Push-Recovery Stability of Control Optimized Human Walking

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Introduction

The stability of a dynamic system refers to the ability of the system to accommodate perturbations. The stability of human gaits has been extensively studied to develop several stability measures, such as kinematic variability, Floquet multipliers and maximum finite-time Lyapunov exponents [1]. Those measures often assume that the perturbations are infinitesimal, so the natural fluctuations that occur during gait can be dealt with. Recently, new measures, such as push-recovery stability [2], are studied to quantify the level of stability under larger, explicit perturbations.

Dynamics and optimization are powerful methodologies for the analysis and predictive simulation of human gaits. Static optimization based on inverse dynamics and dynamic optimization based on forward dynamic simulation have been extensively exploited in previous studies [3]. Measuring the stability of a predictive gait often assumes zero or infinitesimal perturbations because of the lack of perturbation model in the optimization formulations.

A new category of approaches, called *control optimization*, emerged recently to generate feedback control policies for biped locomotion based on optimality principles [4]. Control optimization is distinguished from dynamic optimization in the sense that the result of optimization is a feedback controller that simulates dynamic walking while maintaining balance under external perturbation.

In this study, we measured the push-recovery stability of optimized feedback control policies. The choice of optimization criteria determines the characteristics of control policies. Our experiments demonstrate that there exists a tradeoff between energy-efficiency and gait stability. Control optimization can generate a spectrum of control policies spanned by energy efficiency and resiliency against external perturbation.

Methods

We used a control optimization method by Lee et al. [4]. Our dynamic model with two legs and a lumped upper body has 25 joint DOFs and 92 Hill-type muscles. The criteria for optimization has two major terms.

$$\min \int (w_1\|a\|^2 + w_2\|\tau\|^2 + \mathrm{E})\, dt$$

where $\|a\|^2$ is the total muscle activation and $\|\tau\|^2$ is the total joint torque. Auxiliary terms E include ground reaction force, joint tracking error and end-effector tracking error to regularize the optimization.

The optimization criteria can represent different body conditions with different weight values. The Case I with $w_1 = 500$ and $w_2 = 0$, the optimization minimizes energy consumption assuming that the subject is either relaxed or tired so he/she wants to walk with minimal energy. The control policy thus allows the dynamic model to consume energy barely sufficient for supporting the body and therefore can be fragile even for mild perturbations. The Case II with $w_1 = 0.5e-10$ and $w_2 = 0.1$, torque minimization does not penalize co-contraction of agonist and antagonist muscles and thus can make the control policy less efficient. Case II represents a healthy, energetic body condition.

The push-recovery stability of a control policy measures how well the policy withstands at the presence of external pushes (Figure 1). The policy fails if the musculoskeletal model falls down losing its balance.

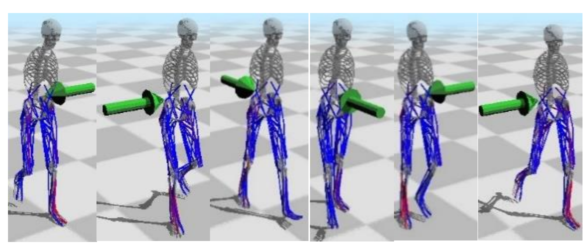

Figure 1. External pushes are applied to the pelvis of our musculoskeletal model from different directions in sequence of {left, right, back, front, left, right} with regular time interval (1.67 seconds).

Force(N)	Minimizing muscle activation (Case I)	Minimizing joint torque (Case II)
100	X	X
80	X	O
70	X	O
60	X	O
50	X	O
40	X	O
30	O	O

Table 1. Push-recovery experiment results.

Results

The control policy passes a push-recovery test if the model withstands six external pushes and maintains its balance during the simulation (10 seconds). Energy-minimizing control policy in Case I resisted up to 30 N pushes, while torque-minimizing control policy in Case II withstood up to 80 N (Table 1). On the other hands, torque-minimizing control policy consumes 25% to 30% more metabolic energy than energy-minimizing control policy. Our experiment confirms that the extra metabolic energy in Case II is used to improve gait stability.

Discussion

Control optimization opens up new possibilities of unveiling the underlying principles of human gaits. We measured the stability of control-optimized human walking at the presence of external perturbations. The tradeoff between efficiency and stability is demonstrated in our experiments.

References

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