RAMP PERTURBATION TESTS ARE TOO SIMPLE TO IDENTIFY A REALISTIC CONTROLLER IN HUMAN STANDING BALANCE

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Summary

Humans use feedback control for standing and walking and our long term goal is to identify the control laws. Here we present the results of indirect identifications where a closed loop model is optimized to fit human responses to mechanical perturbations while standing. It has been reported that one simple linear controller cannot explain responses to multiple ramp perturbations of different amplitudes [1]. We therefore attempt to identify a more complex controller with muscle activation dynamics. The controller could fit the ramp perturbation experiments perfectly, however, the identification was not unique. Our current work is aimed at identifying the more complex controller from long-duration experiments with random surface perturbation signals. These feedback controllers, if could identified, are potentially useful in humanoid robots and exoskeletons.

Introduction

Horizontal displacement of the standing surface is a well-established protocol for studying human control of balance [1, 2]. Responses to ramp displacement profiles could be almost perfectly explained by a two link pendulum model and torques generated by a linear full state proportional-derivative (PD) controller [1]. However, different controller gains were needed to explain the response to perturbations of different magnitude [1]. This suggests that the human control system is more complex than the PD model. PD torque control neglects the nonlinearity of muscle dynamics and also the time delays and low-pass frequency responses of the human neuromuscular system. We hypothesize that a single, more complex, controller exists that can explain human responses to a wide range of unexpected postural perturbations. If such a controller can be identified, it can be implemented in robotic assistive devices such as prostheses and exoskeletons.

In a first step towards this goal, we attempt to use ramp perturbation responses to identify the parameters of a feedback controller that includes muscle activation dynamics.

Methods

A series of ramp perturbations were designed (Table 1) and applied to treadmill when a subject standing on the surface. 25 markers were attached to the subject to record subject's responses under perturbations.

An indirect approach was used to identify feedback controller by defining a simplified two link pendulum model (Fig. 1). The indirect approach considers a closed loop system with perturbation as input, and human motion as output. This requires a model of the plant (human), but avoids the bias that would occur by doing open loop system identification on the controller [4]. Furthermore, we eliminate the need to measure controller outputs (joint torques).

The identification problem is now an optimization problem, to find the controller which produces the best fit of model output to human data (Fig. 1). The direct collocation method was used to make the optimization more efficient, and Ipopt was used as optimization solver [3].

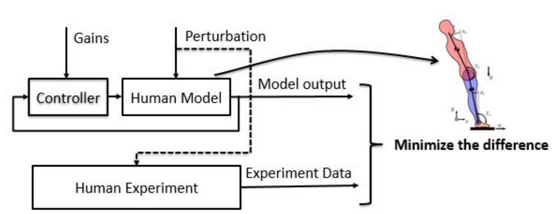

Figure 1: Indirect approach for controller identification.

A controller with 20 parameters was identified in this study. Ankle and hip torques $[\tau_a \ \tau_h]$ are generated by combining the passive muscle mechanics and active neural feedback contributes [4]:

$$\begin{bmatrix}\tau_a\\ \tau_h\end{bmatrix}=\left(\underbrace{\begin{bmatrix}K_{p11} & K_{p12} & K_{p13} & K_{p14}\\ K_{p21} & K_{p22} & K_{p23} & K_{p24}\end{bmatrix}}_{\text{Passive}}+\underbrace{\begin{bmatrix}\frac{1}{T_a s+1} & \frac{1}{T_h s+1}\end{bmatrix}\begin{bmatrix}K_{a11} & K_{a12} & K_{a13} & K_{a14}\\ K_{a21} & K_{a22} & K_{a23} & K_{a24}\end{bmatrix}}_{\text{Active}}\right)\begin{bmatrix}\theta_a-\theta_{a\_ref}\\ \theta_h-\theta_{h\_ref}\\ \dot{\theta}_a\\ \dot{\theta}_h\end{bmatrix}$$

Results

The results of optimizations show that optimal controllers could be found that produce outputs of human balance model that fit the measurements very well for each ramp perturbation (Fig. 2).

The RMS of fit errors was less than 0.7° for all tests. However, when using different initial guesses for the optimization problem, several controllers could be found that fit the same experiment equally well (Fig. 3, Table 2). These controllers were very different, and some were clearly unrealistic, in spite of fitting the data well. For instance, the ankle joint reference angle in controller 2 is -48.6 degrees, which is not realistic.

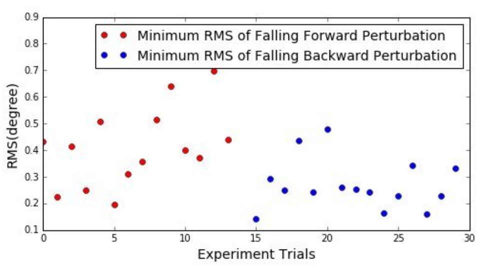

Figure 2: Root mean square of error between feedback model outputs and measurements

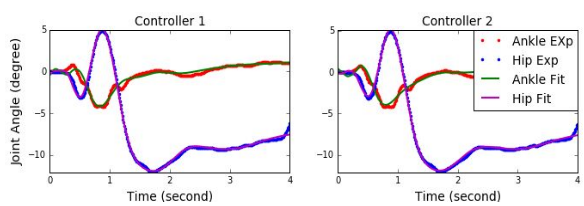

Figure 3: Fit of responses with two different controllers.

Discussion

In this work, we used ramp perturbation tests to identify a human posture controller. To avoid finding different controllers from different tests [1], we added complexity and realism to the controller. However, the opposite problem occurred. The ramp perturbation appears too simple to identify a more complex and realistic controller which includes muscle dynamics. The number of unknown controller parameters (20) is too large.

In our ongoing work, we use random perturbation protocols of long duration. Preliminary results were obtained for a passive PD controller combined with an active PD controller with muscle activation dynamics. The fit with experimental data was not good enough. suggesting either a local optimum in the optimization problem, or that the controller is still too simple to explain humans' response under long term perturbation. Time delay is being added into the above controller to address this. Our long term goal is to identify the feedback controllers that humans use for standing and walking, and use them in humanoid robots and exoskeletons.

References

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Table 1: Parameter Ranges of ramp perturbations. ('+' means perturbation that cause subject falling forward, '-' means perturbation that cause subject falling backward)

Ramp Pert. Direction	Acceleration Range ($m*s^{-2}$)	Velocity Range ($m*s^{-1}$)	Disp. Range (m)
+	0~8	0~0.5	0~0.18
-	0~5	0~0.45	0~0.9

Table 2: Parameters of Controller.

Parameter Name (Unit)	Controller 1	Controller 2
τ_a (second)	0.14	0.78
τ_h (second)	0.14	0.46
θ_{a_ref} (degree)	-8.2	-48.6
θ_{h_ref} (degree)	-4.1	-6
K_{p11} (Nm/radian)	27.2	14
K_{p12} (Nm/ radian)	132.2	811.1
K_{p13} (Nm$\cdot s$ / radian)	598.1	1995.5
K_{p14} (Nm$\cdot s$ / radian)	19.1	424.9
K_{p21} (Nm/ radian)	0	0
K_{p22} (Nm/ radian)	19.6	131
K_{p23} (Nm$\cdot s$ / radian)	117.4	327.2
K_{p24} (Nm$\cdot s$ / radian)	4.6	65
K_{a11} (Nm/ radian)	14.6	3.5
K_{a12} (Nm/ radian)	76	36.2
K_{a13} (Nm$\cdot s$ / radian)	0	0
K_{a14} (Nm$\cdot s$ / radian)	95.4	53.2
K_{a21} (Nm/ radian)	0	0
K_{a22} (Nm/ radian)	56.8	37.6
K_{a23} (Nm$\cdot s$ / radian)	9.4	0
K_{a24} (Nm$\cdot s$ / radian)	23.7	16