Journal of Biomechanics 44 (2011) 1514–1520

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Influence of simulated neuromuscular noise on the dynamic stability and fall risk of a 3D dynamic walking model

Paulien E. Roos*, Jonathan B. Dingwell

Department of Kinesiology, University of Texas, Austin, TX 78712, USA

ARTICLE INFO

Article history:
Accepted 3 March 2011

Keywords:
Dynamic walking
Gait
Neuromuscular noise
Stability
Falling
Elderly
Local stability
Orbital stability

ABSTRACT

Measures that can predict risk of falling are essential for enrollment of older adults into fall prevention programs. Local and orbital stability directly quantify responses to very small perturbations and are therefore putative *candidates* for predicting fall risk. However, research to date is not conclusive on whether and how these measures relate to fall risk. Testing this empirically would be time consuming or may require high risk tripping experiments. Simulation studies therefore provide an important tool to initially explore potential measures to predict fall risk. This study performed simulations with a 3D dynamic walking model to explore if and how dynamic stability measures predict fall risk. The model incorporated a lateral step controller to maintain lateral stability. Neuronal noise of increasing amplitude was added to this controller to manipulate fall risk. Short-term (λ_S^*) local instability did predict fall risk, but long-term (λ_L^*) local instability and orbital stability (*maxFM*) did not. Additionally, λ_S^* was an *early* predictor for fall risk as it started increasing *before* fall risk increased. Therefore, λ_S^* could be a very useful tool to identify older adults whose fall risk is about to increase, so they can be enrolled in fall prevention programs before they actually fall.

1. Introduction

Fall risk increases in older adults and many risk factors contribute to this (Tinetti et al., 1988). Falls in older adults can be reduced by early enrollment in fall prevention programs (Lord et al., 2003; Skelton and Beyer, 2003). Identifying people at high fall risk *before* they have actually fallen would allow earlier enrollment in fall prevention programs and possibly prevent or delay the onset of repetitive falls. To identify those at high fall risk, measures are needed that can easily be obtained without actually inducing falls. Several studies suggested that increased gait variability may prospectively predict future falls (Maki, 1997; Hausdorff et al., 2001; DeMott et al., 2007). Results are however inconclusive on which variables to use (Owings and Grabiner, 2004; Brach et al., 2005; Moe-Nilssen and Helbostad, 2005) and how much of an increase in variability would result in an increase in fall risk (Brach et al., 2010).

A simulation study with a 3D dynamic walking model confirmed that gait variability and fall risk were correlated (Roos and Dingwell, 2010). This relationship was however strongly nonlinear. At very low and very high gait variability levels, an incremental increase in variability affected fall risk little, while at intermediate gait variability levels, a similar increase resulted in a significant increase in fall risk (Roos and Dingwell, 2010). Gait variability therefore might not easily be used as a measure to identify people at risk of falling, as specific increases in gait variability may or may not result in increased fall risk. In this study, we therefore explored different measures that may predict fall risk.

"Local" (and also "orbital") stability refers to how a system responds to infinitesimally small perturbations (Dingwell and Cusumano, 2000). Conversely, "global stability" typically refers to the set of the *largest* possible perturbations a system can withstand. For human walking, falling is a failure of *global* stability. There is, however, no theoretical reason that "local stability" must predict "global stability". This is something that must simply be tested on a case-by-case, system-by-system basis. Local and orbital stability (Dingwell and Cusumano, 2000; Dingwell and Kang, 2007) have been studied in walking. Orbital instability was greater in fall prone older adults than in younger adults and healthy older adults (Granata and Lockhart, 2008) and also greater in post-polio patients than in healthy adults (Hurmuzlu et al., 1996). Other studies examined the influence of gait speed on local dynamic stability (Dingwell and Marin, 2006; England and Granata, 2007; Kang and Dingwell, 2008; Bruijn et al., 2009). Kang and Dingwell (2008) found that both younger and older adults had decreased dynamic instability (local and orbital) when they walked slower and that older adults were more unstable than younger adults at all walking speeds tested. However, none of these previous studies imposed actual perturbations on their subjects or induced actual falls. Therefore, it remains unclear what insights these dynamic stability measures may have for assessing *actual* fall risk.

* Correspondence to: School of Healthcare Studies, Cardiff University, Heath Park, Cardiff, CF14 4XN, USA. Tel.: +1 29 2068 7760; fax: +1 512 4718914.
E-mail address: RoosPE@Cardiff.ac.uk (P.E. Roos).

0021-9290/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jbiomech.2011.03.003

Whether local and/or orbital stability are directly correlated to actual fall risk therefore remains unknown. Simulations provide an important tool to initially explore such measures that could predict fall risk. Exploring such measures experimentally would require either (1) longitudinal studies, which are time consuming and expensive, or (2) tripping or slipping studies, which are complex and potentially dangerous. Simulation models do not get injured, do not learn, and allow total control over the system. Probability of falling increased in a 3D dynamic walking model when neuronal noise of increasing amplitude was applied (Roos and Dingwell, 2010). This model forms an ideal platform to determine the relationship between local and orbital stability and risk of falling.

This work directly extends work by Su and Dingwell (2007) that demonstrated that short-term local instability (λ_S^*) increased, but that orbital stability did not change, when a 2D dynamic walking model was perturbed with increasing magnitude. They however did not perturb their model to the point that it actually fell, and therefore could not relate these measures to fall risk. Additionally, because this model was 2D and not 3D, it was passively stable and incorporated no additional control. Introducing lateral motion in a 3D model leads to qualitatively very different dynamics (Kuo, 1999). Such 3D models are inherently *un*stable in the lateral direction and require active control to prevent falling. Humans are likewise far more sensitive to lateral perturbations during walking (Bauby and Kuo, 2000; Donelan et al., 2004; Dean et al., 2007; O'Connor and Kuo, 2009; McAndrew et al., 2010, 2011), making 3D models uniquely relevant to studying human locomotor control.

The aims of this study were therefore to determine how increased neuronal noise affects local and orbital stability, and if these measures are related to gait variability and can directly predict fall risk in a 3D dynamic walking model. We hypothesized, based on Su and Dingwell (2007), that: (1) orbital stability would not be a good predictor for fall risk, (2) short-term local instability would be a good predictor for fall risk, and (3) long-term local instability would not be a good predictor for fall risk.

2. Methods

Complete technical details on the simulation model are provided in the Supplementary material of this paper and in Roos and Dingwell (2010). Briefly, a 3D dynamic walking model (Kuo, 1999) was replicated in Matlab (Mathworks, R2008a). This model was then adapted to simulate multiple consecutive steps and incorporate simulated neuronal noise. The model comprised a pelvis segment and two rigid legs with semi-circular feet (Fig. 1). The model orientation was prescribed by four angles: (1) ϕ (splay angle), (2) θ_{St}(stance angle), (3) θ_{Roll}(roll angle) and (4) θ_{Sw}(swing angle). The splay angle (ϕ) was a parameter for each individual integration step, and was only adjusted from step-to-step. The state variables of the model therefore comprised the latter three angles with their corresponding angular velocities:

$$\mathbf{S}(t) = [\theta_{Roll}(t),\ \theta_{St}(t),\ \theta_{Sw}(t),\ \dot{\theta}_{Roll}(t),\ \dot{\theta}_{St}(t),\ \dot{\theta}_{Sw}(t)] \in \Re^6 \quad (1)$$

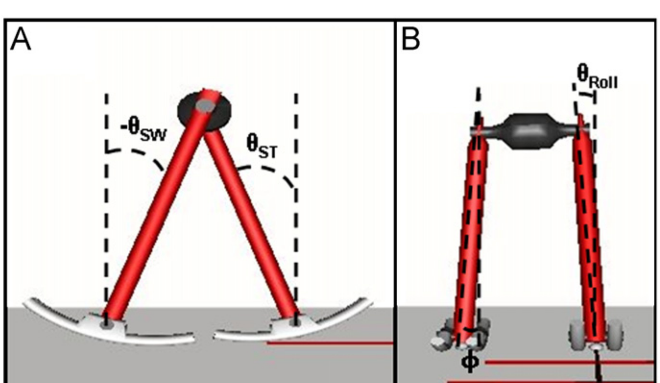

Fig. 1. Schematic picture of the 3D dynamic walking model used in this study. (A) is a side view with the angles of the swing leg (θ_{Sw}) and stance leg (θ_{St}). (B) is a frontal view with the leg splay angle (ϕ) and lateral roll angle (θ_{Roll}) indicated.

Unlike our previous 2D model (Su and Dingwell, 2007), which was passively *stable*, introducing θ_{Roll} enabled lateral movement of the walker causing lateral *in*stability (Kuo, 1999). Lateral stability could only be maintained by also incorporating a controller that made lateral step adjustments. Initial conditions were estimated from Kuo (1999) and further optimized for a moderate walking speed (0.94 m/s).

Neuronal noise, similar to that present in humans, was simulated by applying small random perturbations to the lateral step controller. This added noise represented the changes in neuronal noise that happen with ageing due to multiple physiological factors (Shaffer and Harrison, 2007). Across multiple steps, sequential perturbations were chosen as uniformly distributed random numbers with maximum amplitude $\pm j_{noise}$. Multiple sets of simulations were run where j_{noise} was varied between values that did not make the model fall and values for which the model always fell. For each j_{noise}, 100 walking trials were simulated for 125 consecutive walking steps or until the model fell over. The 125 steps reflected human walking behavior, where 90.5% of walking bouts fall below 100 steps (Orendurff et al., 2008). For each j_{noise}, the probability of falling ($\%_{Fall}$) was computed as the percentage of trials where the model fell. For each simulation, step variability measures were calculated as the standard deviations of step length (SD_{SL}), step width (SD_{SW}) and step time (SD_{ST}). Kinematic state variability ($MSD(\theta_{Tot})$) was calculated by combining the variability of the individual state variables (calculated as in Dingwell and Marin (2006)) in a vector and calculating the length of this vector. A complete analysis of these variability results is presented in Roos and Dingwell (2010).

Orbital stability quantifies from cycle to cycle the tendency of the system's state variables to return to a specific trajectory (the limit cycle) after a small perturbation. Thus, orbital stability can only be calculated for systems that exhibit *periodic* behavior. Orbital dynamic stability was calculated by estimating the maximum Floquet Multiplier (*maxFM*) as in (Hurmuzlu and Basdogan, 1994; Su and Dingwell, 2007). Details on how *maxFM* was calculated are given in the Supplementary material. Consecutive orbits are deemed stable, on average, when $maxFM < 1$ and unstable when $maxFM > 1$.

Local instability quantifies how the system's state variables respond to very small perturbations in real time. Local instability assumes *aperiodic* behavior and therefore that the system dynamics do not return to a limit cycle after small perturbations (Dingwell and Cusumano, 2000). Local instability is calculated by local divergence exponents. These exponents quantify how fast neighboring trajectories of the state space either converge or diverge. Positive exponents indicate that the trajectories are diverging. The larger the magnitude of the exponent, the faster small perturbations from any given trajectory diverge. For walking, a short-term (λ_S^*) and a long-term local divergence exponent (λ_L^*) can be calculated (Dingwell and Cusumano, 2000; Dingwell et al., 2001). Details on how the local divergence exponents were calculated are given in the Supplementary material.

The accuracy of the maximum Floquet Multipliers (*maxFM*) and local divergence exponents (λ_L^* and λ_S^*) may increase with the number of gait cycles used in the calculations (Bruijn et al., 2009). We calculated *maxFM*, λ_L^* and λ_S^* using a varying number of steps (Fig. 2) and found that *maxFM* decreased (became more stable) and λ_L^* and λ_S^* increased (became more *un*stable) when more steps were used. The general trend of the data over the different noise amplitudes however did not change. At higher noise levels there were few trials that walked over 50 steps, and this would reduce statistical precision. We chose to calculate the dynamic stability measures over the first 50 steps of the first 20 trials of each j_{noise} that walked at least 55 steps. The last five steps of each simulation were omitted to exclude potential fall dynamics.

Outcome measures of this study were λ_S^*, λ_L^*, *maxFM* and $\%_{FALL}$. Significant differences in λ_S^*, λ_L^* and *maxFM* for the different values of j_{noise} were analyzed with one-way ANOVA tests, and Bonferroni posthoc tests. Correlations between λ_S^*, λ_L^* and variability measures or *maxFM* were calculated by a Pearson correlation. All statistical analyses were performed using SPSS (Version 17.0, release 17.0.0).

3. Results

The model exhibited periodic gait when no noise was added to the controller. The kinematic variability increased appreciably with added neuronal noise (Fig. 3).

The orbital stability (*maxFM*) did not increase continuously with noise amplitude (j_{noise}) (Fig. 4). Increases in *maxFM* only became statistically significant ($p < 0.01$) at the highest noise amplitudes. As a result, *maxFM* was not a good predictor of fall risk ($\%_{FALL}$) (Fig. 6A). This confirmed our first hypothesis.

The short-term local instability (λ_S^*) increased (i.e., became more unstable) when noise was applied to the model, and leveled out at the higher noise levels (Fig. 5B). λ_S^* started increasing before the probability of falling ($\%_{FALL}$) increased and was therefore a good *early* predictor for fall risk (Fig. 6B). The long-term local instability (λ_L^*) did not change with j_{noise} (Fig. 5C) and was not

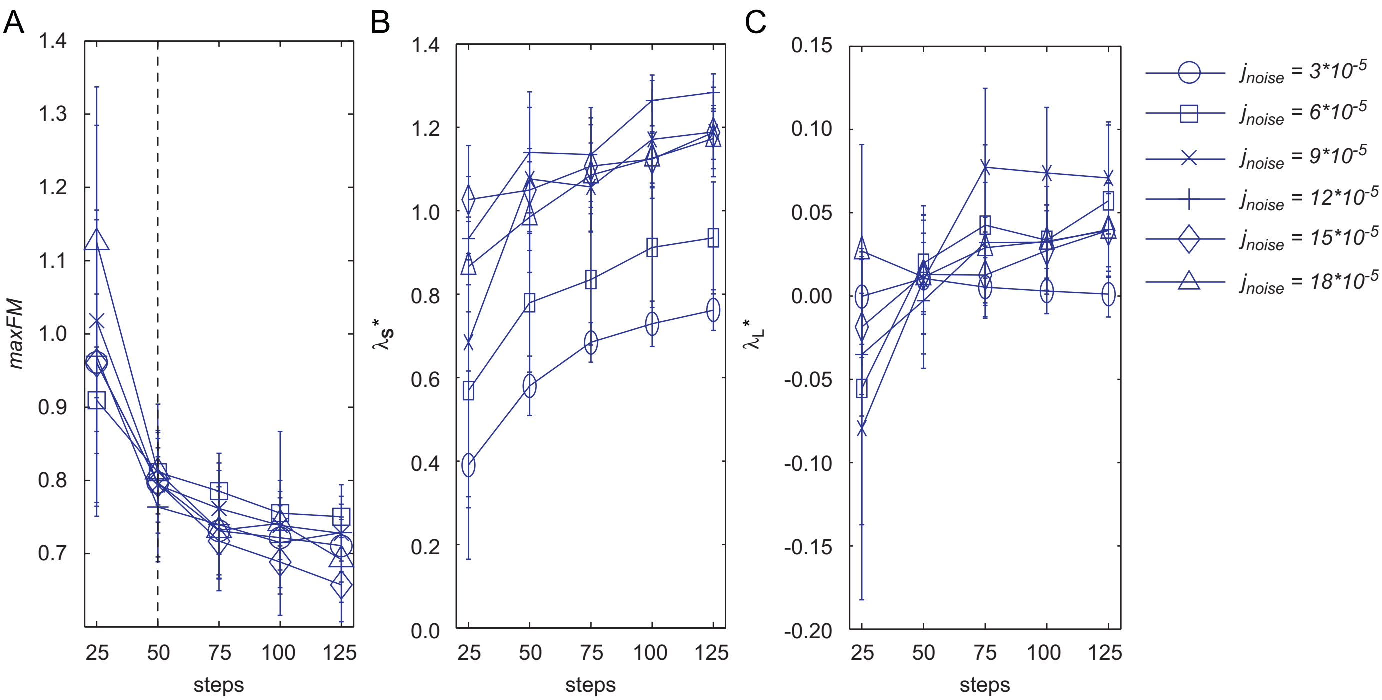

Fig. 2. The number of walking steps used in the calculations (steps) versus (A) *maxFM*, (B) λ_S^* and (C) λ_L^* for the different neuronal noise (j_{noise}) values.

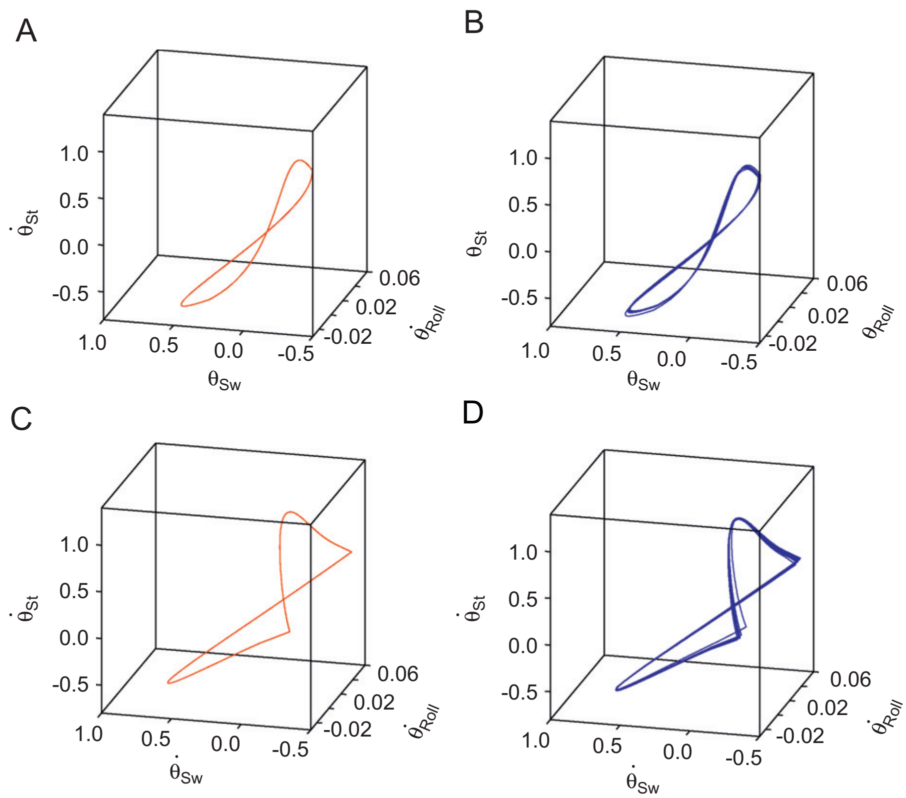

Fig. 3. Phase portraits of the model with the first three state variables in (A) and (B) and the last three in (C) and (D). The red lines in (A) and (C) are the first 25 steps of the noise free simulation and the blue lines in (B) and (D) are the first 25 steps of a trial with $j_{noise}=24\times10^{-5}$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

correlated with fall risk ($\%_{FALL}$) (Fig. 6C). This confirmed our second and third hypothesis.

There were weak correlations that were statistically significant between λ_S^* and the variability measures ($0.367\leq r^2\leq0.378$; $p\leq0.001$) (Fig. 6A). There were no significant correlations between λ_L^* and the variability measures ($0.036\leq r^2\leq0.053$; $p\geq0.475$) (Fig. 6B). *MaxFM* was not correlated with variability measures (not shown). This was not surprising as *MaxFM* already did not change with j_{noise}. Neither short-term (λ_S^*) nor long-term (λ_L^*) local divergence exponents were correlated to orbital

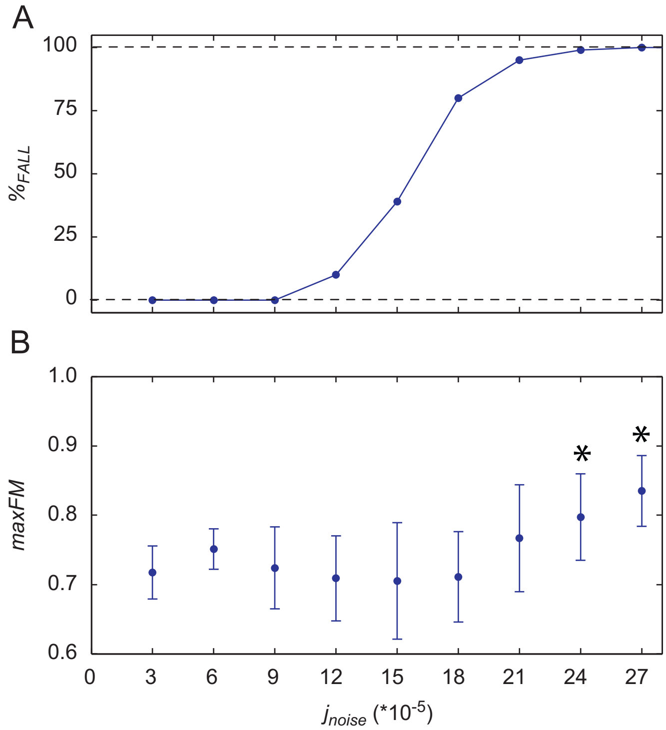

Fig. 4. (A) Probability of falling ($\%_{Fall}$) against noise amplitude (j_{noise}). (B) Local dynamic stability ($maxFM$) against j_{noise}. Error bars represent ± 1 standard deviation. Significant differences ($p<0.01$) *in maxFM* from the value at $j_{noise}=3\times10^{-5}$ are indicated with a $*$.

($maxFM$) stability measures ($r^2=0.120$; $p=0.742$ and $r^2=0.550$ and $p=0.099$, respectively) (Fig. 8).

4. Discussion

Measures that can predict risk of falling are essential for early enrollment of older adults into fall prevention programs. Testing such measures empirically would require time consuming long-term follow up studies to observe frequency of falling. Simulation studies therefore provide an important tool to explore potential measures to predict fall risk. This study performed simulations with a 3D dynamic walking model to determine how well several proposed dynamic stability measures predict fall risk in this model.

Our model (Fig. 1) exhibited stride lengths, stride times, step widths, and walking speeds very comparable to humans. Many predictions derived from the original 3D model (Kuo, 1999) were subsequently confirmed in human experiments. The overall kinematics of human walking are well predicted by this model (Bauby and Kuo, 2000). Likewise, humans exhibited similar changes in stepping kinematics (variability of step length, step width, etc.) when they were externally stabilized in the medio-lateral direction (Donelan et al., 2004; Dean et al., 2007). We recently applied small-to-moderate amplitude pseudo-random noise-like perturbations to humans walking on a treadmill. The changes exhibited by humans in kinematic variability (McAndrew et al., 2010) and in the same dynamic stability measures applied here (McAndrew et al., 2011) were also mostly very consistent with what we demonstrate here for our dynamic walking model.

The limit cycle behavior exhibited by our noise free model was consistent with what would be expected from a central pattern generator (CPG) driven system, where the primary (i.e., average) motor patterns are generated by CPG's in the spinal cord and then modulated by sensory feedback (Holmes et al., 2006; Pinto and Golubitsky, 2006; Ijspeert, 2008). The step width controller applied in our 3D walking model is consistent with a feedback controller that followed a "Minimum Intervention Principle" approach (Todorov, 2004; Dingwell et al., 2010), where active control was applied primarily in the medio-lateral direction where the model was unstable, while anterior–posterior deviations were ignored since these could be negated through passive dynamics (Kuo, 1999). Thus, this 3D dynamic walking model appears to accurately replicate most of the essential features of human walking and the dynamic stability control that humans use.

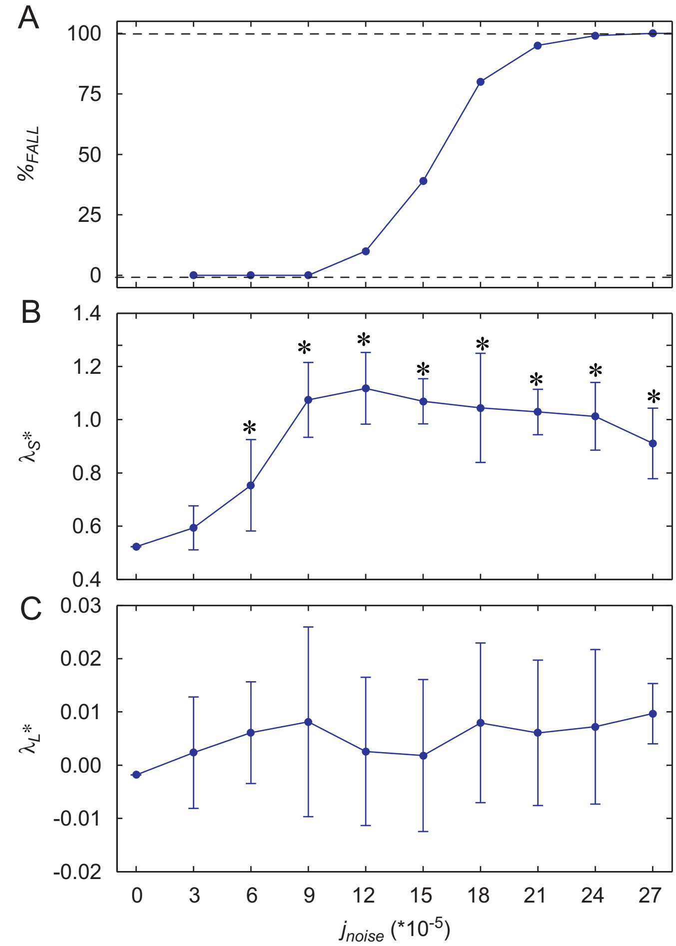

Fig. 5. Probability of falling ($\%_{Fall}$), short-term (λ_S^*) and long-term (λ_L^*) local divergence exponents against noise amplitude (j_{noise}). Error bars represent ± 1 standard deviation. Significant differences ($p<0.01$) in λ_S^* and λ_L^* from the value at $j_{noise}=3\times10^{-5}$ are indicated with a $*$.

The present simulation study extended this previous modeling and experimental work to investigate *actual fall risk* over a much larger range of perturbation magnitudes. Short-term (λ_S^*) local instability was a predictor for fall risk. However, long-term (λ_L^*) local instability and orbital stability ($maxFM$) were not (Figs. 4–6). Moreover, λ_S^* was an *early* predictor for fall risk ($\%_{FALL}$) as it started increasing before $\%_{FALL}$ increased. There was no correlation between long-term divergence exponents or orbital stability and gait variability (Fig. 7), which agreed with previous experimental research (Dingwell et al., 2000, 2001; Dingwell and Marin, 2006). The short-term divergence exponents were however significantly correlated with gait variability (Fig. 7). This correlation was however driven by the two outlying points with low λ_S^* for the low gait variability relative to the grouped similar λ_S^* for the remainder higher gait variability values. Due to the nonlinearity of this relationship, it is difficult to interpret the r^2 values of this correlation.

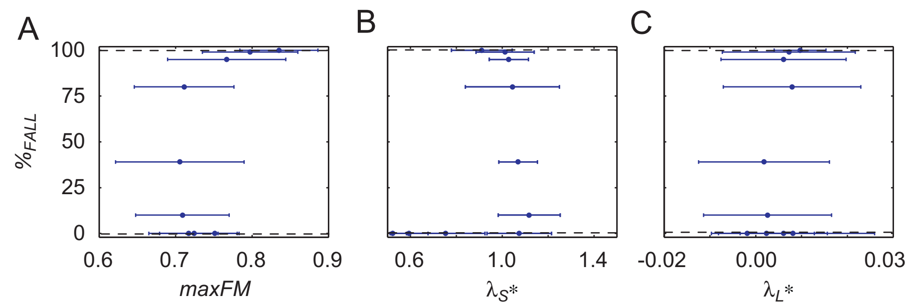

Fig. 6. Probability of falling ($\%_{FALL}$) against (A) local dynamic stability (*maxFM*), (B) short-term (λ_S^*) and (C) long-term (λ_L^*) local divergence exponents. Error bars represent ± 1 standard deviation.

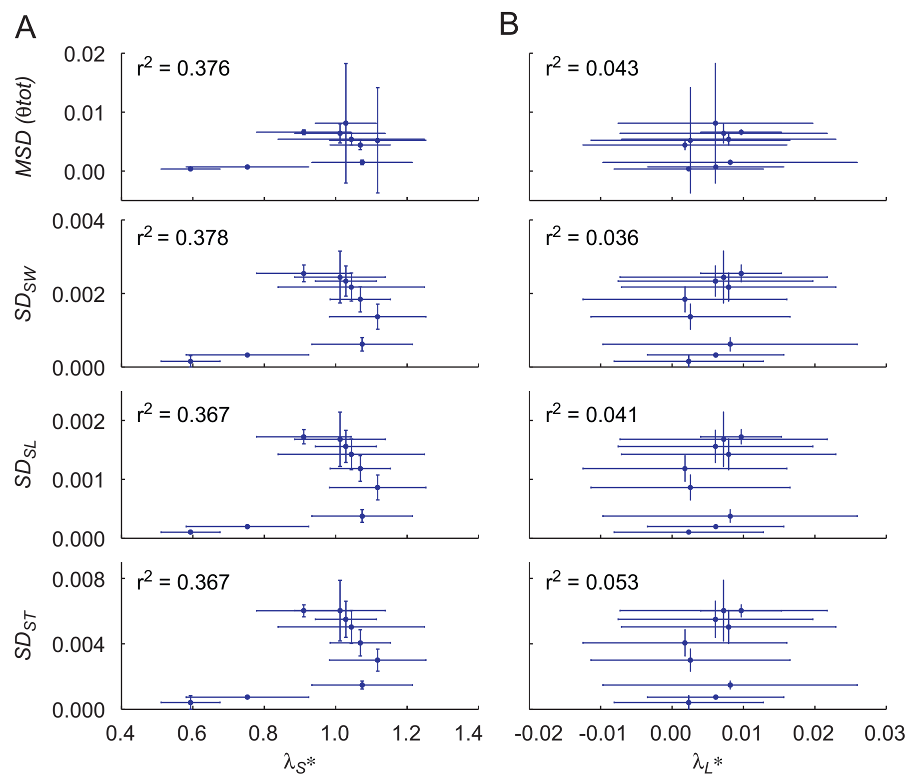

Fig. 7. (A) Short-term local instability (λ_S^*) against the variability in SD_{SW}, SD_{SL}, SD_{ST} and $MSD(\theta_{Tot})$. (B) Long-term local instability (λ_L^*) against the variability in SD_{SW}, SD_{SL}, SD_{ST} and $MSD(\theta_{Tot})$ on the right. Error bars represent ± 1 standard deviation. Correlations of λ_S^* with the variability measures were significant ($0.367 \leq r^2 \leq 0.378$; $p \leq 0.001$) and correlations of λ_L^* with the variability measures were not statistically significant ($0.036 \leq r^2 \leq 0.053$; $p \geq 0.475$).

All *maxFM* values were smaller than 1.0 (Fig. 4). The model was therefore orbitally stable even for the high j_{noise} values where the model fell over in most or all simulations. For the high j_{noise} values ($j_{noise} \geq 24 \times 10^{-5}$), *maxFM* values were however greater (less stable) than those for $j_{noise}=3 \times 10^{-5}$. It has to be kept in mind that fall dynamics were excluded from analysis; for these fall dynamics state space trajectories would have diverged very quickly away from the limit cycle and this would lead to very large *maxFM* values. Short-term local divergence exponents (λ_S^*) were all positive and therefore local instability was present in the model, consistent with previous simulation (Su and Dingwell, 2007) and experimental studies (Dingwell and Kang, 2007; Dingwell et al., 2007). The long-term divergence exponents (λ_L^*) were all around zero and did not change with j_{noise}, which indicated that the noise applied to the controller was dampened out quickly.

The methods we used to calculate the local and orbital stability influenced the outcomes quantitatively. Both methods would have yielded different quantitative results if more steps were used in their calculations (Bruijn et al., 2009). To allow grouping of trials with the same conditions, a consistent number of steps was used. Trends in the results did not change if more or fewer steps were used (Fig. 2). Since the aim of this study was to show the general relationship between fall risk and stability measures, and not to give exact numerical values, we chose to use a relatively small number of steps (50) in our calculations. There was a sufficient number of trials available that each contained this number of steps to yield statistical precision. To make valid comparisons of the local divergence exponents at the different j_{noise} values, we resampled all data to get a consistent mean number of samples per stride (England and Granata, 2007).

Orbital dynamic stability (*maxFM*) changed little and not continuously with noise amplitude (j_{noise}) (Fig. 4). This supports earlier findings by Su and Dingwell (2007). *MaxFM* was not a good predictor for fall risk ($\%_{FALL}$), as significant changes in *maxFM* occurred too late to predict $\%_{FALL}$ (Fig. 4). Experimental studies however found *maxFM* to be higher in fall prone older adults than in healthy subjects (Kang and Dingwell, 2007; Granata and Lockhart, 2008). As our study only quantified changes in fall risk

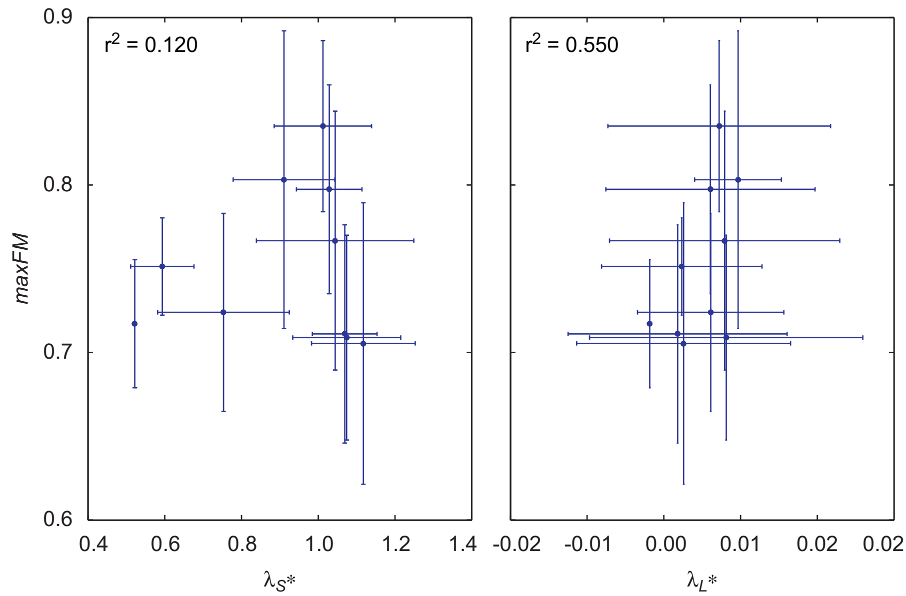

Fig. 8. Short-term (λ_S^* on the left) and long-term (λ_L^* on the right) stability versus orbital stability (*maxFM*). Error bars represent ± 1 standard deviation. Both correlations were not statistically significant ($r^2=0.120$; $p=0.742$ and $r^2=0.550$ and $p=0.099$, respectively).

induced by increased neuronal noise, we may conclude that the increased *maxFM* in fall prone older adults is caused by other risk factors that were not included in our model (such as reduced muscle force and/or response times).

This study extended previous research by Su and Dingwell (2007). The model in this study differed from that in Su and Dingwell (2007) as it was 3D and not 2D, because of this it was inherently unstable and active control was required. Su and Dingwell (2007) also did not perturb their model as such that it fell over. Despite these differences and additional complexity, our study had similar conclusions; short-term local instability (λ_S^*) increased when the model was perturbed with increasing magnitude and orbital stability did not change significantly when the model was perturbed more. As the model actually fell over in our study we could directly correlate the stability measures to fall risk and demonstrated that short-term local dynamic stability (λ_S^*) was an *early* predictor for fall risk.

We previously showed that gait variability could significantly predict fall risk (Roos and Dingwell, 2010). This relationship was however highly nonlinear and the gait variability measures largely *parallelled* changes in fall risk. Therefore, the initial level of gait variability (depending on a person's physiology and external factors) greatly influences the increase in fall risk with a certain increase in gait variability (Roos and Dingwell, 2010). Here, we explored whether dynamic stability measures would better predict fall risk. We found that short-term local instability predicted fall risk in a different manner than gait variability. Increases in the short-term local divergence exponents (λ_S^*) calculated in this study *preceeded* changes in fall risk. This suggests that λ_S^* might be more sensitive early predictors of fall risk. This would make them more useful for early identification of increased fall risk than gait variability.

The principal contribution of our study was to demonstrate that short-term local divergence exponents, but not long-term divergence exponents or *maxFM*, were good early predictors for increased fall risk. They could therefore be a very useful tool to identify older adults who are at high fall risk, thereby allowing the possibility to enroll them in fall prevention programs before they actually become frequent fallers. The findings of this study may however be specific to the model used and it needs further investigation how these findings translate to humans.

Conflict of interest statement

The authors declare that there are no conflicts of interest associated with this work.

Acknowledgment

Funding for this project was provided by Grant #1-R21-EB007638-01A1 from the National Institutes of Health.

Appendix. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jbiomech.2011.03.003.

References

Bauby, C.E., Kuo, A.D., 2000. Active control of lateral balance in human walking. Journal of Biomechanics 33 (11), 1433–1440.
Brach, J.S., Berlin, J.E., VanSwearingen, J.M., Newman, A.B., Studenski, S.A., 2005. Too much or too little step width variability is associated with a fall history in older persons who walk at or near normal gait speed. Journal of NeuroEngineering and Rehabilitation 2 (1), 21.
Brach, J.S., Perera, S., Studenski, S., Katz, M., Hall, C., Verghese, J., 2010. Meaningful change in measures of gait variability in older adults. Gait & Posture 31 (2), 175–179.
Bruijn, S.M., Dieen van, J.H., Meijer, O.G., Beek, P.J., 2009. Statistical precision and sensitivity of measures of dynamic gait stability. Journal of Neuroscience Methods 178 (2), 327–333.
Dean, J.C., Alexander, N.B., Kuo, A.D., 2007. The effect of lateral stabilization on walking in young and old adults. IEEE Transactions on Biomedical Engineering 54 (11), 1919–1926.
DeMott, T.K., Richardson, J.K., Thies, S.B., Ashton-Miller, J.A., 2007. Falls and gait characteristics among older persons with peripheral neuropathy. American Journal of Physical Medicine and Rehabilitation 86 (2), 125–132.
Dingwell, J.B., Cusumano, J.P., 2000. Nonlinear time series analysis of normal and pathological human walking. Chaos 10 (4), 848–863.
Dingwell, J.B., Cusumano, J.P., Sternad, D., Cavanagh, P.R., 2000. Slower speeds in patients with diabetic neuropathy lead to improved local dynamic stability of continuous overground walking. Journal of Biomechanics 33 (10), 1269–1277.
Dingwell, J.B., Cusumano, J.P., Sternad, D., Cavanagh, P.R., 2001. Local dynamic stability versus kinematic variability of continuous overground and treadmill walking. ASME Journal of Biomechanical Engineering 123 (1), 27–32.
Dingwell, J.B., John, J., Cusumano, J.P., 2010. Do humans optimally exploit redundancy to control step variability in walking? PLoS Computational Biology 6 (7), e1000856 〈http://dx.doi.org/10.1371/journal.pcbi.1000856〉.

Dingwell, J.B., Kang, H.G., 2007. Differences between local and orbital dynamic stability during human walking. Journal of Biomechanical Engineering 129 (4), 586–593.
Dingwell, J.B., Kang, H.G., Marin, L.C., 2007. The effects of sensory loss and walking speed on the orbital dynamic stability of human walking. Journal of Biomechanics 40 (8), 1723–1730.
Dingwell, J.B., Marin, L.C., 2006. Kinematic variability and local dynamic stability of upper body motions when walking at different speeds. Journal of Biomechanics 39 (3), 444–452.
Donelan, J.M., Shipman, D.W., Kram, R., Kuo, A.D., 2004. Mechanical and metabolic requirements for active lateral stabilization in human walking. Journal of Biomechanics 37 (6), 827–835.
England, S.A., Granata, K.P., 2007. The influence of gait speed on local dynamic stability of walking. Gait & Posture 25 (2), 172–178.
Granata, K.P., Lockhart, T.E., 2008. Dynamic stability differences in fall-prone and healthy adults. Journal of Electromyography and Kinesiology 18 (2), 172–178.
Hausdorff, J.M., Rios, D.A., Edelberg, H.K., 2001. Gait variability and fall risk in community-living older adults: a 1-year prospective study. Archives of Physical Medicine and Rehabilitation 82 (8), 1050–1056.
Holmes, P., Full, R.J., Koditschek, D., Guckenheimer, J., 2006. The dynamics of legged locomotion: models, analyses, and challenges. SIAM Review 48 (2), 207–304.
Hurmuzlu, Y., Basdogan, C., 1994. On the measurement of dynamic stability of human locomotion. Transactions of the ASME 116 (1), 30–36.
Hurmuzlu, Y., Basdogan, C., Stoianovici, D., 1996. Kinematics and dynamic stability of the locomotion of post-polio patients. ASME Journal of Biomechanical Engineering 118 (3), 405–411.
Ijspeert, A.J., 2008. Central pattern generators for locomotion control in animals and robots: a review. Neural Networks 21 (4), 642–653.
Kang, H.G., Dingwell, J.B., 2007. Speed controlled comparison of gait variability in healthy young and older adults. In: Proceedings of the XXI ISB Congress, Taipei, Taiwan.
Kang, H.G., Dingwell, J.B., 2008. Effects of walking speed, strength and range of motion on gait stability in healthy older adults. Journal of Biomechanics 41 (14), 2899–2905.
Kuo, A.D., 1999. Stabilization of lateral motion in passive dynamic walking. The International Journal of Robotics Research 18 (9), 917–930.
Lord, S.R., Castell, S., Corcoran, J., Dayhew, J., Matters, B., Shan, A., Williams, P., 2003. The effect of group exercise on physical functioning and falls in frail older people living in retirement villages: a randomized, controlled trial. Journal of the American Geriatrics Society 51 (12), 1685–1692.
Maki, B.E., 1997. Gait changes in older adults: predictors of falls or indicators of fear? Journal of the American Geriatric Society 45 (3), 313–320.
McAndrew, P.M., Dingwell, J.B., Wilken, J.M., 2010. Walking variability during continuous pseudo-random oscillations of the support surface and visual field. Journal of Biomechanics 43 (8), 1470–1475.
McAndrew, P.M., Wilken, J.M., Dingwell, J.B., 2011. Dynamic stability of human walking in visually and mechanically destabilizing environments. Journal of Biomechanics 44 (4), 644–649.
Moe-Nilssen, R., Helbostad, J.L., 2005. Interstride trunk acceleration variability but not step width variability can differentiate between fit and frail older adults. Gait & Posture 21 (2), 164–170.
O'Connor, S.M., Kuo, A.D., 2009. Direction-dependent control of balance during walking and standing. Journal of Neurophysiology 102 (3), 1411–1419.
Orendurff, M.S., Schoen, J.A., Bernatz, G.C., Segal, A.D., Glenn, K., 2008. How humans walk: bout duration, steps per bout, and rest duration. Journal of Rehabilitation Research and Development 45 (7), 1077–1090.
Owings, T.M., Grabiner, M.D., 2004. Step width variability, but not step length variability or step time variability, discriminates gait of healthy young and older adults during treadmill locomotion. Journal of Biomechanics 37 (6), 935–938.
Pinto, C., Golubitsky, M., 2006. Central pattern generators for bipedal locomotion. Journal of Mathematical Biology 53 (3), 474–489.
Roos, P.E., Dingwell, J.B., 2010. Influence of simulated neuromuscular noise on movement variability and fall risk in a 3d dynamic walking model. Journal of Biomechanics 43 (15), 2929–2935.
Shaffer, S.W., Harrison, A.L., 2007. Ageing of the somatosensory system: a translative perspective. Physical Therapy 87 (2), 193–207.
Skelton, D.A., Beyer, N., 2003. Exercise and injury prevention in older people. Scandinavian Journal of Medicine & Science in Sports 13 (1), 77–85.
Su, J.L., Dingwell, J.B., 2007. Dynamic stability of passive dynamic walking on an irregular surface. Journal of Biomechanical Engineering-Transactions of the ASME 129 (6), 802–810.
Tinetti, M.E., Speechley, M., Ginter, S.F., 1988. Risk factors for falls among elderly persons living in the community. The New England Journal of Medicine 319 (26), 1701–1707.
Todorov, E., 2004. Optimality principles in sensorimotor control. Nature Neuroscience 7 (9), 907–915.