Perturbation Responses of a Model of Biped Locomotion

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1 Introduction

Our research goal is to understand how our nervous system uses sensory feedback to achieve stable and adaptive locomotion. Our approach toward this goal is to use nonparametric system identification to characterize how human locomotion responds to external perturbations and mechanistic modeling to interpret these responses. A realistic model of human locomotion should include sensory feedback in order to respond to sensory perturbations and, more importantly, to produce stable walking. Among detailed models of biped locomotion, only a minority includes sensory feedback (e.g. Geyer & Herr, 2010; Taga, 1995).

In this study, as a first step toward our modeling goal, we started with a simple model of human locomotion with proprioceptive feedback (Geyer, Seyfarth, & Blickhan, 2003), added visual feedback, and characterized the model's responses to visual and mechanical perturbations.

2 Background

This study was inspired by a research characterizing how human walking responds to broadband motion of the visual scene (Kiemel et al., in prep.; Logan et. al., in prep.). In these studies, the muscular and kinematic responses to movement of the visual scene were first characterized in the frequency domain by harmonic transfer functions (HTFs; see Methods). Then, the HTFs were converted into the time domain, resulting in a phase-dependent impulse response function (IRF) (Fig. 1).

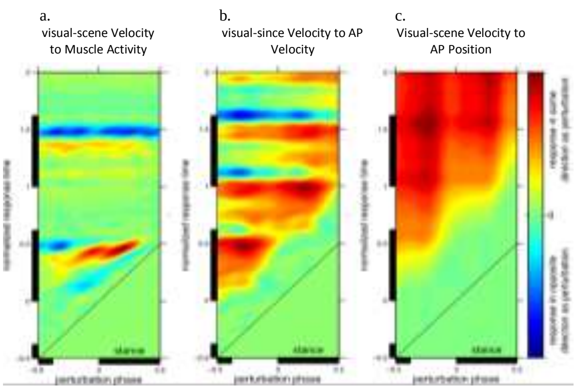

Figure 1: Experimental responses to visual-scene movement (Kiemel et. al., in prep.).

An IRF describes how a perturbation at any phase of the gait cycle, indicated on the horizontal axis, produces responses at times indicated on the vertical axis. The diagonal line corresponds to a response measured at the same time as the perturbation, so non-zero responses only occur above the diagonal line. For example, Fig. 1a shows that when the visual scene moves forward during late swing or early stance, activity of the lateral gastrocnemius muscle, a plantarflexor, increases during late stance. The responses of this and other muscles causes the person's anterior-posterior (AP) velocity to increase (Fig. 1b) and the person to move forward on the treadmill (Fig. 1c).

3 Methods

In this study, we modified a simple locomotion model with proprioceptive feedback (Geyer al. 2003) by adding visual feedback. Then, we perturbed the model with broadband visual-scene motion and analyzed its responses in the same way as human data.

The model

The model has a two-segment leg with one Hill-type extensor muscle. The neural stimulation of the muscle, $S(t)$, consists of two feedback components, proprioceptive positive force feedback and visual negative velocity feedback:

$$S(t) = S_0 + G_P F_{MTC}(t - \Delta_P)$$
$$-G_V(\alpha)\big(V_{COM}(t - \Delta_V) - V_V(t - \Delta_V)\big),$$

where S_0 is the constant stimulation bias, G_P is the constant proprioceptive gain factor, $F_{MTC}(t)$ is the force of the muscle-tendon complex, and Δ_P is the proprioceptive time delay. In contrast to G_P, the visual gain G_V is not constant, but is instead a Gaussian function of α, the angle of the leg axis from the "foot" to the "hip". We wanted leg-extensor activity to be modulated in late stance, as suggested by experimental data, so the maximum of G_V was set to occur at an α during late stance. Visual feedback depends on the difference between $V_{COM}(t)$, the AP center-of-mass velocity, and $V_V(t)$, the AP visual-scene velocity, and occurs after a visual time delay Δ_V.

To perturb the model, we let visual-scene velocity (V_V) be small-amplitude low-pass-filtered white noise with a cut-off frequency of about $3 \times Gait\ Frequency$. The model is able to produce a stable gait.

The HTFs and IRFs

To characterize responses in the frequency domain, we first estimated the phase of the gait cycle based on heel-strike times. The response variables were then expressed as functions of estimated phase, so that the system's dynamics near the limit cycle could be approximated as being linear time periodic (LTP). For an LTP system, input at frequency

f produces output at frequencies $f + kf_0$ for all integers k, where f_0 is the gait frequency. So the input-output mapping for an LTP can be described by a harmonic transfer function (HTF) $H(f)$ in the frequency domain:

$$Y(f) = \sum_{k=-\infty}^{\infty} H_k(f - kf_0)U(f - kf_0) \qquad (2)$$

where $U(f)$ and $Y(f)$ are the Fourier transforms of the input and output signals, respectively.

To convert the HTF to a phase-dependent IRF in the time domain, a two-dimensional (in frequency f and index k) inverse Fourier transform was applied to the HTF. A correction is made for the mapping from time to estimated phase, so that, to first order, the IRF does not depend on the particular method used to estimate phase.

4 Results

We computed the model's responses to visual and mechanical perturbations for various model parameters. Figure 2 shows an example of responses to visual-scene motion. These responses were highly phase dependent, reflecting our specification of the visual feedback. We observed that forward visual perturbations during the swing phase increases the extensor muscle activation level in the late stance (Fig. 2a), which eventually results in kinematic responses of the person, increasing the AP velocity (Fig. 2b) and AP position (Fig. 2c). In other words, when the visual scene moves forward during swing, the extensor muscle activation increases during push-off, causing the person to increase walking speed in the next step and move forward.

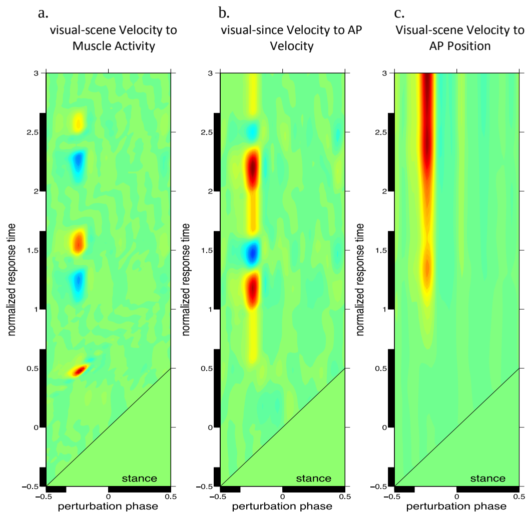

Figure 2: Model responses to visual-scene movement.

5 Discussion

The model's modulation of push-off muscle activity during late stance was similar to human data, except that humans respond to a wider range of perturbation phases. To capture this aspect of human data in which a perturbation over a wide range of phases produces a response over a much more restricted range of phases, it may be necessary to add additional state variables to the model, such as those describing a central pattern generator. We will explore this and other modifications in future work exploring models with additional mechanical degrees of freedom and muscles.

References

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