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Walking variability during continuous pseudorandom oscillations of the support surface and visual field

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Abstract

Walking on uneven surfaces or while undergoing perturbations has been associated with increased gait variability in both modeling and human studies. Previous gait research involving continuous perturbations has focused on sinusoidal oscillations, which can result in individuals predicting the perturbation and/or entraining to it. Therefore, we examined the effects of continuous, pseudo-random support surface and visual field oscillations on 12 healthy, young participants. Participants walked in a virtual reality environment under no perturbation (NOP), anterior-posterior (AP) walking surface and visual oscillation and mediolateral (ML) walking surface and visual oscillation conditions. Participants exhibited shorter ($p \leq 0.005$), wider ($p < 0.001$) and faster ($p < 0.001$) steps relative to NOP during ML perturbations and shorter ($p \leq 0.005$) and wider ($p < 0.001$) steps during AP perturbations. Step length variability and step width variability both increased relative to NOP during all perturbation conditions ($p < 0.001$) but exhibited greater increases for the ML perturbations ($p < 0.001$). Participants exhibited greater trunk position variability and trunk velocity variability in the ML direction than in the AP direction during ML perturbations relative to NOP ($p < 0.001$). Significantly greater variability in the ML direction indicates that to maintain stability, participants needed to exert greater control in the ML direction. This observation is consistent with prior modeling predictions. The large and consistent responses observed during ML visual and walking surface perturbations suggest potential for application during gait training and patient assessment.

Keywords

Variability; walking; optic flow; walking surface; perturbation

INTRODUCTION

In daily life, people are exposed to many challenges to walking stability including cracks in the sidewalk, slippery surfaces, uneven terrain, etc. These situations sometimes lead to unintentional falls, which are the leading cause of non-fatal injury in the US for those aged 25

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest associated with this work.

and older (www.cdc.gov). More consistently, however, these situations lead to increased variability in various gait characteristics. This increased gait variability might reflect an increased risk of falling (Maki 1997; Demott et al. 2007). Alternatively, however, increased variability might instead result directly from the perturbations themselves and/or reflect appropriate responses to perturbations. What is needed is a more clear understanding of how different specific types of perturbation environments affect gait and gait variability.

The effects of continuous perturbations on gait have been studied using both visual and physical oscillations. Virtual reality (VR) technology provides a safe environment in which to apply both visual and physical perturbations of repeatable and varying magnitude. Manipulating visual field information such as the complexity of the VR scene, the tilt angle of the visual projection and optical flow can all cause individuals to walk with shorter and wider steps and with increased stride velocity and step width variability (Hollman et al. 2006; Nyberg et al. 2006; Hollman et al. 2007; Lamontagne et al. 2007). Sinusoidally oscillating visual scenes produce anisotropic changes (i.e., changes of different magnitude in different directions) in gait characteristics (Warren et al. 1996; O'Connor and Kuo 2009). However, sinusoidal oscillations might not increase gait variability because individuals can predict them and therefore entrain to them (Warren et al. 1996). No studies have yet examined how continuous, but unpredictable (e.g. pseudo-random) visual field oscillations affect human walking.

In general, physically perturbing individuals by translating the support surface on which they stand results in increased body displacement (Horak et al. 1994; Pyykko et al. 1995; Henry et al. 1998). The effects of continuous, sinusoidally oscillating surface translations on human walking were examined with a static scene and induced increased step width variability (Brady et al. 2009). No studies have yet examined how unpredictable support surface perturbations affect how individuals ambulate in virtual environments with speed appropriate optical flow.

The present study examined the magnitude and direction of changes in gait parameters in response to continuous pseudo-random oscillations of the visual scene and support surface in a virtual environment with speed appropriate optical flow. Our goal was to determine how humans responded to unpredictable (pseudo-random), continuous perturbations. We hypothesized that participants would: 1) exhibit greater variability when ambulating with continuous, small magnitude pseudo-random perturbations than without and 2) exhibit greater increases in variability with ML than with AP perturbations.

METHODS

Twelve healthy young adults (Table 1) participated. Participants were active duty U.S. Service members and were required to have no prohibitive impairments in order to hold this status. In addition, participants were required to have no history of lower extremity injury, surgery or any neurological condition which could affect their gait. This study was approved by the Institutional Review Board at Brooke Army Medical Center, Ft. Sam Houston, TX, and all participants provided written, informed consent prior to participation.

All participants walked in a Computer Assisted Rehabilitation ENvironment (CAREN) system (Motek, Amsterdam, Netherlands; Fig. 1). The CAREN system consists of a 7m-diameter dome with a virtual environment projected 300° around the subject, from 40° below eye level to 60° above eye level on the inside of the dome. In the bottom of the dome is a 2m × 3m instrumented treadmill embedded in a 4m-diameter platform capable of motion with six degrees-of-freedom. Also mounted on the platform, out of the subject's field of view is a metal frame to which the subject's safety harness is attached. A 24-camera motion capture system (VICON Peak, Oxford, UK) is mounted inside the dome.

Participants completed a 5 minute warm-up followed by five 3-min trials of unperturbed walking (NOP) and then five 3-min trials under each of the following test conditions: 1) anterior-posterior platform (APP) and 2) visual field (APV) translations, 3) mediolateral platform (MLP) and 4) visual field (MLV) translations. Rest breaks were provided between conditions. The order of presentation for all perturbation conditions was randomized for each individual and balanced across participants to account for potential learning effects.

During all conditions, participants walked at constant, normalized, speed $v_w = Fr \cdot \sqrt{g \cdot l}$, where Fr is the Froude number, which was 0.40 for this study, $g = 9.8 \text{ m/s}^2$ and l is leg length in meters. During NOP trials, participants walked at constant speed with normal visual optic flow and no support surface perturbations. In the MLP and APP conditions, the platform translated pseudo-randomly in the ML and AP directions, respectively, while the subject progressed through the virtual environment at v_w . During the MLV and APV conditions, pseudo-random oscillations of the visual field were superimposed on top of the constant average flow field velocity v_w , and the platform remained stationary. For the ML perturbation, instead of a purely ML oscillation, there was a small element of rotation such that the center of the path was fixed on the horizon directly in front of the subject but the center of the path “closer” to the subject moved mediolaterally.

The VR scene used in the CAREN system depicted a path through a forest with mountains in the background (Fig. 1). The path was lined on both sides with 2.4 m tall white posts spaced every 3 m to increase motion parallax (Bardy et al. 1996).

Pseudo-random oscillations were pre-programmed from:

$$D(t) = A \cdot [1.0 \cdot \sin(0.16 \cdot 2\pi t) + 0.8 \cdot \sin(0.21 \cdot 2\pi t) + \dots + 1.4 \cdot \sin(0.24 \cdot 2\pi t) + 0.5 \cdot \sin(0.49 \cdot 2\pi t)] \quad (1)$$

where $D(t)$ was the translation distance (m), A was a scaling factor and t was time (sec). The four frequencies (0.16, 0.21, 0.24 and 0.49 Hz) in (1) were selected because they are within the range of frequencies which have been previously studied in human gait (Bardy et al. 1996; Warren et al. 1996; Kay and Warren 2001; O'Connor and Kuo 2009). The platform and visual oscillations were scaled with $A = 0.05$ and $A = 0.50$, respectively.

These values were chosen so that participants would exhibit visibly noticeable responses to all perturbations, but would not walk off the edge of the treadmill or fall during the experiment.

Kinematic data were collected at 60Hz using a 24-camera infrared motion capture system (Vicon Motion Systems, Oxford, UK). Each subject wore 22 reflective markers. Four were placed on the head (right and left sides, front and back) and four markers were placed on each foot (first and fifth metatarsal heads, the lateral heel and the heel). Ten additional markers were placed on the right and left acromium processes, the C7 and T8 vertebrae, sternum, xyphoid process, right and left posterior superior iliac spine (PSIS), and right and left anterior superior iliac spine (ASIS).

All data reduction and analyses were performed using MatLab (Mathworks R2008a). Responses to perturbations were quantified by spectral analysis and kinematic variability. Individual strides were defined by consecutive heel strikes of the ipsilateral foot, as determined from the marker trajectory data.

The C7 vertebral marker was used to quantify the three-dimensional movement of the trunk (Dingwell and Marin, 2006). Therefore, spectral analysis was performed on unfiltered C7 marker position data. Maximum power spectral density (MPSD) at each of the 4 perturbation

frequencies (Eq. 1) was determined and MPSD were compared using two-factor (subject $\times$ condition) analysis of variance (ANOVA).

Step length (SL) was calculated as the distance between the heel markers in the AP direction at heel strike. Step width (SW) was calculated as the lateral distance between the two heel markers at heel strike. Stride time (ST) was the amount of time between consecutive heel strikes of the same foot. Means and standard deviations of SL, SW and ST, respectively, were then calculated for each trial for each condition for each subject.

To quantify overall variability of participants' movement on the treadmill relative to a stationary reference frame, we calculated mean standard deviation (MeanSD) of the C7 marker position for each trial. Because MeanSD of position exhibits nonstationarities (i.e. "drift") associated with the subject's displacement on the treadmill (Dingwell and Marin, 2006), we also calculated MeanSD of C7 marker velocities to quantify *cycle-to-cycle* movement variability. Marker velocity was calculated as the first derivative of the marker position using a 3-point difference formula.

Two-factor (subject $\times$ condition) repeated measures analysis of variance (ANOVA) were used to test for statistically significant differences of gait parameters, gait variability and C7 position and velocity variability between NOP and the four experimental conditions. Tukey post-hoc analyses were then used to assess differences between specific conditions. Results were considered statistically significant if $p < 0.05$. All statistical analyses were performed using SPSS (SPSS Inc., Chicago, IL).

RESULTS

There was an increase in power spectral density (PSD) at the four frequencies of the pseudo-random oscillation signal (Eq. 1) in each of the experimental conditions relative to NOP, indicating that participants' movements were being affected by the perturbations. The greatest increases in PSD corresponded to the perturbation direction (Fig. 2). For example, PSD in the ML direction at $f = 0.16$ Hz was significantly greater for the MLP ($p < 0.001$) and MLV ($p < 0.001$) perturbations than for the APP ($p = 0.810$) and APV ($p = 0.388$) perturbations relative to NOP (Fig 2). All experimental conditions demonstrated greater PSD than NOP in the AP direction for $f = 0.16$ Hz (Fig. 2d). However, APP had greater PSD than MLP ($p < 0.001$) and APV had greater PSD than MLV ($p < 0.001$), indicating that for $f = 0.16$ Hz participants exhibited direction-specific responses to the perturbation inputs.

Participants took significantly shorter ($p \leq 0.005$) and wider ($p < 0.001$; Fig. 3) steps during all perturbation conditions relative to NOP. Participants also took shorter ($p < 0.001$) and wider ($p < 0.001$) steps during ML perturbations than during AP perturbations (Fig. 3). Stride times during AP perturbations were not statistically different from NOP ($p = 0.288$ and 0.444 , for APP and APV, respectively; Fig. 3) whereas stride times were significantly shorter during MLP and MLV relative to NOP ($p < 0.001$).

Participants exhibited greater variability in SL and SW for all perturbation conditions relative to NOP ($p < 0.001$; Fig. 4), and greater SW variability for ML perturbations relative to AP perturbations ($p < 0.001$). SL variability was not significantly different between the APP and MLP conditions ($p = 0.961$) but was significantly greater during MLV relative to APV ($p < 0.001$). ST variability was not statistically different between APP and MLP ($p = 0.115$) or between APP ($p = 0.113$) and MLP ($p = 1.000$) and NOP. ST variability was not statistically different between APV and NOP ($p = 0.176$), but it was statistically greater between MLV and NOP ($p < 0.001$; Fig. 4).

ML perturbations induced statistically greater MeanSD for both position and velocity in the ML direction relative to NOP ($p < 0.001$; Fig. 5A and C). APP and APV position variability in the ML direction was not statistically different from NOP ($p = 1.000$ and $p = 0.998$, respectively). Similarly, velocity variability in the ML direction was not statistically different for APP or APV perturbations relative to NOP ($p = 0.078$ and 0.814 , respectively). The APP and MLP perturbations increased position variability in the APP direction relative to NOP ($p < 0.001$) but APV and MLP perturbations did not ($p = 0.570$ and 0.994 , respectively). Position variability in the AP direction was statistically greater during APP than MLP ($p = 0.001$) but there was no significant difference between the APV and MLV conditions ($p = 0.815$). All experimental conditions induced greater velocity variability in the AP direction compared to NOP ($p < 0.001$). APP perturbations induced significantly greater velocity variability than MLP perturbations ($p < 0.001$), but there was no statistical difference between the APV and MLV conditions ($p = 0.282$).

DISCUSSION

Our results confirmed our hypotheses that individuals would 1) exhibit greater variability when walking during continuous, pseudo-random oscillations of the support surface or visual environment and 2) be more sensitive to ML than to AP perturbations. Responses were anisotropic (Fig. 2). Participants took shorter, wider and faster steps during the ML than the AP and NOP perturbation conditions (Fig. 3). Collectively, our results indicate that individuals' gait was affected by the applied perturbations and that the perturbations affected step variability.

Participants were indeed affected by all four frequencies of the perturbation signal (Fig. 2). The perturbation frequencies exhibited greater spectral power in the same direction in which perturbations were applied. Thus, subject responses were direction-specific. Therefore, to challenge how someone is walking, we should apply perturbations in the direction in which change is desired. Anecdotally, participants perceived that the MLV condition provided the most challenging environment in which to walk followed by the MLP condition, whereas APV was the least challenging. Another surprising finding was that all perturbations significantly affected C7 motion in the AP direction but only ML perturbations significantly affected motion in the ML direction (Fig. 2). Because humans tend to be more unstable in the ML than the AP direction (Bauby and Kuo 2000; Donelan et al. 2004; Dean et al. 2007; O'Connor and Kuo 2009), we anticipated that any perturbation would have affected ML motion, but this was not the case.

On average, participants took shorter, wider and faster steps during all experimental conditions (Fig. 3). More noteworthy, however, is the increase in variability of these parameters relative to NOP (Fig. 4). Participants were unable to consistently respond to these perturbations using their normal (unperturbed) walking strategy. Instead, they had to change their average walking strategies in both the AP and ML directions, although more so in the ML direction.

Increases in gait variability might be caused by either proper or improper responses to perturbations, or possibly a combination of both. Increased variability that is caused by a proper response to perturbations would be "good." Conversely, increased variability that is due to improper responses to perturbations would be "bad," or detrimental. Given the perturbations applied here, observing *no* change in variability would probably have been a "bad" response. Applying the present experimental paradigm in patient populations would require determining what constitutes "good" and "bad" responses for the specific population, or individual, so that we could determine if patients were or were not responding appropriately to the perturbations.

A subject's risk of falling would increase if their motion changed such that it would take a smaller additional perturbation to induce an actual stumble or fall. Participants in the present study tended to lurch, stumble and quicken their steps more during perturbation trials than during NOP trials. This suggests that their actual *risk* of falling was likely increased during these perturbation trials. These observations are consistent with the previous modeling work of Su and Dingwell (2007), which showed that although the biped model never fell, increased variability and short-term local instability predicted the model's increased risk of falling.

Individuals generally responded more to ML perturbations and more in the ML direction regardless of perturbation (AP or ML) applied. Kuo and colleagues showed that a dynamic walking model was passively unstable in the ML direction and that this instability must be actively controlled (Kuo 1999; Bauby and Kuo 2000). The increased movement in the ML direction during walking, particularly during perturbed walking as demonstrated in Figs. 2 and 6 in this study, is consistent with Kuo's results (1999) and imply that participants exerted greater control over their ML motions. Additionally, increases in SW and SW variability during ML perturbations (Fig. 4) are supported by findings that ML foot placement (step width) partially stabilized ML body motion in human walking (Donelan et al. 2004). Although in the present experiments the increases in SW and SW variability in response to the AP perturbations were more subtle, they are also supported by Kuo (1999), which indicated that models had greater responses to perturbations in the ML compared to the AP direction.

One possible reason participants respond more to ML perturbations in VR is the relative velocity affect. This occurs because the AP perturbations are added to v_w in the AP direction, whereas the ML perturbations are added to zero constant velocity in the ML direction. Weber's law indicates that individuals will have more difficulty detecting visual oscillations that are superimposed on v_w (Nakayama 1981). Warren et al. (1996) tested this affect by removing the constant base velocity from visual (sinusoidal) oscillations and found that base velocity influenced AP and ML responses equally. Thus, superimposition of oscillations on a base velocity, as occurred during our AP perturbations, would likely not have influenced our results.

Brady et al (2009) also subjected individuals to sinusoidal lateral oscillations of the treadmill on which they were walking. Those individuals "settled into a comfortable and repeatable walking pattern" within 5 minutes of beginning the trial (Brady et al. 2009). SW magnitudes remained relatively unchanged and participants also timed their steps to occur at approximately the same phase of the applied oscillation. This indicates relatively strong entrainment to these sinusoidal oscillations. In our study, the unpredictable, pseudo-random nature of the applied oscillations prevented any such entrainment. However, in spite of entrainment, Brady et al. (2009) also reported that their participants continued to exhibit increases in both SW and SW variability, similar to our findings (Fig. 3 and Fig. 4). Thus, participants in both studies appear to have exhibited more "cautious" gait characteristics in response to very different types of support surface perturbations.

Our SW variability results are consistent with those of O'Connor and Kuo (2009), where SW variability was also greatest for ML perturbations. However, we also observed greater SL variability for ML perturbations, while O'Connor and Kuo found that SL variability did not change significantly with perturbation direction. However, their study used sinusoidal oscillations. Thus participants likely entrained to the motion of the perturbation signal, which may have decreased changes in variability. Second, the treadmill in our study (2m wide by 3m long) was much larger than that used in their study (1.1m wide by 1.9m long) (Collins et al. 2009; O'Connor and Kuo 2009). This provided our participants a much greater space in which to step without stepping off the treadmill belt. Third, the VR scene in our study was significantly larger and farther away from the subject. A closer, smaller screen may have influenced how

individuals moved anterior-posteriorly, thus affecting their step length and step length variability differently.

Direct comparisons between visual and platform perturbations from this study need to be made with some caution. Equation 1 was scaled to induce noticeable responses to oscillations in the platform and visual field but to not cause our healthy, uninjured adults to fall. To ensure all participants responded to all perturbations, the scaling factor was set one order of magnitude greater for visual perturbations ($A = 0.50$) than for platform perturbations ($A = 0.05$). Therefore, we cannot directly compare the results obtained from these visual and platform perturbations. However, the mere fact that we had to increase the scaling factor one order of magnitude in order to obtain noticeable responses for the visual perturbations demonstrates that, in general participants were more sensitive to the platform perturbations than to the visual perturbations.

Further research is still needed before applying continuous pseudo-random perturbations to clinical gait training programs. Appropriate scaling factors for different types of oscillations for different patient populations (and quite possibly individual patients) need to be determined as do the best methods for affecting AP movements. However, the present study demonstrates that both visual and platform perturbations can successfully challenge and elicit consistent ML responses from individuals, which may be more important for decreasing fall risk during walking.

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Figure 1.
Schematic (a), photograph (b) and scene (c) of the CAREN system (Motek).

Figure 2.

Representative C7 power spectral densities (PSD) in the ML (a) and AP (b) directions in response to the ML perturbations. Arrows indicate the four frequencies comprising the perturbation signal (Eq. 1). (c) Natural log of the power spectral density (Ln PSD) at $f = 0.16$ Hz for C7 movements in the mediolateral (ML) direction for all test conditions. ML C7 movements exhibited the greatest spectral power in response to ML perturbation conditions. (d) Ln PSD at $f = 0.16$ Hz for C7 movements in the anterior-posterior (AP) direction for all test conditions. AP C7 movements exhibited the greatest spectral power in response to AP perturbation conditions. Error bars indicate between-subject $\pm$ SD. Stars (*) indicate statistically significant differences from NOP ($p < 0.05$).

Figure 3.

Mean $\pm$ 1 SD step length (a), step width (b) and stride time (c) for all experimental conditions.

Stars (*) indicate statistically significant differences from NOP ($p < 0.05$).

Figure 4. Within-subject variability of step length (a), step width (b) and stride time (c) for all experimental conditions. Error bars indicate between-subject ± 1 SD. Stars (*) indicate statistically significant differences from NOP ($p < 0.05$).

Figure 5.

MeanSD of C7 marker position in the ML (a) and AP (b) directions for all test conditions. MeanSD of C7 marker velocities in the ML (c) and AP (d) directions in response to all perturbation conditions. Note that although participants were exposed to perturbations in only one direction at a time (i.e. either ML or AP), their responses were quantified in both (ML and AP) directions for all perturbation conditions. Symbols are the same as Fig. 3. Error bars indicate between-subject ± 1 SD. Stars (*) indicate statistically significant differences from NOP ($p < 0.05$).

Table 1

Subject characteristics.

Subject Characteristics (n = 12)	
Age (yrs)	29 ± 7.5
Sex (female/male)	5/7
Height (m)	1.72 ± 0.1
Leg Length (m)	0.92 ± 0.04
Body Mass (kg)	72.0 ± 7.5