Deriving the human walking controller from perturbed walking data

Varun Joshi[1] and Manoj Srinivasan
Department of Mechanical and Aerospace Engineering
The Ohio State University
[1]joshi.142@osu.edu

Introduction.

We have previously discussed foot placement and leg-force generation strategies for humans walking on a treadmill under the effect of discrete perturbations [1]. Here, we use this data to derive a controller for bipedal walkers.

Experimental Methods.

Subjects walked on an instrumented split-belt treadmill at 1.1 – 1.2 ms^{-1} in bouts of approximately 4 mins. While they walked we recorded kinematic data from 28 markers placed on the body and ground reaction force data from force plates under each belt of the treadmill. For each subject, either fore-aft or lateral perturbations were applied by humans through inelastic cords. To ensure safety, subjects wore a harness connected to the ceiling.

These perturbations were randomly distributed over each bout with a time gap of at least 15 s and at most 25 s. All perturbation forces were measured through a uni-axial load cell in series with the inelastic cord. To prevent anticipatory response to inadvertent visual and audio cues all subjects wore blinders and noise damping headphones. In order to account for proprioceptive cues 20% of all perturbations were “fake” where the experimenter went through the motion of pulling but applied very low or no perturbing force on the subject.

Derivation of the Controller.

We propose two methods for controller derivation:

1. Consider a biped that controls its center of pressure (CoP) position and ground reaction forces (GRF) to maintain stability. We can derive linear relations that tell us how to modulate these control variables in response to a perturbation. Figure 1 shows how a 0.2 m/s change in mid-stance velocity would affect GRFs over the following stride and Figure 2 shows how CoP is modulated over the following step.

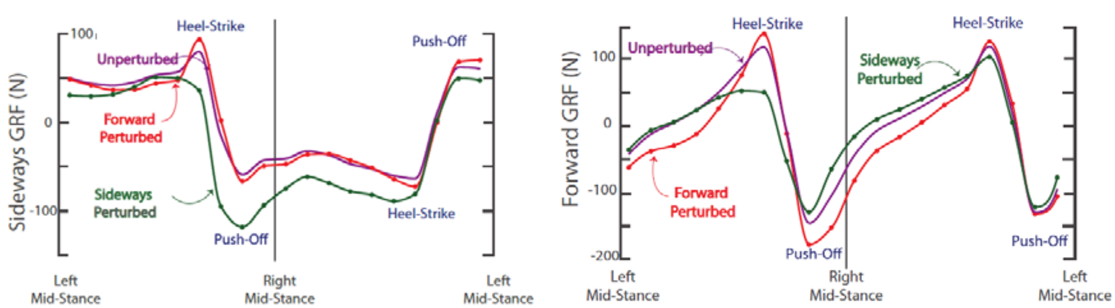

Figure 1. If a perturbation produces a 0.2 m/s deviation in mid-stance velocity in the forward (red curves) or rightward (green curve) direction how are sideways and forward GRFs modulated

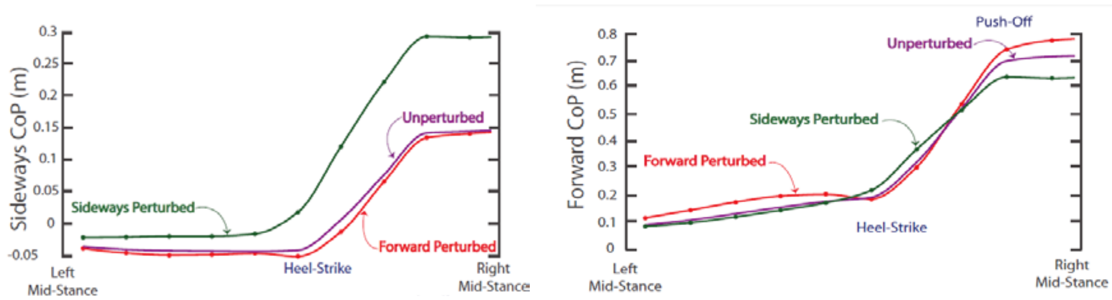

Figure 2. If a perturbation produces a 0.2 m/s deviation in mid-stance velocity in the forward (red curves) or rightward (green curve) direction how are sideways and forward CoP positions modulated.

2. We can use experimentally collected data to determine the linear function that maps the mid-stance state deviations of human walkers from the nth step to the n+1th step.

$$\Delta \begin{bmatrix} X_{\text{torso}}(n+1) \\ Z_{\text{torso}}(n+1) \\ \dot{X}_{\text{torso}}(n+1) \\ \dot{Y}_{\text{torso}}(n+1) \\ \dot{Z}_{\text{torso}}(n+1) \end{bmatrix} = J_1.\Delta \begin{bmatrix} X_{\text{torso}}(n) \\ Z_{\text{torso}}(n) \\ \dot{X}_{\text{torso}}(n) \\ \dot{Y}_{\text{torso}}(n) \\ \dot{Z}_{\text{torso}}(n) \end{bmatrix}$$

Consider a model of a walking biped with feedback control, say using foot-placement and push-off impulse for stability. Given a nominal motion for this biped, say the two-step periodic energy optimal gait, we find a linear function mapping the nth mid-stance state deviations and control action deviations to the n+1th mid-stance state.

$$\Delta \begin{bmatrix} X_{\text{torso}}(n+1) \\ Z_{\text{torso}}(n+1) \\ \dot{X}_{\text{torso}}(n+1) \\ \dot{Y}_{\text{torso}}(n+1) \\ \dot{Z}_{\text{torso}}(n+1) \end{bmatrix} = J_2.\Delta \begin{bmatrix} X_{\text{torso}}(n) \\ Z_{\text{torso}}(n) \\ \dot{X}_{\text{torso}}(n) \\ \dot{Y}_{\text{torso}}(n) \\ \dot{Z}_{\text{torso}}(n) \end{bmatrix} + J_3.\Delta \begin{bmatrix} I \\ t_{\text{step}} \end{bmatrix}$$

We seek a linear function mapping state-deviations to control-action deviations.

$$\Delta \begin{bmatrix} I \\ t_{\text{step}} \end{bmatrix} = J_4.\Delta \begin{bmatrix} X_{\text{torso}}(n) \\ Z_{\text{torso}}(n) \\ \dot{X}_{\text{torso}}(n) \\ \dot{Y}_{\text{torso}}(n) \\ \dot{Z}_{\text{torso}}(n) \end{bmatrix}$$

This gives us the effective state transition matrix as –

$$\Delta \begin{bmatrix} X_{\text{torso}}(n+1) \\ Z_{\text{torso}}(n+1) \\ \dot{X}_{\text{torso}}(n+1) \\ \dot{Y}_{\text{torso}}(n+1) \\ \dot{Z}_{\text{torso}}(n+1) \end{bmatrix} = J_2.\Delta \begin{bmatrix} X_{\text{torso}}(n) \\ Z_{\text{torso}}(n) \\ \dot{X}_{\text{torso}}(n) \\ \dot{Y}_{\text{torso}}(n) \\ \dot{Z}_{\text{torso}}(n) \end{bmatrix} + J_3.J_4.\Delta \begin{bmatrix} X_{\text{torso}}(n) \\ Z_{\text{torso}}(n) \\ \dot{X}_{\text{torso}}(n) \\ \dot{Y}_{\text{torso}}(n) \\ \dot{Z}_{\text{torso}}(n) \end{bmatrix}$$

In order to match experimentally derived dynamics, we solve for J_4 such that we minimize the error between J_1 and a corresponding linear map $J_1^* = J_2 + J_3 \cdot J_4$

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References.

1. V. Joshi and M. Srinivasan, "Understanding foot placement and leg-force generation in humans using perturbation experiments", Dynamic Walking 2016.