Human running controller derived from steady state running variability

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Summary

Constant-speed human running is not exactly periodic. For instance, the body states of the person at mid-flight fluctuate about a mean value. In the absence of control, these noise-like fluctuations would cause people to fall down. Here, we mine the variability in human running data to find out how people control their leg forces, foot placement, stance duration and leg length to run without falling down. We then implement the derived controller on a simple point mass telescoping leg model and show that it can withstand a large range of perturbations. The simple model discovers some control behaviors that have been found in past running perturbations experiments. In the past, Maus et al. (2015) attempted to explain steady-state running stability with variants of a spring-mass model. Here, we show that spring-mass assumptions are not needed to explain human running stability to steady-state perturbations.

Methods

Subjects (N = 8, 5 male, 3 female) ran on a treadmill at 2.5. 2.7 and 2.9 m/s while motion of the hip, motion of the foot and ground reaction forces were collected for a few minutes. Using linear least squares methods similar to those used in Yang et al. (2014), we derived a linear model by mining the variability in the data. Using this linear model, we find out if the deviations in control variables like leg force, foot placement, stance duration and leg length during stance are explained by the deviations in the body states at mid-flight. The inputs to the controller and coordinate notation are shown in Figure 1. We implement this derived controller on a simple point mass telescoping leg model by finding the model gains that best match the step-to-step map in the data. We apply these gains to the simple model during stance to control for any perturbations added during flight. We perturb the sideways velocity, fore-aft velocity and vertical position of the model at flight apex, one and two at a time. We obtain the basin of attraction for the model by using a 200 x 200 grid of perturbations and letting the model simulate for 20 steps at each grid point. A fall is defined as when the model's body goes below the ground.

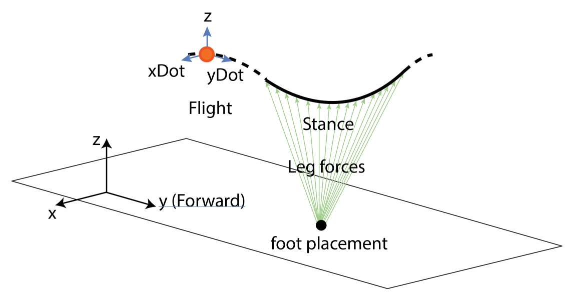

Figure 1. A linear map from flight states to stance controls is inferred.

Experiment Results:

The linear model obtained from experimental data found that a sideways velocity perturbation at flight apex is, on average, completely corrected by the sideways impulse during the next step (R^2=0.55). Around 80% of fore-aft velocity deviation at flight apex is corrected by the fore-aft impulse during the next step (R^2=0.35). Impulses can be modulated by modulating leg forces and stance duration. However, we find that stance duration does not play a role in correcting velocity deviations. Stance duration decreases in response to an upward vertical perturbation and increases in response to a downward vertical perturbation at flight apex. The ground reaction force modulation depends on stance phase and the gains from experiment are shown in Figure 2. We find that, in response to fore-aft velocity deviations, the negative part of the GRF is modulated more than the positive part. We find that people place their foot in the direction of the velocity perturbation. This foot placement control is more exaggerated in the sideways than in the fore-aft direction. Finally, we find that the landing leg length is changed proportionally in response to a vertical perturbation at flight apex. All gains were independent of running speed and station-keeping was not found to be a priority for the controller inferred. The step-to-step map, stride map and the eigenvalues of the states corroborate the gains from the linear model. All experimentally obtained gains are statistically significant with $p<10^{-4}$.

Model Results:

The simple point mass telescoping leg model was first simulated with experimentally obtained control gains and some perturbations were applied. These gains were then adjusted to make sure that the step-to-step map for the model matched that from experiment. The adjusted model gains were found to be similar to experimental gains and are shown in Figure 2 below.

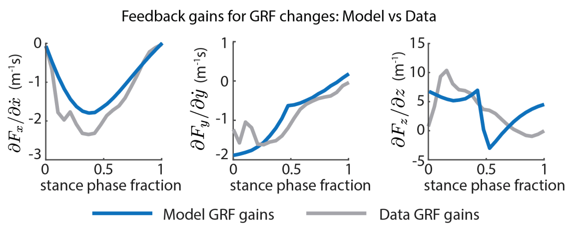

Figure 2: Experimental and model gains for GRF control. The model gains are similar to experimentally obtained gains.

With the controller turned on, the model has an asymptotically stable running motion. It recovers from fore-aft and sideways velocity perturbation and also from vertical position perturbations, as shown in figure 3. Although not explicit in the model's controller, the model discovers a steeper leg angle in response to an upward perturbation at flight apex.

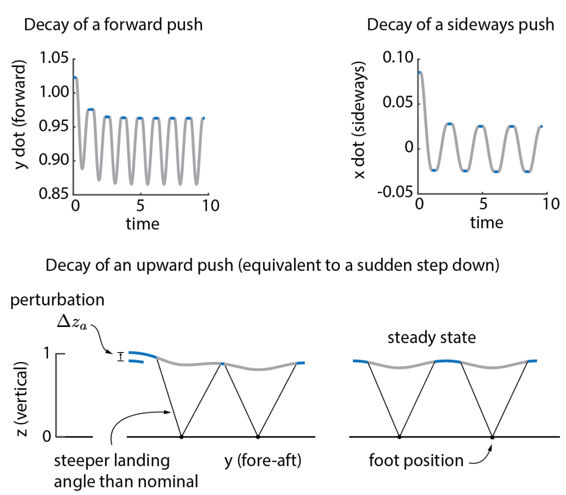

Figure 3: The model is stable to perturbations in fore-aft and sideways velocities and vertical position.

The model's basin of attraction (Figure 4) shows us that it can recover from perturbations almost four times larger than the variablity from which it was derived. We find that the basin of attraction is wider for fore-aft than for sideways perturbations. We also find that the model is more robust to upward than to downward vertical perturbations.

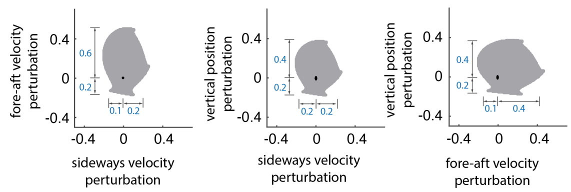

Figure 4: Basin of attractions for the simple model.

Discussion

The control strategies found here are obtained from actual human running data and provide an empirical basis for the more abstract running controllers currently in use. The foot placement control found here appears to be qualitative similar to that used by people when walking as found in Yang et al. (2014). Our simple model discovers a steeper leg angle in response to an upward perturbation and this has previously been reported in papers with step-up and step-down perturbations for running birds and humans. An energy-conservative spring cannot explain the control gains observed here. Thus, we find that spring-mass assumptions for running control are insufficient to explain human running stability for even small steady-state perturbations such as those in our experiments. The methods used here to study running stability do not need any contraptions to apply external perturbations. Thus, they can be easily reproduced and used to study differences in control strategies among different populations. Since our controller is primarily derived from human running data, it can be used to make exoskeletons and prosthetic legs respond to the users in a more natural and seamless manner.

References

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Acknowledgements

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