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Influence of neuromuscular noise and walking speed on fall risk and dynamic stability in a 3D dynamic walking model

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ABSTRACT

Older adults and those with increased fall risk tend to walk slower. They may do this voluntarily to reduce their fall risk. However, both slower and faster walking speeds can predict increased risk of different types of falls. The mechanisms that contribute to fall risk across speeds are not well known. Faster walking requires greater forward propulsion, generated by larger muscle forces. However, greater muscle activation induces increased signal-dependent neuromuscular noise. These speed-related increases in neuromuscular noise may contribute to the increased fall risk observed at faster walking speeds. Using a 3D dynamic walking model, we systematically varied walking speed without and with physiologically-appropriate neuromuscular noise. We quantified how *actual fall risk* changed with gait speed, how neuromuscular noise affected speed-related changes in fall risk, and how well orbital and local dynamic stability measures predicted changes in fall risk across speeds. When we included physiologically-appropriate noise to the 'push-off' force in our model, fall risk increased with increasing walking speed. Changes in kinematic variability, orbital, and local dynamic stability did not predict these speed-related changes in fall risk. Thus, the increased neuromuscular variability that results from increased signal-dependent noise that is necessitated by the greater muscular force requirements of faster walking may contribute to the increased fall risk observed at faster walking speeds. The lower fall risk observed at slower speeds supports experimental evidence that slowing down can be an effective strategy to reduce fall risk. This may help explain the slower walking speeds observed in older adults and others.

1. Introduction

The risk of falling while walking increases significantly with age (Tinetti et al., 1988). People with high fall risk typically slow their walking speed (Maki, 1997; Lazaro et al., 2011), adopting more 'cautious' gait (Kesler et al., 2005; Hallemans et al., 2010; Tersteeg et al., 2012). There is much evidence to suggest people slow down as a compensatory strategy to reduce fall risk (Maki, 1997; Rogers et al., 2005; Tsai and Lin, 2013). Somewhat counter-intuitively then, slower speeds sometimes predict increased fall risk (Bergland et al., 2003; Taylor et al., 2013). However, slow speeds may not *cause* falls. Slow speeds might instead reflect fear of falling (Maki, 1997) and/or specific impairments (Kerrigan et al., 1998) that instead cause falls.

Indeed, in a 4-year prospective study of 8,378 community-dwelling women that accounted for multiple clinical screening factors, *faster* preferred walking speeds actually predicted increased fall risk (Faulkner et al., 2009). Slower walking speeds lead to more *indoor* falls (Quach et al., 2011; Kelsey et al., 2012). However, faster speeds lead to more *outdoor* falls (Bergland et al., 2003; Quach et al., 2011; Kelsey et al., 2012), more multiple falls (Callisaya et al., 2012), and more serious injuries from indoor falls (Kelsey et al., 2012). Likewise, faster walking speeds increase the risks of both tripping (Pavol et al., 1999, 2001; van den Bogert et al., 2002) and slipping (Cham and Redfern, 2002; Troy et al., 2008) and increase the effort required to recover from such perturbations (Roos et al., 2010).

At both faster and slower speeds, gait variability also increases (Dingwell and Marin, 2006; Kang and Dingwell, 2008; Callisaya et al., 2010) and increased variability may also predict increased fall risk (Maki, 1997; Hausdorff et al., 2001; Verghese et al., 2009). This also presents a paradox: if walking slower leads to greater variability and increased variability indicates greater fall risk, then slowing down would be antithetical to the goal of being more 'cautious'. Thus, a better understanding of how fall risk, gait speed, and dynamic stability are related is still needed.

In humans, forward propulsion is generated by muscles. Faster walking requires greater propulsion, which requires larger muscle forces (Neptune et al., 2008). However, greater muscle activation causes increased signal-dependent neuromuscular noise (Harris

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and Wolpert, 1998; Faisal et al., 2008; Dideriksen et al., 2012). Indeed, the variability of muscle activations (EMG) in humans does increase at faster walking speeds (Kang and Dingwell, 2009). Likewise, increased neuromuscular noise applied at a single walking speed increased actual fall risk in our dynamic walking model (Roos and Dingwell, 2011). This suggests speed-related increases in neuromuscular noise may contribute to increased fall risk at faster walking speeds.

Investigating true fall risk experimentally requires longitudinal follow-up studies. Stability measures may provide a plausible alternative. Local and orbital stability reflect a system's responses to infinitesimally small perturbations (Dingwell and Cusumano, 2000), while global stability relates to the largest possible perturbations a system can tolerate. In human walking, a fall constitutes a failure of global stability. Nonlinear local instability measures like Floquet multipliers and local divergence exponents can distinguish younger from older adults (Kang and Dingwell, 2008) and fallers from non-fallers (Granata and Lockhart, 2008; Hamacher et al., 2011; Toebes et al., 2012). It therefore seems plausible that increased global instability (i.e., actual falls) might be preceded by increased local instability (Roos and Dingwell, 2011).

Multiple independent studies found that slower walking was more stable than faster walking (Dingwell and Marin, 2006; Dingwell et al., 2007; England and Granata, 2007; Kang and Dingwell, 2008; Manor et al., 2008, 2009). Conversely, Bruijn et al. (2009a) found that the relationship between walking speed and local divergence exponents depended on the plane of the movement analyzed and was therefore more equivocal. Hobbelen and Wisse (2007) found their simulation model's robustness to perturbations decreased at slower speeds. In Hak et al. (2012), healthy subjects did not voluntarily slow down when subjected to medio-lateral perturbations. However, for medio-lateral perturbations, slowing down is likely not the most advantageous strategy and in a follow-up study using the same perturbations, subjects did slow down (Hak et al., 2013). The exact relationships between gait speed, orbital and local stability measures and *actual fall risk* (i.e. global stability) therefore need to be more thoroughly examined.

Here, we used a 3D simulation model to calculate *actual fall risk* without having to induce falls in humans. We systematically varied walking speed, both without and with added physiologically-appropriate signal-dependent neuromuscular noise (Faisal et al., 2008) to assess how these manipulations affected fall risk. We determined how fall risk changed with gait speed, how neuromuscular noise affected speed-related changes in fall risk, and if orbital or local stability measures would predict changes in fall risk across speeds. We hypothesized that fall risk would increase with gait speed, as seen in humans (Callisaya et al., 2012; Kelsey et al., 2012), that neuromuscular noise would contribute to speed-related increases in fall risk, and that fall risk would be related to changes in local (England and Granata, 2007; Kang and Dingwell, 2008) but not orbital stability (Roos and Dingwell, 2011).

2. Methods

The 3D dynamic walking model used here (Fig. 1) was developed by Kuo (1999). This model was adapted in Matlab (Mathworks, R2008a) as in (Roos and Dingwell, 2010, 2011). The adaptations made to the original model by Kuo (1999) were to 1) simulate multiple consecutive steps, 2) to incorporate simulated neuromuscular noise applied to the step controller, and 3) to simulate neuromuscular noise applied to the 'push-off' force.

The model consisted of a pelvis segment connected to two leg segments with semi-circular feet (Fig. 1). The model had six primary state variables; θ_{St}: the sagittal plane angle of the stance leg with the ground, θ_{Sw}: the sagittal plane angle of the swing leg with the ground, θ_{Roll}: the frontal plane angle of the stance leg with the ground, and their derivatives. This model was laterally unstable due to θ_{Roll} (Kuo, 1999). Lateral stability could only be maintained by adding a lateral step controller. This controller instantly adjusted the splay angle (φ: the angle at which the legs were attached to the pelvis) at each instant of ground contact. Steps were adjusted so the state variables were returned as close as possible to their 'noise free' limit cycle solutions.

Forward propulsion was provided by gravity, to simulate walking down a gentle slope. Instead of modeling the slope itself, gravity was applied at an angle to the model (Kuo, 1999). This angle was varied from 2% to 6% in 1% increments to make the model walk across a range of speeds (Fig. 2). Initial conditions were optimized separately for each speed. Importantly, walking down a moderate slope is *identically equivalent* to walking over level ground and applying an impulsive 'push-off' force to the trailing foot at each step (Kuo, 2002; Su and Dingwell, 2007). Similarly, Hobbelen and Wisse (2008) imposed several different means of achieving faster speeds in their model and found that the speed-related changes in their model's walking stability were the same, regardless of how those changes in speed were accomplished.

First, we generated 100 simulations for each walking speed with noise applied only to the lateral step controller ('controller noise' simulations). This lateral noise induced mediolateral (i.e., step width) variability similar to that which is believed to be important for balance control in humans (Bauby and Kuo, 2000; Owings and Grabiner, 2004). Neuromuscular noise, similar to that present in humans (Harris and Wolpert, 1998), was simulated by applying small random perturbations to the lateral step controller. This noise was applied instantaneously, as the lateral step controller made instantaneous adjustments to ϕ. Across multiple steps, sequential perturbations were chosen as uniformly distributed random numbers with maximum amplitude $\pm j_{noise} = 6 \times 10^{-5}$ (in dimensionless units). To generate signal-

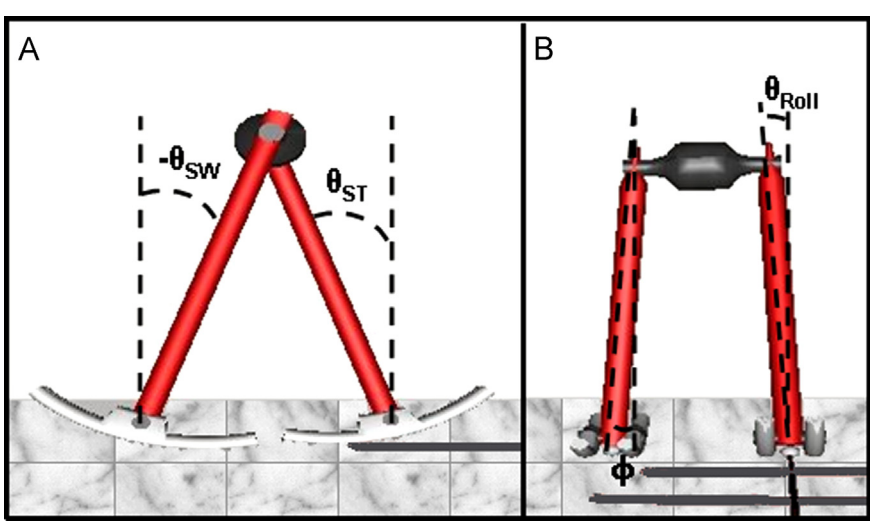

Fig. 1. Schematic representation of the 3D dynamic walking model. A) Side view showing the angles of the swing leg (θ_{Sw}) and stance leg (θ_{St}). B) Frontal view showing the leg splay angle (φ) and lateral roll angle (θ_{Roll}). All other variables in the model were non-dimensionalized as in Kuo (1999). All lengths were normalized to the machine's leg length, *l*. All masses were normalized to the machine's total mass, *M*. Times were normalized by the reciprocal of the machine's characteristic frequency, $\sqrt{l/g}$.

dependent noise (i.e., noise whose variance increases proportional to control signal magnitude, (Harris and Wolpert, 1998)), this amplitude was multiplied by the change in splay angle relative to the previous step.

Then, to determine if neuromuscular noise might contribute to speed-related changes in fall risk, we generated a second set of 100 simulations where we also applied 'push-off' noise to the model. We imposed this noise by adding random variations at each step to the angle of the gravity vector. This was exactly equivalent to adding noise to the impulsive 'push-off' force that would be applied to a model that walked over level ground (Kuo, 2002; Gates et al., 2007). Sequential perturbations were again chosen as uniformly distributed random numbers, here with maximum amplitude $\pm j_{push\text{-}off} = 9 \times 10^{-4}$ (in dimensionless units). These were again made signal-dependent by multiplying this noise by the angle of the gravity vector imposed at that step (i.e., equivalent to multiplying by the model's walking speed). These simulations also included the same 'controller noise' as the previous simulations, as described above. These 'push-off noise' simulations thus simulated, in a physiologically realistic "signal-dependent" way (Harris and Wolpert, 1998), the neuromotor noise observed during the push-off phase of human walking (Neptune et al., 2008; Kang and Dingwell, 2009).

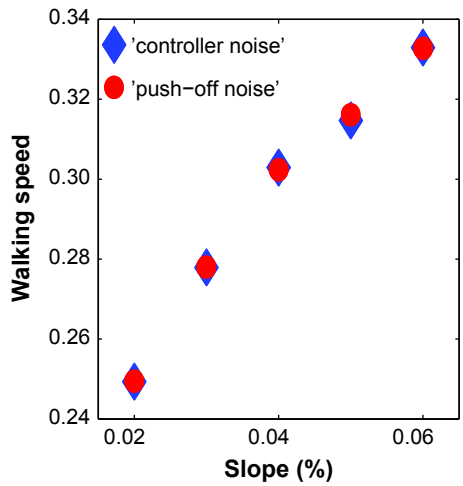

Fig. 2. The non-dimensionalized walking speeds that corresponded to each of the slopes the model walked down. Blue diamonds indicate 'controller noise' trials. Red circles indicate 'push-off noise' trials. In all cases, changes in slope directly corresponded to changes in walking speed. Speeds were non-dimensionalized to $\tilde{v} = v/\sqrt{gl}$ as in Kuo (1999). For a leg length of 1 m, the non-dimensionalized speed of $\tilde{v} = 0.24$ corresponds to $v = \sim 0.752$ m/s and $\tilde{v} = 0.34$ corresponds to $v = \sim 1.065$ m/s.

To calculate fall risk for each walking speed, 100 walking trials were simulated in which each simulation ran either until the model fell over or until it completed 125 consecutive walking steps (since humans take fewer than 100 steps more than 90% of the time during daily life (Orendurff et al., 2008)). Fall risk was calculated as the percentage of trials where the model fell ($\%_{Fall}$). $\%_{Fall}$ was therefore a direct measure of fall risk as it directly quantifies how frequently the model fell under each condition. We then also calculated the number of steps taken prior to falling (*STF*), as we did previously (Roos and Dingwell, 2010, 2011).

Kinematic state variability ($MSD(\theta_{Tot})$) was computed by calculating the Euclidean norm of a vector that contained the mean standard deviations of all state variables (Roos and Dingwell, 2010). Variability in step length, step width and step time were also analyzed. However, these showed the same trends as $MSD(\theta_{Tot})$. Therefore, results are presented only for $MSD(\theta_{Tot})$.

For each simulation, orbital dynamic stability was calculated by estimating the maximum Floquet Multiplier (*maxFM*) as in (Hurmuzlu and Basdogan, 1994; Su and Dingwell, 2007). *MaxFM* was calculated using the model's six state variables that were normalized for each step within the stride (Su and Dingwell, 2007). Walking was orbitally stable when $maxFM < 1$.

Local instability was estimated by calculating short-term local divergence exponents (λ_S^*), as in (Roos and Dingwell, 2011). These calculations used the continuous-time state variable data to compute λ_S^*. Walking was locally unstable when $\lambda_S^* > 0$. Larger positive λ_S^* indicates greater local instability, or greater sensitivity to small perturbations (Dingwell and Cusumano, 2000).

Both *maxFM* and λ_S^* were calculated over the first 50 steps of the first 20 trials of each j_{noise} for which the model walked at least 55 steps. This number of steps was chosen to be able to calculate *maxFM* and λ_S^* for trials where the model fell over

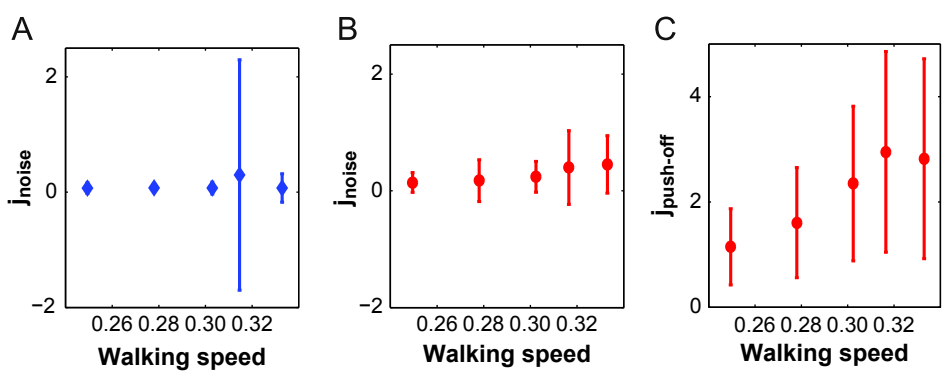

Fig. 3. A) Mean maximum 'controller noise' (j_{noise}) amplitude ($\times 10^{-8}$) vs. non-dimensional walking speed ($\tilde{v}$) for the 'controller noise' simulation trials (blue diamonds). B) Mean maximum 'controller noise' (j_{noise}) amplitude ($\times 10^{-8}$) vs. non-dimensional speed for the 'push-off noise' simulation trials (red circles). C) Mean maximum 'push-off noise' ($j_{push\text{-}off}$) amplitude ($\times 10^{-5}$) vs. non-dimensional speed for the 'push-off noise' trials (red circles). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

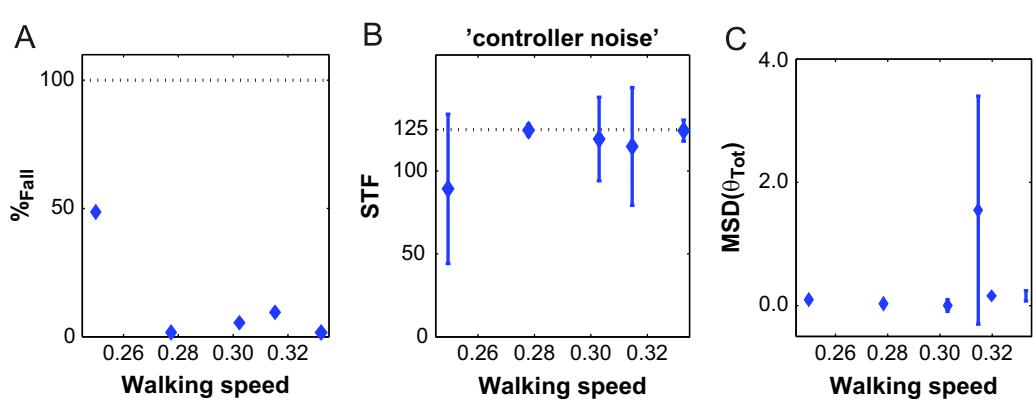

Fig. 4. 'Controller Noise' Simulation Results. A) fall risk ($\%_{Fall}$), B) steps to fall (STF), and C) gait variability ($MSD(\theta_{Tot})$) ($\times 10^{-3}$) vs. non-dimensional walking speed. At the slowest speed, $\%_{Fall}$ was the highest and *STF* was lowest. Conversely, $MSD(\theta_{Tot})$ was significantly increased only at the non-dimensional speed of $\tilde{v} = 0.31$ ($p = 6 \times 10^{-8}$).

before completing 125 steps. Because the values of *maxFM* and λ_S^* may depend on the number of strides used in the calculations (Kang and Dingwell, 2006; Bruijn et al., 2009b), we used the same number of strides for all calculations and comparisons across conditions (Roos and Dingwell 2011).

Each dependent measure was computed for each simulated trial for each walking speed. Significant differences in *STF*, $MSD(\theta_{Tot})$, λ_S^* and *maxFM* across walking speeds were analyzed with one-way ANOVA and Bonferroni posthoc tests. All statistical analyses were performed using SPSS (Version 18.0, release 18.0.2).

3. Results

The mean maximum amplitude of 'controller noise' in the 'controller noise' simulations was increased at the speed of 0.31, but otherwise changed little with gait speed (Fig. 3A). Conversely, for the 'push-off noise' simulations, the mean maximum amplitude of 'controller noise' increased with walking speed (Fig. 3B). The mean maximum amplitude of 'push-off noise' also increased with walking speed and had the highest amplitude at the speed of 0.31 (Fig. 3C). Unlike the 'controller noise' simulations, this increased noise amplitude at faster speeds in the 'push-off noise' simulations was consistent with both physiological principles (Harris and Wolpert, 1998; Neptune et al., 2008) and experimental findings (Kang and Dingwell, 2009).

For the 'controller noise' simulations, fall risk ($\%_{Fall}$) increased at the slowest speed (48%) but remained below 10% for all faster speeds (Fig. 4A). Steps to fall (*STF*) was lowest at the slowest speed (*STF*=89) and higher for all faster walking speeds (STF∈[114, 125]; Fig. 4B). Unlike $\%_{Fall}$, overall kinematic variability ($MSD(\theta_{Tot})$) was significantly greater only at the speed of 0.31 ($p=6\times10^{-8}$, Fig. 4C).

Also for this model, maximum Floquet multipliers (*maxFM*) were only significantly different between the fastest two speeds ($p=0.007$) and otherwise did not change with speed (Fig. 5A). Short-term local divergence exponents (λ_S^*) were significantly decreased (indicating less locally unstable) for the walking speed of 0.31 ($p=4\times10^{-15}$, Fig. 5B).

The 'push-off noise' simulations conversely exhibited increased $\%_{Fall}$ with increasing walking speed, with the model always falling over at the fastest speed (Fig. 6A), consistent with epidemiological evidence in humans (Faulkner et al., 2009). Not surprisingly, *STF* showed an inversed trend with walking speed, with the fewest *STF* for the fastest speed (Fig. 6B). Likewise, $MSD(\theta_{Tot})$ also significantly increased at the fastest walking speeds (Fig. 6C), but did not increase monotonically with $\%_{Fall}$.

For these simulations, maximum Floquet multipliers (*maxFM*) significanlty decreased (i.e., orbitally more stable) at walking speed 0.31 ($p=5\times10^{-6}$), but were not significantly different for any other speeds (Fig. 7A). λ_S^* significanlty increased (i.e., locally more unstable) at walking speed 0.31 ($p=3\times10^{-12}$), but were not significantly different for any other speeds (Fig. 7B).

Neither *MaxFM* nor λ_S^* changed significantly with walking speed. Fall risk ($\%_{Fall}$) did not consistently increase or decrease with gait variability ($MSD(\theta_{Tot})$), *maxFM*, or λ_S^* (Fig. 8).

4. Discussion

It is essential to identify what determines increased fall risk in the elderly to develop effective interventions. It has been widely

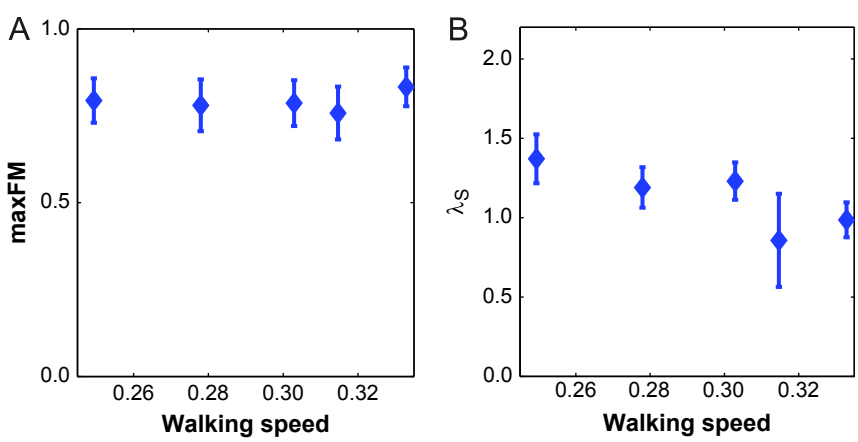

Fig. 5. 'Controller Noise' Simulation Results. A) Maximum Floquet Multipliers (*maxFM*) vs. walking speed. M*axFM* was only significantly different between non-dimensional walking speeds $\tilde{v}=0.31$ and $\tilde{v}=0.33$ ($p=0.007$) and otherwise did not change with speed. B) Short-term local divergence exponents (λ_S^*) vs. non-dimensional walking speed. λ_S^* was significantly decreased (indicating less locally unstable) for the non-dimensional walking speed of $\tilde{v}=0.31$ ($p=4\times10^{-15}$).

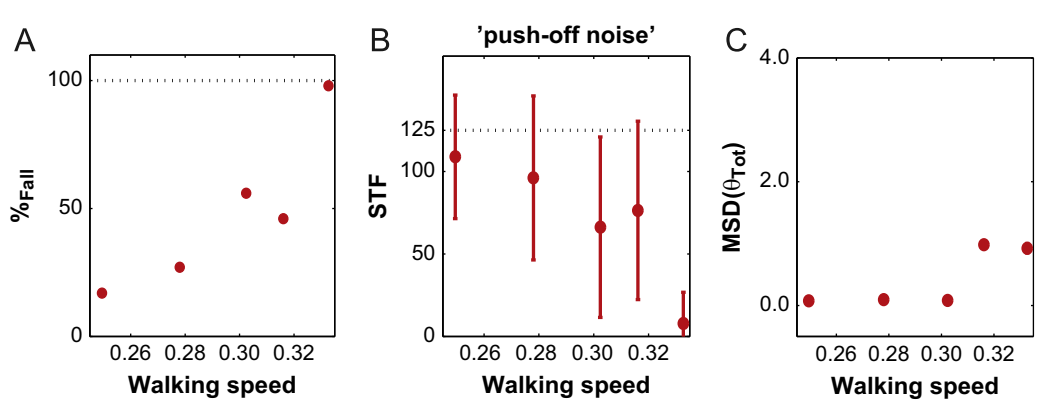

Fig. 6. 'Push-off noise' Simulation Results. A) fall risk ($\%_{Fall}$), B) steps to fall (STF), and C) gait variability ($MSD(\theta_{Tot})$) ($\times10^{-3}$) vs. non-dimensional walking speed. With increasing walking speed, $\%_{Fall}$ increased and *STF* decreased. $MSD(\theta_{Tot})$ was significantly increased at the two fastest walking speeds, $\tilde{v}=0.31$ and $\tilde{v}=0.33$.

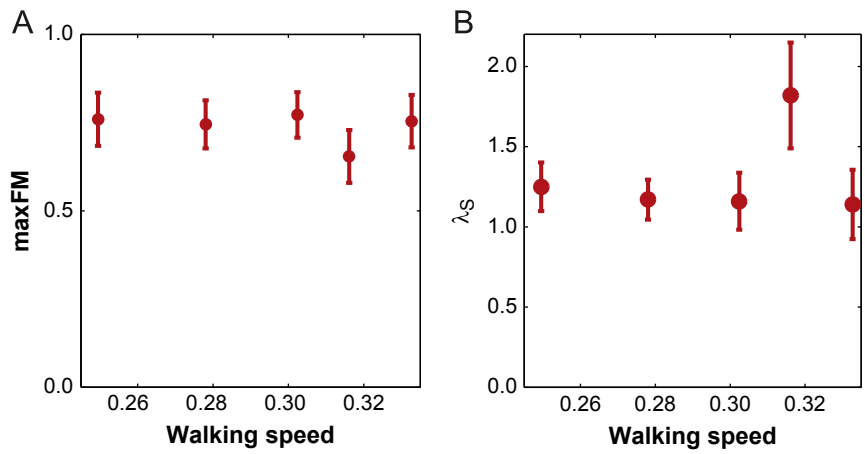

Fig. 7. 'Push-off noise' Simulation Results. A) Maximum Floquet Multipliers (*maxFM*) vs. non-dimensional walking speed. *MaxFM* significanlty decreased (more stable) at walking speed $\tilde{v}=0.31$ ($p=5\times10^{-6}$), but was not significantly different for any other speeds. B) Short-term local divergence exponents (λ_S^*) vs. non-dimensional walking speed. λ_S^* significanlty increased (more unstable) at walking speed $\tilde{v}=0.31$ ($p=3\times10^{-12}$), but was not significantly different for any other speed.

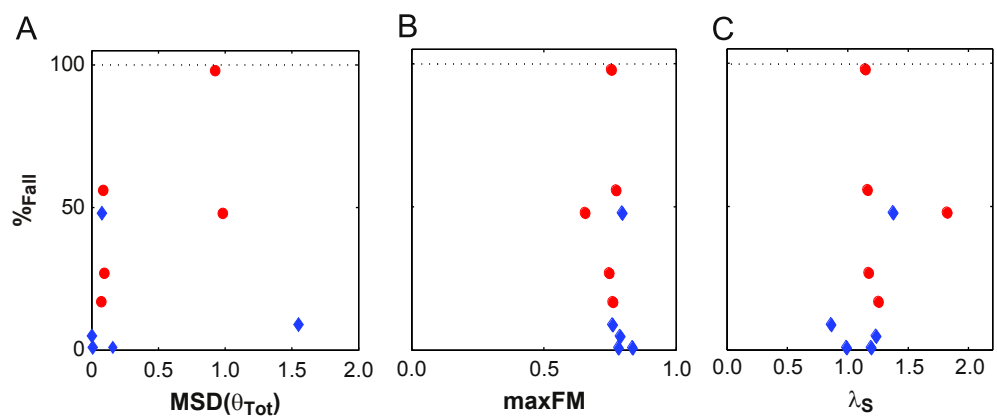

Fig. 8. Fall risk ($\%_{Fall}$) as predicted by (A) gait variability, $MSD(\theta_{Tot})$ ($\times10^{-3}$), (B) maximum Floquet Multipliers (*maxFM*), and (C) short-term local divergence exponents (λ_S^*). As in previous figures, blue diamonds indicate 'controller noise' simulation trials. Red circles indicate 'push-off noise' simulation trials. All variables, $MSD(\theta_{Tot})$, *maxFM*, and λ_S^*, were poor predictors of fall risk for this model, as $\%_{Fall}$ varied erratically with changes in each of these variables. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

suggested that elderly and others with high fall risk slow down (Maki, 1997; Dingwell et al., 2000; Lazaro et al., 2011) to be more 'cautious' (Kesler et al., 2005; Hallemans et al., 2010; Tersteeg et al., 2012; Tsai and Lin, 2013). Nevertheless, slow gait speeds predict *in*creased fall risk in general (Bergland et al., 2003; Kelsey et al., 2012; Taylor et al., 2013). However, more detailed epidemiological (Faulkner et al., 2009; Callisaya et al., 2012; Kelsey et al., 2012) and biomechanical (Pavol et al., 1999, 2001; van den Bogert et al., 2002; Troy et al., 2008) studies suggest faster speeds are in fact more dangerous. Here, we used a 3D dynamic walking model to investigate the biomechanical and neuromuscular factors that might contribute to the increased fall risk observed at faster walking speeds. Our model replicated features of human walking most relevant to adressing this question. These included cyclical behaviour, signal-dependent neuromuscular noise (Harris and Wolpert, 1998; Neptune et al., 2008), and active lateral balance control (Bauby and Kuo, 2000; Dean et al., 2007).

In the simulations where we applied only 'controller noise' to our walking model, fall risk increased only when walking slowly (Fig. 4A). However, the magnitude of noise applied to this model did not vary systematically with changes in walking speed (Fig. 3A). This was not consistent with the well-established principal that neuromuscular noise is 'signal-dependent' (Harris and Wolpert, 1998), which induces increased EMG variability at faster walking speeds (Kang and Dingwell, 2009) due to increased muscle force requirements (Neptune et al., 2008). Our first set of simulations did *not* adequately reflect these basic physiological findings.

When biologically realistic 'push-off noise' was added to the model, the amplitude of this noise did increase with increasing walking speed (Fig. 3C). $\%_{Fall}$ then also increased with walking speed (Fig. 6A). This supported both our first hypothesis that fall risk would increase with speed and our second hypothesis that signal-dependent neuromuscular noise would contribute to this increased fall risk. The increasing push-off noise (Fig. 3C) also created a need for increased lateral step corrections (Fig. 3B), at faster walking speeds. However, the speed-related trends in j_{noise}, $j_{push\text{-}off}$, and $\%_{Fall}$ did differ, suggesting that the increased fall risk was likely caused by both the increased speed itself and the increased noise amplitudes due to increased speed.

These findings extend our previous work, where we showed that increasing the noise to the system through external perturbations also directly increased the risk of falling in this model (Roos and Dingwell, 2010). These results thus demonstrate that the increased neuromuscular variability (Kang and Dingwell, 2009) that results from increased signal-dependent noise (Faisal et al., 2008) necessitated by the larger muscle forces of faster walking (Neptune et al., 2008) may contribute to the increased fall risk that is observed with faster walking speeds.

These findings are supported by epidemiological (Bergland et al., 2003; Faulkner et al., 2009; Quach et al., 2011; Callisaya

et al., 2012; Kelsey et al., 2012), experimental (Pavol et al., 1999, 2001; Cham and Redfern, 2002; Troy et al., 2008) and modeling (van den Bogert et al., 2002) results, all showing that faster walking speeds increase fall risk. These findings are also consistent with experimental results by our group (Dingwell et al., 2000, 2001; Dingwell and Marin, 2006; Dingwell et al., 2007; Kang and Dingwell, 2008) and others (England and Granata, 2007; Manor et al., 2008, 2009) showing that humans are more stable when they walk slower than when they walk faster.

Some have recently questioned whether slower speeds are really "more stable" (Bruijn et al., 2009a; Hak et al., 2012). Bruijn et al. (2009a) found local dynamic stability measures varied inconsistently across walking speeds. When Hak et al. (2012) applied *medio-lateral* perturbations, subjects increased step width, but did not voluntarily slow down to compensate for those perturbations. However, Hak et al. did not systematically vary walking speed and for medio-lateral perturbations, increasing step width seems a naturally more logical strategy than slowing down anyway. Moreover, in a subsequent study, subjects *did* slow down in response to the same perturbations (Hak et al., 2013). Most importantly, none of these studies induced actual falls, so we cannot know for certain how these observed changes may or may not have related to actual fall risk. Here, because we directly quantified *actual fall risk itself* (i.e., $\%_{Fall}$), our results show that slowing down *is* a relevant potential strategy to reduce fall risk (Fig. 6A). However, slowing down has to be understood as only *one of several possible strategies* humans might adopt (separately, or in combination) to mitigate fall risk in different contexts. Which specific strategy, or set of strategies, is adopted will depend on the physical and physiological capabilities of each individual and on the type(s) of perturbations they anticipate encountering.

Our simulation results also differ slightly from another simulation study (Hobbelen and Wisse, 2008) that implemented a more complex model of a robot walking. However, their model walked across a much slower range of speeds (non-dimensional speeds from ~0.12 to ~0.27) than our model (Fig. 2). Although their model initially became more robust to perturbations as speed was increased from the slowest speeds up to speeds of ~0.22, their disturbance rejection measure then sharply declined at speeds exceeding ~0.22 to ~0.24 (their Fig. 9), which corresponds to the beginning of the range of speeds we tested here (our Fig. 2). Thus, our findings actually largely agree with those of Hobbelen and Wisse (2008).

Neither set of simulations exhibited an increase in gait variability at slower walking speeds (Figs. 4 and 6C), as typically seen in humans (Dingwell and Marin, 2006; Kang and Dingwell, 2008). This is likely because physiological mechanisms other than signal-dependent noise contribute to increased variability of *slow* movements. These could include differences in motor planning (Doeringer and Hogan, 1998; Reynolds and Day, 2005), increased need for on-line corrective responses driven by visual and/or somatosensory feedback (Russell and Sternad, 2001; Reynolds and Day, 2005), and/or changes in the number and/or synchronization of active motor units within muscles (Yao et al., 2000; Celik and O'Malley, 2011). Future work incorporating these types of mechanisms may help explain why slow walking speeds also predict increased fall risk in some contexts (Bergland et al., 2003; Kelsey et al., 2012; Taylor et al., 2013).

Our third hypothesis, that fall risk would be related to changes in local but not orbital stability across varying walking speeds was not supported in our model (Fig. 8). The inconsistent changes in *maxFM* and λ_S^* were similar to other studies showing similarly inconsistent results in both humans (Bruijn et al., 2009a) and models (Hobbelen and Wisse, 2007; Bruijn et al., 2011). However, these results contrast with findings that these measures are relevant for predicting fall risk in humans (Hurmuzlu et al., 1996; Kang and Dingwell, 2008; Granata and Lockhart, 2008; Hamacher et al., 2011; Roos and Dingwell, 2010). This could be because the range of allowable speeds in our dynamic walking model was less than in humans, due to the inherent instability of the model. The model may not have been able to achieve a wide enough range of speed to exhibit significant changes in gait variability or orbital or local stability. Future work incorporating reflexes and feedback into the model could enable it to achieve faster speeds and possibly more physiological responses to loss of balance.

Conflict of interest statement

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

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