Adding variability to a moderately-complex human walking model

Anne E. Martin[1], Dario J. Villarreal[2], and Robert D. Gregg[2]
[1]The Pennsylvania State University, [2]The University of Texas at Dallas
Email: aem34@psu.edu

Summary

The ability to accurately quantify fall risk using a dynamic model could help identify individuals most at risk of falling. The variability in human walking appears to provide information about fall risk but the exact relationship between the two is unknown. The structure of the variability at each joint is also unknown. This abstract presents a method to characterize joint-level variability and incorporate it into a hybrid-zero-dynamics-based (HZD) model of human walking.

Introduction

Providing targeted physical therapy to individuals with increased fall risk could improve their quality of life while reducing health care costs. While increased variability is often correlated with increased fall risk (Hamacher et al., 2011), variability and stability are not equivalent (Dingwell et al., 2001), and healthy human systems are variable (Hausdorff, 2007). Determining the relationship between variability and fall risk in bipedal walking is difficult to do experimentally, but it may be possible using dynamic models. To reduce the problem to a tractable one, a moderately complex model that includes human-like joint variability, even if it does not explain why the variability occurs, is needed. HZD-based models have previously been used to accurately predict the mean motion of healthy human walking (Martin and Schmiedeler, 2014), so such a model is a promising starting point. To add variability, a model of human joint-level variability as a function of time (or phase) is needed. Direct measures of joint angle variability have been obtained through nonlinear dimensionality reduction techniques (Dingwell and Cusumano, 2000; Zhang et al., 2010), but these methods do not provide an intuitive representation of variability as a function of time. This abstract summarizes submitted work in characterizing and modeling the joint-level kinematic variability as a function of time (Martin et al., in review) and in incorporating variability into an HZD-based dynamic model (Martin and Gregg, accepted).

Methods

To characterize the variability, experimental kinematic data for ten young adults walking overground was used (Martin et al., in review). The stance and swing periods were analyzed separately because it improved the results. The kinematic data was first centered so that only the variability remained. For each step at each joint, the best fit Fourier series was found for the variability. A second order series was used for the stance joints and a first order series was used for the swing joints. Because each step had its own unique Fourier series defined by unique magnitude coefficients and fundamental frequencies, the statistical variation of the variability was described using Gaussian distributions of the magnitude coefficients and fundamental frequencies. In addition, correlations between the magnitude coefficients were described using equations. To model the variability, the required magnitude coefficients and fundamental frequencies were chosen randomly from the appropriate Gaussian distribution and/or using the equations describing the between-coefficient correlations (Martin et al., in review). To create a dynamic model with variability, the modeled variability was added to the mean motion along with start-of-step correction polynomials (Martin and Gregg, accepted). The correction polynomials were needed to prevent unbounded growth of the magnitude coefficients.

Results

The fitted Fourier series captured the experimental variability well with root mean square errors of $< 2.3°$. The twenty-four magnitude coefficient distributions all had means of zero and were grouped into three combined distributions based on standard deviation. The frequency distributions for all three stance joints were similar, so they were combined into a single distribution. The mean swing frequencies were greater than the mean stance frequency and increased as the joint became more distal. Because position and velocity are continuous across the step-to-step transition, the magnitude coefficients for each joint are correlated. In addition, the hip and knee joint coefficients are linearly correlated. The dynamic model was consistently able to take 100 steps without falling and had similar variability to the original experimental data (Fig. 1).

Discussion

Since it appears the only cross-joint correlation occurs between the hip and knee, this may suggest

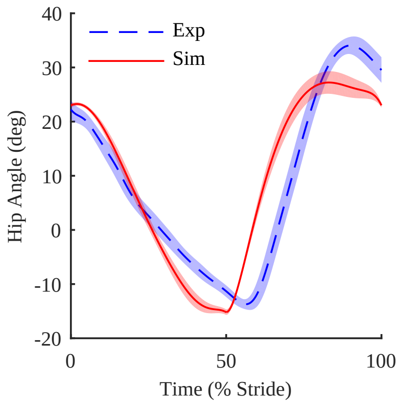

Figure 1: Total experimental and simulated hip angle. The line indicates the mean and the band represent plus/minus one standard deviation. Both the mean motion and the variability are similar. The variability is similar at all joints.

active control of variability because all three joints should be correlated if the variability resulted from neural control noise. This supports the proximo-distal gradient hypothesis (Daley et al., 2007) which proposes that the hip and knee joints share a controller (and therefore variability) while the ankle controller is distinct. Within the dynamic model, the need for correction polynomials indicates that the double support period may be used to help stabilize the gait. In human gait, the double support period can likely easily reject destabilizing disturbances because there are redundant actuators. The model double support period is both unactuated and instantaneous, which tends to magnify differences between the mean and actual motion. This work provides a promising first step in including variability within a moderately-complex human model but much work remains. The next step is to incorporate a finite-time double-support period within the dynamic model. For temporal variability, there are long-term long-range correlation between steps (Hausdorff, 2007) but it is unknown if these correlations are also present in the joint-level variability, and if they are, whether they provide useful information. The grand challenge is to correlate easily measured parameters with fall risk.

References

Daley, M.A., Felix, G., Biewener, A.A., 2007. Running stability is enhanced by a proximo-distal gradient in joint neuromechanical control. The Journal of Experimental Biology 210, 383–94. doi:10.1242/jeb.02668.

Dingwell, J.B., Cusumano, J.P., 2000. Nonlinear time series analysis of normal and pathological human walking. Chaos 10, 848–63. doi:10.1063/1.1324008.

Dingwell, J.B., Cusumano, J.P., Cavanagh, P.R., Sternad, D., 2001. Local dynamic stability versus kinematic variability of continuous overground and treadmill walking. Journal of Biomechanical Engineering 123, 27–32. doi:10.1115/1.1336798.

Hamacher, D., Singh, N.B., Van Dieën, J.H., Heller, M.O., Taylor, W.R., 2011. Kinematic measures for assessing gait stability in elderly individuals: a systematic review. Journal of the Royal Society, Interface 8, 1682–98. doi:10.1098/rsif.2011.0416.

Hausdorff, J.M., 2007. Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking. Human Movement Science 26, 555–89. doi:10.1016/j.humov.2007.05.003.

Martin, A.E., Gregg, R.D., accepted. Incorporating human-like walking variability in an HZD-based bipedal model. IEEE Transactions on Robotics .

Martin, A.E., Schmiedeler, J.P., 2014. Predicting human walking gaits with a simple planar model. Journal of Biomechanics 47, 1416–21. doi:10.1016/j.jbiomech.2014.01.035.

Martin, A.E., Villarreal, D.J., Gregg, R.D., in review. Characterizing and modeling the joint-level variability in human walking. Journal of Biomechanics .

Zhang, J., Zhang, K., Feng, J., Small, M., 2010. Rhythmic dynamics and synchronization via dimensionality reduction: application to human gait. PLoS Computational Biology 6, e1001033. doi:10.1371/journal.pcbi.1001033.