Influence of Simulated Neuromuscular Noise on Movement Variability and Fall Risk in a 3D Dynamic Walking Model

Paulien E. Roos and Jonathan B. Dingwell
Department of Kinesiology, University of Texas, Austin, TX 78712 USA

Supplementary Material

Supplementary Methods:

Here, we provide additional technical details of the 3D dynamic walking model used in this study. Forward propulsion was supplied by gravity by having the model walk down a gentle slope (4%). Following Kuo (1999), this slope was modeled by applying the gravity at an angle to the model instead of modeling the slope itself. All model parameters were non-dimensionalized (Kuo, 1999) with all lengths normalized to leg length (*L*), masses to body mass (m) and time to the reciprocal of the characteristic pendulum frequency ($\sqrt{L/g}$).

Model Configuration

The feet of the model were fixed relative to the corresponding leg, and the ankle joint was therefore a fixed joint. The feet did not have a width, so the contact between the foot and the ground was modeled as a point contact with the contact point moving over the foot surface. There was no slipping between the foot and the ground. The θ_{Roll} quantified the lateral roll angle of the stance limb over this contact point. This contact point acted as a passive pin joint while this leg was in contact with the ground. As the foot rolled over the ground, the contact point moved forward under the foot.

State Variables

The stance limb formed angles θ_{St} with the ground in the sagittal plane and θ_{Roll} in the frontal plane. The swing leg formed angle θ_{Sw} with the ground in the sagittal plane. The six primary state variables of the model for the swing phase were:

$$\mathbf{S}(t) = \left[\theta_{Roll}(t), \theta_{St}(t), \theta_{Sw}(t), \dot{\theta}_{Roll}(t), \dot{\theta}_{St}(t), \dot{\theta}_{Sw}(t)\right] \tag{1}$$

The splay angle (ϕ) was not a state variable that is integrated during each swing phase. For each individual integration step, ϕ is a parameter. However, ϕ is updated once each stride (at the instant of ground contact), based on the dynamic moments of the model. The splay angle is therefore not a constant parameter either.

Ground Contact Detection

During the simulations, the equations of motions were integrated until ground contact was detected. This was detected by calculating the distance of the swing foot from the ground at each time step in the integration. At ground contact, the swing leg of the previous step became the stance leg of the next step and vice versa. Ground contact was modeled instantaneously and as a perfectly inelastic collision. The new state variables after this impact were calculated so that the angular momentum of the whole model about the point of contact, the angular momentum of the whole model (minus the stance foot) around the bottom of the stance leg and the angular momentum of the trailing leg about the hip were all conserved (Kuo, 1999).

Finding Initial Conditions for Limit Cycle Solutions

In the optimization, state variables at the start and end of a stride were matched as closely as possible, using the Matlab 'lsqnonlin' function. After initial optimizations, additional steps were simulated from the optimized initial conditions until the phase portraits fully converged (~400 steps), as determined by visual inspection. A single 'noise free' simulation was then performed. The step time variability of the noise free solution was minimal ($<1.14\times10^{-4}$), thus verifying that this trial had fully converged. The state variables (Eq. 1) at foot strike from this trial were then used by the controller as a reference.

Lateral Step Controller

Lateral stability of the model was realized by a controller that made instantaneous lateral step adjustments at the instant of foot contact. The splay angle (ϕ) was adjusted at the instant of ground contact to match the state variables as closely as possible to their 'noise free' solution values. At each instant of ground contact the model exited the integration and the controller actively changed the splay angle by either increasing or decreasing it. Just changing the splay angle would however result in the foot not being in contact with the ground. Therefore, to find the splay angle for which the state variables matched their noise free solutions as close as possible, the model reran the step with the adjusted splay angle. Because of this, the change in splay angle resulted in a change in all state variables. The state variables at ground contact at the start of the step were compared to those at the end of the step and the splay angle was adjusted by a small fixed increment or decrement ($\pm10^{-6}$) if needed. This was repeated until the difference between the state variables and their noise free solutions was below a set tolerance (10^{-13}) or until changing the splay angle did not improve the match of the state variables anymore. In doing so, the controller weighted deviations in all state variables equally (i.e., there were no "preferred states" that the controller tried to minimize more than others). This optimized step was used in the actual simulation and this process was repeated every step. This mechanism also ensured that the foot did not end up under the ground.

Adding Noise to the Lateral Step Controller

Noise was applied to the lateral step controller by adding small errors (δ_{cont}) to each optimized ϕ that was determined by the lateral step controller. The noise was therefore added directly to the output of the controller after the optimal value of ϕ had been determine, such that these perturbed control inputs were never able to fully return the model to it's optimized limit cycle trajectory. The ϕ was only changed at the instant of ground contact and each perturbed ϕ produced deviations in all six state variables.

Simulations

The equations of motions were integrated with the Matlab ode45 differential equation solver, which is used to solve non-stiff differential equation using the medium order method. The absolute and relative tolerances for ode45 were set to 1e-7 and 1e-6, respectively. While these integration tolerances are not exceptionally tight, highly accurate integrations were not required here since we applied noise perturbations to the final end result anyway. Integration was stopped using the ode45 events function when ground contact was detected. For each j_{noise}, 100 walking trials were simulated. The model was able to reset to the original pattern very well, as the noise free condition did not fall over, even after a number of steps substantially larger than 125. The model fell over as noise was added to the lateral step controller after it returned to the original pattern, i.e. the controller did not return exactly to the original pattern as noise was added. When the model fell over this was either because the noise amplitude was so large that the model fell over before the next foot contact occurred and the controller could actually correct for this perturbation, or the model would fall over if it could not fully correct for the noise and this accumulated over consecutive steps.

References

Kuo, A.D., 1999. Stabilization of lateral motion in passive dynamic walking. *The International Journal of Robotics Research* 18(9): 917-930.

Supplementary Results:

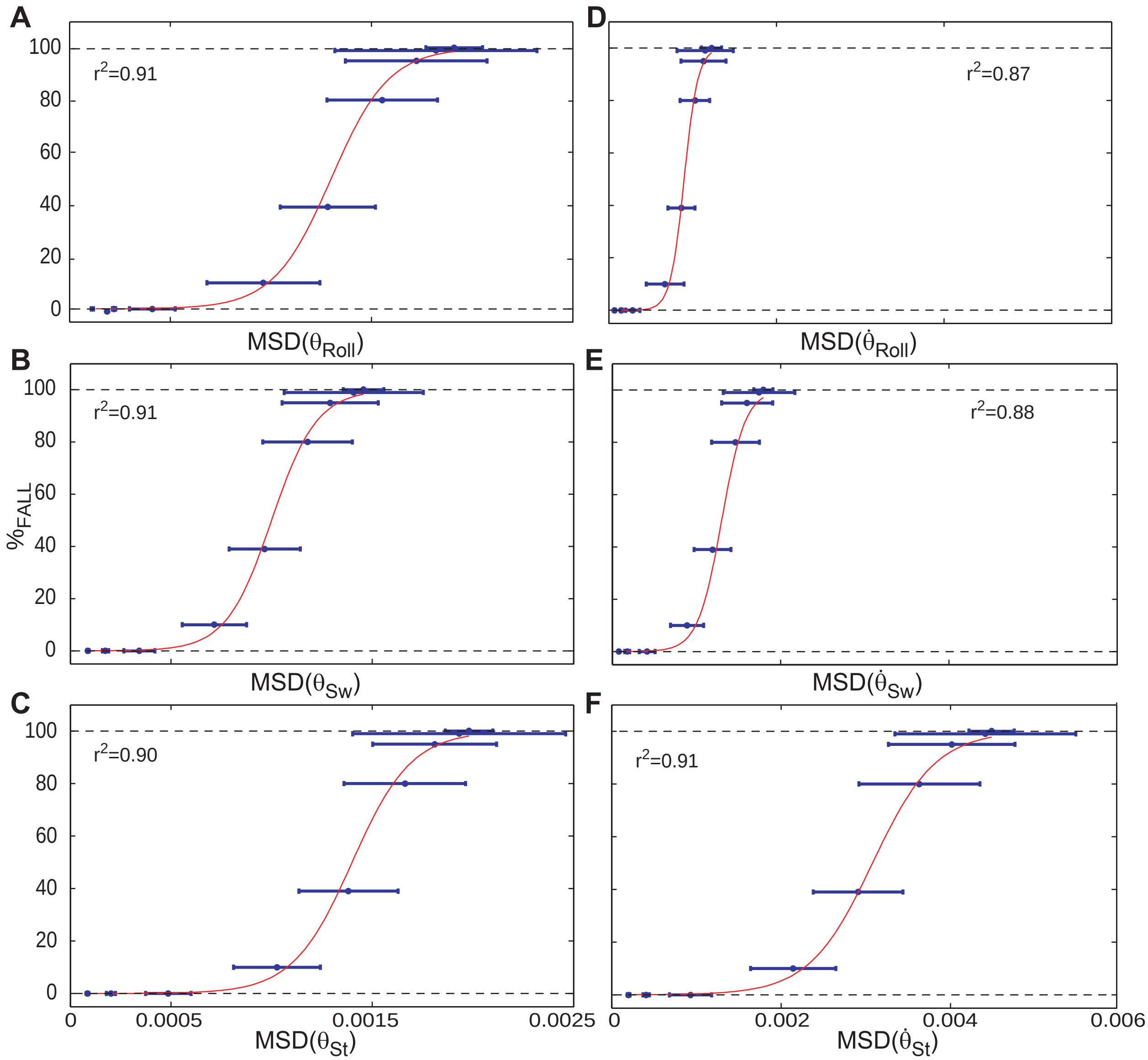

Figure S1) Kinematic state variability versus the probability of falling ($\%_{FALL}$). The data points are the average values and the red lines are sigmoidal functions fitted to the average data. The r^2 values are shown for each sigmoidal fit. The horizontal error bars are between-trial standard deviations of each variability measure. All r^2 values were ≥ 0.87 and all associated p-values were $\leq 2.3 \times 10^{-4}$ (Table S1).

Table S1) Sigmoidal fits of all variability measures to probability of falling ($\%_{FALL}$).

	Sigmoidal fit	r^2-value	p-value
$SD(SW)$	$f(x)=\frac{100}{1+e^{(x-0.0019)*-5766.4}}$	0.87	2.3×10^{-4}
$SD(SL)$	$f(x)=\frac{100}{1+e^{(x-0.0012)*-7738.7}}$	0.91	0.7×10^{-4}
$SD(ST)$	$f(x)=\frac{100}{1+e^{(x-0.0043)*-2019.2}}$	0.90	0.8×10^{-4}
$MSD(\theta_{Roll})$	$f(x)=\frac{100}{1+e^{(x-0.0013)*-6974.1}}$	0.91	0.6×10^{-4}
$MSD(\theta_{Sw})$	$f(x)=\frac{100}{1+e^{(x-0.0010)*-8892.5}}$	0.91	0.7×10^{-4}
$MSD(\theta_{St})$	$f(x)=\frac{100}{1+e^{(x-0.0014)*-6787}}$	0.90	1.1×10^{-4}
$MSD(\dot{\theta}_{Roll})$	$f(x)=\frac{100}{1+e^{(x-0.0009*12097.4}}$	0.87	2.3×10^{-4}
$MSD(\dot{\theta}_{Sw})$	$f(x)=\frac{100}{1+e^{(x-0.0013)*-7071.7}}$	0.88	1.9×10^{-4}
$MSD(\dot{\theta}_{St})$	$f(x)=\frac{100}{1+e^{(x-0.0031)*-2657.1}}$	0.91	0.7×10^{-4}
$MSD(\theta_{Tot})$	$f(x)=\frac{100}{1+e^{(x-0.0046)*-1942.7}}$	0.90	0.9×10^{-4}

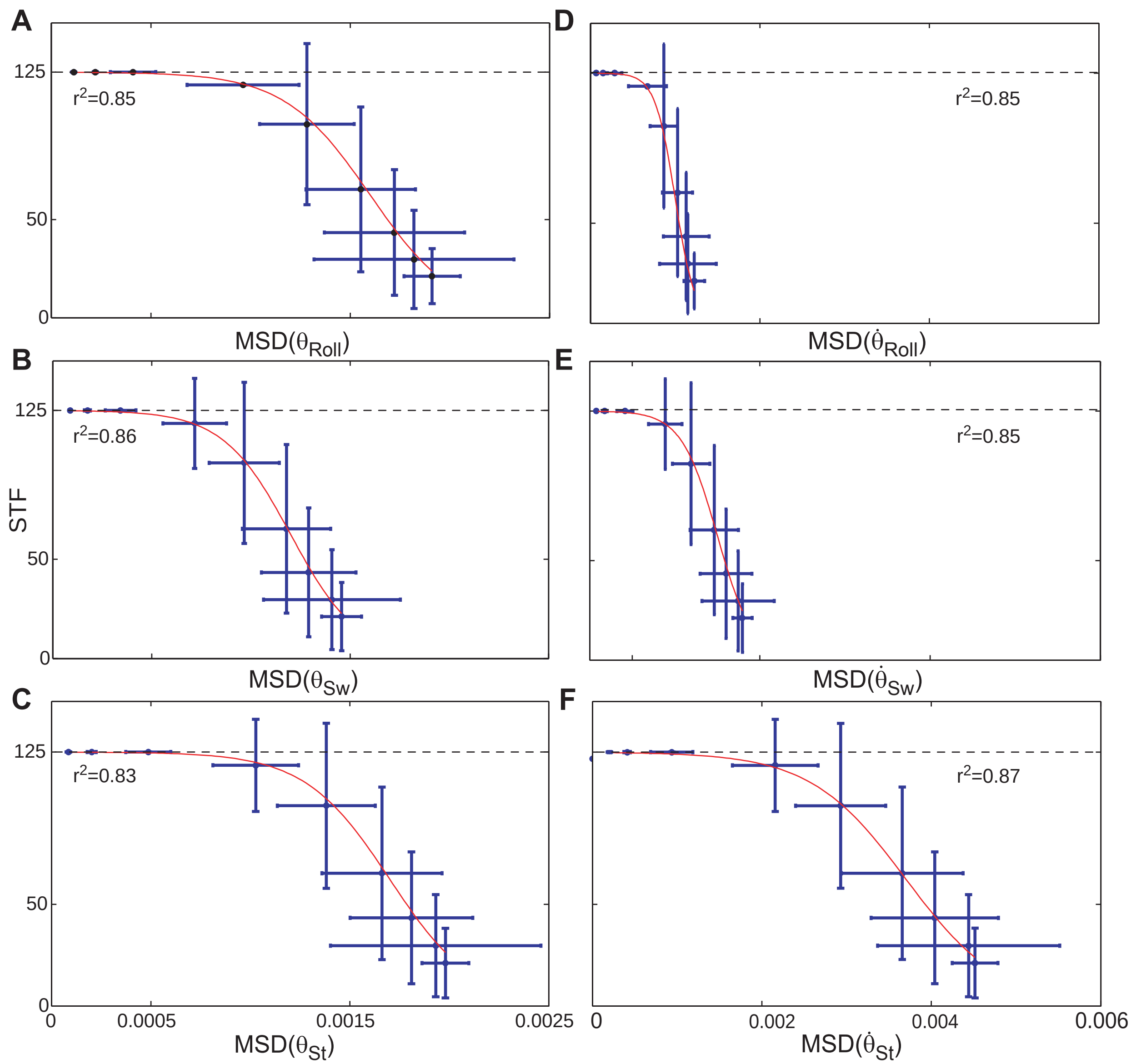

Figure S2) Kinematic state variability (MSD) measures versus the average number of steps taken before falling (STF). The data points are the average values and the red lines are sigmoidal fits to the average data. The r^2 values are shown for each sigmoidal fit. Horizontal error bars represent between-trial standard deviations of each variability measure. Vertical error bars indicate between-trial standard deviations of STF. All r^2 values were ≥ 0.81 and all associated p-values were $\leq 8.9 \times 10^{-4}$ (Table S2).

Table S2) Sigmoidal fits of all variability measures to the average number of steps taken before falling (STF).

	Sigmoidal fit	r^2-value	p-value
$SD(SW)$	$f(x)=\frac{125}{1+e^{(x-0.0022)*4086.9}}$	0.81	8.9×10^{-4}
$SD(SL)$	$f(x)=\frac{125}{1+e^{(x-0.0014)*5191.1}}$	0.87	2.4×10^{-4}
$SD(ST)$	$f(x)=\frac{125}{1+e^{(x-0.0051)*1393.3}}$	0.86	3.0×10^{-4}
$MSD(\theta_{Roll})$	$f(x)=\frac{125}{1+e^{(x-0.0016)*4661.5}}$	0.85	4.3×10^{-4}
$MSD(\theta_{Sw})$	$f(x)=\frac{125}{1+e^{(x-0.0012)*5863.0}}$	0.86	3.0×10^{-4}
$MSD(\theta_{St})$	$f(x)=\frac{125}{1+e^{(x-0.0017)*4694.8}}$	0.83	0.2×10^{-4}
$MSD(\dot{\theta}_{Roll})$	$f(x)=\frac{125}{1+e^{(x-0.0010)*8431.1}}$	0.85	4.5×10^{-4}
$MSD(\dot{\theta}_{Sw})$	$f(x)=\frac{125}{1+e^{(x-0.0015)*4737.6}}$	0.85	4.0×10^{-4}
$MSD(\dot{\theta}_{St})$	$f(x)=\frac{125}{1+e^{(x-0.0037)*1773.1}}$	0.87	2.3×10^{-4}
$MSD(\theta_{Tot})$	$f(x)=\frac{125}{1+e^{(x-0.0054)*1313.9}}$	0.86	2.9×10^{-4}