System identification and stability analyses of steady human locomotion

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1 One line summary

We present a data-driven method to analyze stability of human locomotion, by inferring multiple Poincare sections around the periodic orbit, and construct a piecewise model to simulate and predict transient responses of human locomotion under various circumstance.

2 Introduction

Gait variability. Steady human walking and running is only approximately periodic, in which while every stride is similar to every other stride, the strides are not quite identical as in figure 1. It is not completely settled what the source of this stride-to-stride variability is in human walking, but it likely is a mixture of noisy muscle forces [3], sensory noise [5], and perhaps imperceptibly small external perturbations. A number of researchers have attempted to characterize the variability of human locomotion by using linear and and nonlinear time series techniques. A review of some these techniques can be found in [8]. However, the actual dynamics around the periodic orbit has not been fully explored.

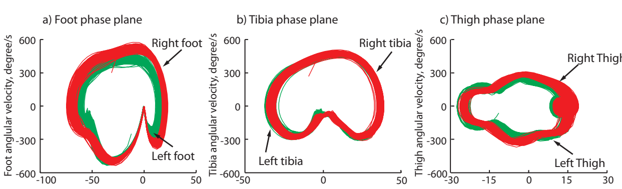

Figure 1: Nearly periodic human running

Nonlinear dynamics techniques. If we had differential equations describing the periodic motion of these systems, we could understand the dynamics and stability of such periodic motions by analyzing the differential equations in the neighborhood of the nominal periodic orbit. In particular, given a nonlinear dynamical system with an isolated periodic motion, also called a limit cycle [2], one typically considers the linearization of the dynamical system near the periodic orbit to understand the stability of the periodic orbit. The linearization of the Poincare map around $\mathbf{x}^*$ as in figure 2a is given by:

$$\mathbf{x}^{(i+1)} - \mathbf{x}^* = J \cdot (\mathbf{x}^{(i)} - \mathbf{x}^*) \tag{1}$$

where J is the Jacobian of the function $P(\cdot)$ at $\mathbf{x}^*$. This linearization, specifically the eigenvalues of the Jacobian J, is generically sufficient to test local stability of the periodic motion.

3 Previous approaches

Eigenvalue estimation and system identification around a period orbit using experimental data. Once we have a dynamical system driven by noise with known statistical properties, we can fit a linear model of the dynamics to the data, say in a manner that minimizes the least squared residuals of the model given the data. This is an old idea, even in legged locomotion, but it has not been explored thoroughly and rigorously. Hurmuzlu [4] used this idea to obtain estimates of the linearization to the Poincare map and the corresponding eigenvalues using events like heel strike or toe off as specific Poincare sections. Dingwell [1] and coauthors have used variants of this technique in a series of articles since then. Revzen and Guckenheimer [7] recently revisited this idea, in which instead of considering smooth transverse surfaces for Poincare section, they used data-derived phase coordinates [6]; they used this method to examine the stability of cockroach locomotion. Along the way, Revzen and Guckenheimer compute the so-called Floquet coordinates corresponding to the dynamics near the periodic motion, providing a simple description of the continuous dynamics around the periodic orbit; they also provide detailed estimates of the error in their infererred Jacobians and their eigenvalues by bootstrapped versions of the data. More recently, Maus and Revzen (DW, 2011) applied these techniques to human running.

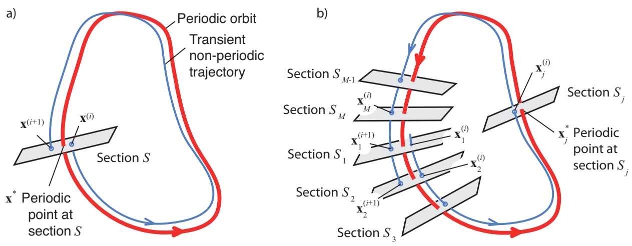

Figure 2: Periodic motions and Poincare sections.

4 Our contribution

Our first contribution is to the system identification literature, developing methods for estimating dynamical models and stability information near noise-driven periodic motions. We introduce the idea of representing the continuous dynamics as mappings between multiple Poincare sections and then inferring these mappings (see Figure 2b). From a large number of these discrete mappings, one could infer continuous (differential equation) dynamics around the periodic orbit. We have tested these methods in detail using synthetic data from both discrete and continuous systems, how well these methods work under various assumptions, providing some proofs for certain results. It appears that the inference of multiple Poincare maps simultaneously slightly reduces the error estimates in the presence of noise, compared to the inferring single Poincare maps from data. More significantly, the method provides a data based simulation of responses to novel perturbations. Our second contribution is to the biomechanics literature, in which we attempt to use the method of multiple Poincare sections to construct a data-derived model not only to represent steady human locomotion, but also predict other various transient responses. Right now, we are using process-noise-driven steady state human data, but we also propose to use perturbation data as below.

Proposed work in the near future: Perturbation experiments. We are planning experiments in which the human subjects undergo transients from which we hope to infer some of these dynamics. Two types of transients are planned – due to (1) self-imposed perturbations (2) external perturbations. Self-imposed perturbations are when a subject intentionally takes a single long or short or high or wide step, and then continues to walk or run normally. From the transient after the abnormal step, we hope to infer some dynamical information about the locomotion. Small external perturbations will be applied that slightly perturb the hip in some direction, and from the responses, we hope to infer the dynamics (at least along some directions).

Key Words: Data-driven method, Stability, Human locomotion dynamics, response to perturbations, variability. **Format:** We wish to give a poster and apply for a student travel grant.

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