improved performance in the presence of noise.

Biological systems function despite imperfect sensors and the presence of disturbances. Neural oscillators are thought to act as Central Pattern Generators (CPGs) of rhythmic motor commands, producing FF commands even in the absence of sensory FB. But this FB is also thought to play an important role in normal behavior, and FF compensates poorly for disturbances. How can the apparent feedforward behavior of CPGs be reconciled with FB? We previously proposed [1] that the neural oscillators could be interpreted as an internal model of limb dynamics. In control theory, internal models can estimate the system state and associated sensory output. Errors in sensory prediction are used to refine the state estimate, which is then used for FB control. In this interpretation, the internal model produces FF commands even when error FB is removed. The optimal motor combination of FF and FB is determined by the presence of two types of noise: *process noise* refers to unpredictable disturbances that are detrimental to pure FF control, and *sensor noise* refers to sensor imperfections that are detrimental to high gain FB. To demonstrate this interpretation, we applied a controller with state estimation to a simple walking model under the presence of both types of noise. We tested whether step variability would be minimized with a predicted optimum combination of FF and FB, as opposed to using either control strategy alone.

METHODS

We employed a simple passive dynamic model of two-dimensional, straight legged biped walking [2], but with added actuation of the hips. The hip torque had two components: a torque applied in proportion to the angle between the legs, as estimated by the internal model, and a constant torque to add energy lost in collisions during double support.

The control system (Figure 1) uses a CPG to model the dynamics of limbs, producing an estimate of the system state used to drive hip torque. The error signal, from model stretch sensors, was used to refine the state estimate via an estimator feedback gain, L, which scales the relative influences of FF and FB on the controller (i.e. small L produces pure FF and large L produces pure FB control). State estimation theory predicts an optimal value of L given characteristics of process and sensor noise.

Walking simulations were conducted over many steps for a range of L between pure FF and pure FB. Process and sensor

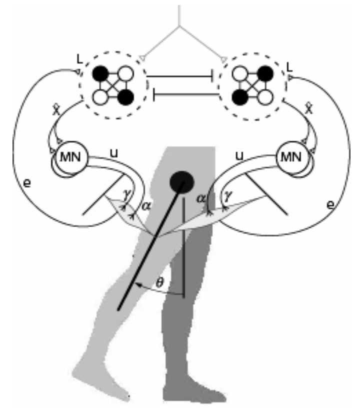

Figure 1: Model of CPG control of hip torque

noise were applied to the system with equal weight such that both had the equivalent strength of 10% of the maximum hip torque produced by the walker. Step-to-step variability was calculated from the standard deviation of leg angles and velocities at the end of each double support period.

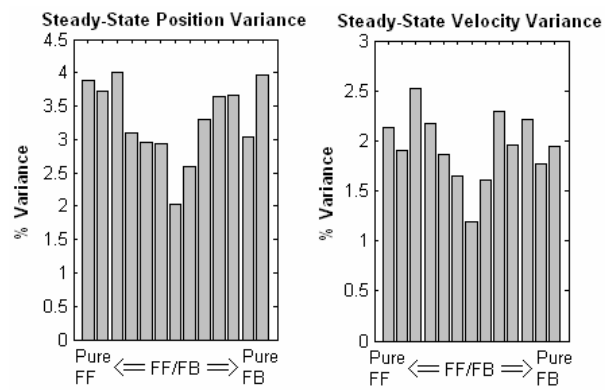

Figure 2: Percent variation of leg angle and velocity over a range of values of the estimator feedback gain.

RESULTS AND DISCUSSION

The model demonstrates (Figure 2) that step-to-step variability is minimized when the relative roles of FF and FB are appropriately balanced. In the presence of noise, there is an optimal combination that produces better performance over either FF or FB alone. CPGs may be interpreted to act as local internal models of limb dynamics. In this sense, CPGs are not seen to simply produce motor commands for muscle activation, but also to process sensory information. Further application of state estimation theory may provide insight into the role of CPGs in biological movement.

REFERENCES

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