Constraints on dynamic stability during forward, backward and lateral locomotion in skilled football players

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Abstract

The aim of this study was to investigate effects of speed and plane of motion on stability during locomotion in skilled football players. Ten male national-level football players participated in this study to run forwards, backwards and in lateral directions on a treadmill at 80%, 100%, and 120% of their preferred running speeds. The coordinate data of passive reflective markers attached to body segments were recorded using motion capture systems. Time series data obtained from the ankle marker were used for further analyses. The largest finite-time Lyapunov exponent (LyE) and maximum Floquet multiplier (maxFM) were adopted to quantify local and orbital dynamic stabilities, respectively. Results showed that speed did not significantly change local and orbital dynamic stabilities in any of running patterns. However, both local and orbital dynamic stability were significantly higher in the secondary plane of progression. Data revealed that in running, unlike walking, stability in the direction perpendicular to the direction of running is significantly higher, implying that less active control is required in the secondary plane of progression. The results of this study could be useful in sports training and rehabilitation programs where development of fundamental exercise programs that challenge both speed and the ability to maintain stability might produce a tangible enhancement of athletic skill level.

Keywords: Running; Sports performance; Motor skills; Nonlinear dynamics; Largest Lyapunov exponent; Maximum Floquet multiplier.

Introduction

Maintaining locomotion stability under different task constraints of walking and running is an important factor to both prevent falling and enhancing agility performance in dynamic environments such as sport (Mehdizadeh, Arshi, & Davids, 2014). Maintaining stability is also important in developing athletic running speed, especially when different directions of locomotion are required (e.g., forward, backward and lateral locomotion in team games like Association Football). Developing this fundamental ability could thus assist an athlete in achieving higher on-field speeds. Speed as a task constraint, on the other hand, has been shown to be inversely proportional to stability during forward locomotion in both walking (Dingwell & Marin, 2006; Kang & Dingwell, 2006; England & Granata, 2007; Manor, Wolenski & Li, 2008; Manor, Wolenski, Guevaro & Li, 2009; Jordan, Challis, Cusumano, & Newell, 2009; Roos & Dingwell, 2013) and running tasks (Look et al., 2013; Mehdizadeh et al., 2014).

It has, however, been argued that mechanisms of maintaining stability are different between primary and secondary planes of progression (Donelan, Shipman, Kram, & Kuo, 2004; O'Connor & Kuo, 2009; McAndrew, Dingwell & Wilken, 2010; McAndrew, Dingwell & Wilken, 2011; Wurdeman & Stergiou, 2013) reflecting different control strategies in different planes of progression. In particular, it has been shown that during forward walking, stability in the anterior-posterior (AP) direction (primary plane of progression) is controlled through increased *passive* mechanisms, whilst it is controlled through increased *active* control mechanisms in the medio-lateral (ML) direction (i.e. secondary plane of progression). This performance outcome was predicated on observations of greater levels of variability of foot placement in ML compared to AP directions (O'Connor & Kuo, 2009; McAndrew et al., 2010) as well as higher sensitivity of body movement to perturbations in ML direction (McAndrew et al., 2011). In a recent study on lateral walking, it was demonstrated that dynamic stability was greater in the ML direction (primary plane of progression) compared to AP (i.e. secondary plane of progression) which is an indication of increased active control in ML direction (Wurdeman & Stergiou, 2013). This study indicated that the stability of walking depends on direction of progression. Surprisingly, despite this work, there have been no previous attempts to investigate the effect of planes of progression on dynamic stability under the task constraint of running. Since running is mechanically different to walking (i.e. walking is modeled as two inverted pendulums while running is modeled as a spring-mass system), and it is an inherent feature of performance in dynamic environments like team sports, the effect of planes of progression on dynamic stability is likely to differ from that during walking.

From a dynamical system perspective, stability during human locomotion has been quantified, using methods of: (i) largest finite-time Lyapunov exponent (LyE), and (ii), maximum Floquet multiplier (maxFM). These two methods have been extensively implemented to study stability of human movement patterns in walking (Bruijn, van Dieen, Meijer, & Beek, 2009; Dingwell, Kang, & Marin, 2007; Dingwell & Marin, 2006; England & Granata, 2007; Stergiou, Moraiti, Giakas, Ristanis, & Georgoulis, 2004) and running (Jordan et al., 2009; Mehdizadeh et al., 2014), and have quantified different aspects of stability. The LyE measures the exponential rate of divergence of neighboring trajectories of the state space constructed by observations of kinematic data obtained from a movement system during performance (Dingwell & Marin, 2006; Rosenstein, Collins, & De Luca, 1993). That is, inherent infinitesimal perturbation during walking and/or running result in local divergence of state space trajectories. If a movement system is able to attenuate these perturbations more quickly, the associated trajectories of the state space will not grow rapidly and remain converged. Therefore, the rate of convergence/divergence of the state space trajectories could be considered as an indication of the ability of the movement system to respond to perturbation and thus to maintain stability. This type of system stability is considered as *local dynamic stability* since LyE quantifies the ability to respond to small local perturbations during movement performance (Dingwell & Marin, 2006). Since LyE measures the rate of divergence of the trajectories, a greater LyE value is indicative of a lower level of local dynamic stability. The maxFM on the other hand, quantifies the system's response to local perturbations from one cycle to the next (Dingwell et al., 2007). In other words, maxFM quantifies the rate of convergence/divergence of state-space trajectories toward a limit cycle (Hurmuzlu & Basdogan, 1994). To explain, the trajectories of the state space constructed from kinematics of gait pattern form a closed loop or limit-cycle (Figure 1B). The maxFM evaluates the ability of the movement system (e.g. running) to return to the limit cycle after a perturbation. The system has lower stability if it takes more strides to return to the limit cycle (Hurmuzlu & Basdogan, 1994; Kurz, Arpin & Corr, 2012). This type of stability has been termed *orbital stability*. Research studies have shown that while an individual's speed might affect local dynamic stability, it may not influence orbital stability (Dingwell et al., 2007). However, due to the lack of previous research on orbital dynamic stability in running, there is a clear need to examine how speed and plane of progression affect orbital dynamic stability under the specific task constraint of running.

Based on the main findings of this body of work, it is important to investigate the effect of speed and plane of progression on dynamic stability in running pattern to show how it differs to walking pattern. The aims of this study were thus two-fold. First, the effect of speed as a constraint on system stability during running in forward, backward and lateral directions in skilled athletes needed to be determined. Second, a comparison of the degree of stability between the AP and ML directions of progression was also undertaken. The LyE and maxFM measures were adopted for quantification of local and orbital dynamic stabilities in each athlete, respectively. We predicted that the degree of system stability exhibited would be different between primary and secondary planes of progression.

Methods

Participants

The 10 male participants in this study were national-level football players. These participants were selected for observation based on their extensive experience of running in forward, backward and lateral directions during performance, as well as their regular participation in running exercises during training. Participants had played football at national level for an average of 8.8±3.2 years. In addition, they undertook an average of 11.2±2.6 hours of training per week. Their average age was 23.3±2.9 years with average mass and height of 71.6±4.8 kg and 1.79±0.04 m, respectively. None of the participants suffered from any musculoskeletal injuries at the time of the experiment. All participants provided written informed consent before participation in the study. The ethics committee of Amirkabir University of Technology approved the experimental procedure.

Marker placement

Seventeen passive reflective markers (14 mm diameter) were attached to the skin of each participant at the right and left bony landmark on the second metatarsal head (toe), calcaneus (heel), lateral malleolus (ankle), mid-tibia, lateral epicondyle of knee (knee), midthigh, anterior superior iliac spine and also on the sacrum, midway between posterior superior iliac spines, 10th thoracic vertebrae (T10) and 7th cervical vertebrae (C7).

Task

Before starting the experiment, participants had enough time to familiarize themselves with running in forward, backward and lateral directions on the treadmill. During the actual tests, all participants ran in the three directions on a motorized treadmill (Cosmed® T150, Rome, Italy) at 80%, 100%, and 120% of their preferred running speeds. Preferred running speeds (PRS) in each direction, were recorded following a top-down and bottom-up approach similar to protocols described in Dingwell & Marin (2006) and Jordan et al. (2009). Participants began by running on the treadmill at a slow speed (self-defined by each participant), followed by a gradual increases of 0.1 km/h increments until each participant declared that he was running at his PRS. This speed value was recorded and increments were introduced until each participant defined the speed as 'fast'. From this point on, the speed value was gradually decreased until once again the participant reported that he was running at his PRS. This speed was also recorded. The average value of these two recorded PRSs was consequently determined. This procedure was repeated three times and the mean value of three average PRSs was considered as each participant's self-declared PRS. During acquisition of the PRS data, participants were not allowed to view the speed at which they were running on the treadmill (Jordan, Challis, & Newell, 2007). The average PRS over all participants was 8.29±0.87, 4.53±0.58 and 4.59±0.72 km/h for forward, backward and lateral running tasks, respectively. Each participant was then asked to run for 2 minutes in every one of the 3 test trials in each direction. The trials were conducted at speeds of 80%, 100%, and 120% of self-declared PRS values for each participant in random order (Dingwell & Marin, 2006). In lateral running, all participants ran to their right side of the body while looking forward. They were not allowed to cross their feet in lateral running. In addition, participants were not allowed to use handrails in any of the running patterns. Sufficient rest periods were allocated between the tests to allow participants to recover.

Data recording

The three-dimensional coordinate data of the markers were recorded using five Vicon® VCAM motion capture calibrated cameras (Oxford Metrics, Oxford, UK) at the sampling frequency of 100 samples/second. Reconstruction and labelling were performed using Vicon® Workstation software (Oxford Metrics, Oxford, UK). Data associated with x and y components of the ankle marker motion were analyzed. Applying the nonlinear time series analysis methods (e.g. LyE) requires stationary time series. However, time series of human gait data might contain non-stationary parts. One accepted solution to make the gait time series more stationary is to use velocity instead of position time series (first differentiation) (Dingwell & Marin, 2006; Kantz & Schreiber, 2004). In addition, due to possible loss of information at critical points, data were analyzed without filtering (Kantz & Schreiber, 2004).

Data analysis

To calculate the LyE and maxFM first, a state space with appropriate dimension and time delay was reconstructed based on Takens' (1981) theory (Kantz & Schreiber, 2004; Takens, 1981; equation (1)):

$$X(t)=\left[x(t),x(t+\tau),x(t+2\tau),\ldots x\left(t+\left(d_E-1\right)\tau\right)\right]^T \quad (1)$$

where $X(t)$ is the re-constructed state vector, $x(t)$ is the original velocity time vector, τ is the time delay and d_E is the dimension of the state space, i.e. the embedding dimension (Kantz & Schreiber, 2004; Takens, 1981). Time delay is determined as the first local minimum of Average Mutual information (AMI) function (Fraser, 1986). The AMI is a statistical measure from theory of information that shows how much information about a random variable can be obtained from the information of another random variable (Shelhamer, 2006). In this method, mutual information between a time series $x(t)$ and its time shift $x(t+\tau)$ is calculated for different values of τ until the mutual information is minimized (Shelhamer, 2006). A time delay of 10 samples was found to be appropriate for data associated with the three AP and ML directions. In addition, a Global False Nearest Neighbors (GFNN) measure was used to determine embedding dimension, d_E (Kennel, Brown, & Abarbanel, 1992). False Nearest Neighbors are points which are close together in dimension d_E but not in dimension d_E+1 (Shelhamer, 2006). Based on this method, the dimension is gradually increased until the number of false nearest neighbors is reduced to zero. For the purpose of this study, an embedding dimension of $d_E = 5$ was calculated for data associated with AP and ML directions.

For the purpose of calculating LyE, all time series were time-normalized to an equal length of 10000 points. For each trial, a total number of 100 consecutive strides were analyzed. The LyE measures the exponential rate of divergence of neighboring trajectories in the state space (Rosenstein et al., 1993). Since LyE measures the rate of divergence of the trajectories, a greater LyE value indicates lower levels of local dynamic stability of a system. The approach implemented in this study was introduced by Rosenstein et al. (1993), which is most suitable for a finite time series. Here, the largest finite-time Lyapunov Exponent (λ_1) could be determined using equation (2):

$$d(t) = C\exp(\lambda_1 t) \quad (2)$$

where $d(t)$ is the average distance between neighboring points at time t , and the initial separation of the neighboring points is represented by *C*. According to expression (2), for the j^{th} pairs of neighboring points in state space we have:

$$d_j(i) \approx C_j \exp(\lambda_1(i\,\Delta t)) \quad (3)$$

Taking the logarithm from both sides of (3) results in:

$$\ln[d_j(i)] \approx \ln[C_j] + \lambda_1(i\,\Delta t) \quad (4)$$

λ_1 is determined using a linear fit to the following curve:

$$y(i) = (1/\Delta t)\langle d_j(i)\rangle \quad (5)$$

where $\langle d_j(i)\rangle$ denotes the average over all pairs of *j*. The LyE was determined from the slopes of a linear fit in the divergence diagrams in the range ($i\,\Delta t$) of 0 to 0.5 stride (approximately 0 to 50 samples) (Bruijn et al., 2009) (Figure 1). In the present study, all LyE values were presented as the rate of divergence/stride.

To quantify orbital stability, maximum Floquet multiplier (maxFM) was calculated (Figure 1) (Dingwell et al., 2007; Hurmuzlu & Basdogan, 1994). The maxFM quantifies the system's response to local perturbations from one cycle to the next (Dingwell et al., 2007). In other words, the maxFM quantifies the rate of convergence/divergence of the reconstructed state-space trajectories toward a limit cycle

(Hurmuzlu & Basdogan, 1994). Since Floquet theory assumes that a system is strictly periodic, each individual stride associated with AP and ML directions was time-normalized to 101 data points (0–100%) (Dingwell et al., 2007). Individual strides were identified by applying a peak-picking algorithm to the ankle marker's AP time series. According to this theory, the state of the system after one cycle (i.e. one stride; S_{k+1}) is a function of its current state (i.e. current stride; S_k):

$$S_{k+1}=F(S_k) \tag{6}$$

It should be noted that, the limit cycle of a system corresponds to a fixed point in the Poincaré section. The Poincaré section is a lower dimensional section perpendicular to the trajectories at a specific point in the state space (Figure 1B and E). Now, from equation (6), for the fixed point S^* in the Poincaré section, we have:

$$S^*=F(S^*) \tag{7}$$

The effect of small perturbations on the fixed point, S^*, could be evaluated using a linearization to equation 7:

$$[S_{k+1}-S^*]=J(S^*)[S_k - S^*] \tag{8}$$

where $J(S^*)$ is the Jacobian matrix of the system at each Poincaré section. The Floquet multipliers are determined as the eigenvalues of $J(S^*)$ (Dingwell et al., 2007; Hurmuzlu & Basdogan, 1994). For a limit cycle to be orbitally stable, the magnitude of all Floquet multipliers must be less than 1. For this study, a Poincaré section was made at each percent of the stride cycle (i.e. 101 Poincaré sections). The fixed point, S^* was calculated as the average of all points at that Poincaré section. The largest Floquet multiplier at that Poincaré section was then determined. The maxFM was determined as the greatest maximum Floquet multiplier over all Poincaré sections (i.e. at each percent of stride cycle).

Statistical analysis

To evaluate the effects of plane of motion and speed on the local dynamic and orbital stability, a two-way analysis of variance (ANOVA) with repeated measures on the factor of speed was performed. In this test, the LyE and maxFM were set as dependent variables and plane of progression (AP or ML) and speed (80%, 100% and 120% of PRS) were set as factors. Mauchly's test was performed to test the sphericity assumption of the speed factor. If the sphericity assumption was violated, appropriate Huyn-Feldt correction was performed. Statistical significance levels were set at $P<0.05$.

Results

The results of ANOVAs are presented in Table 1 and Figure 2. For LyE, results indicates that there was no significant interaction effect in any of the running patterns ($P>0.05$). In addition, speed did not affect the LyE value in any of the running patterns ($P>0.05$). The main effect of plane of progression however, was significant in all running patterns ($P<0.05$). Post hoc analyses (Figure 2) revealed that in all running patterns, the value of LyE was significantly lower ($P<0.001$) in the secondary plane of progression (i.e. ML in forward and backward, and AP in lateral running) indicating greater local dynamic stability.

Furthermore, there were no significant effects of speed and interaction on the value of maxFM ($P>0.05$). Plane of progression affected the maxFM value significantly in all running patterns ($P<0.05$). Post hoc analyses (Figure 2) revealed that the value of maxFM was significantly lower ($P<0.05$) in the secondary plane of progression (i.e. ML in forward and backward and AP in lateral running) indicating greater orbital dynamic stability.

Discussion

This study investigated the effects of speed and plane of progression on stability during forward, backward and lateral running in skilled footballers. The LyE and maxFM measures were adopted to record local and orbital dynamic stabilities of participants, respectively. Data revealed that speed did not significantly change local and orbital dynamic stabilities in any of running patterns. However, both local and orbital dynamic stability were affected by the plane of progression in all running patterns with the secondary plane of progression being more locally and orbitally stable.

Effect of speed on local and orbital dynamic stability

Results of this study showed that the effect of speed on local dynamic stability (i.e. LyE) was not significant in any of the three running patterns (Table 1 and Figure 2). The results of one study by Look et al. (2013) which demonstrated that local dynamic stability decreased as speed increased in forward running, contradicted by our data. This lack of congruence between the data sets might be due to methodological differences between the two studies. That is, in contrast to our study, Look et al. (2013) did not normalize the values of LyE to stride time which might have skewed their study outcomes. It has been indicated previously that stride time might influence the value of LyE (England & Granata, 2007). In particular, higher running speeds on treadmill are associated with shorter stride times which consequently result in the value of LyE being greater at higher speeds. This, in turn, implies that local dynamic stability decreased as speed increased. Normalizing the stride time to a fixed number of data points on the other hand, will eliminate the effect of stride time on the value of LyE. Therefore, the values of LyE in the study of Look et al. (2013) might have been affected by different stride times associated with different running speeds, which was not the case in our study. Additionally, in their study, Look et al. (2013) assigned a fixed range of treadmill speeds to all participants (3-9 km/h). However, in our study, the running speed was assigned based on each participant's self-defined PRS (80% to 100% PRS with 20% increments). In another study on walking, where both of these issues (i.e. normalizing the value of LyE to stride time and assigning speed based on participants' PRS) were taken into consideration, no change in local dynamic stability with increasing speed was reported (Stergiou et al., 2004).

The findings of this study also demonstrated that the value of maxFM was not affected by speed in any of the three running patterns (Table 1 and Figure 2), signifying that speed did not constrain orbital dynamic stability. This finding is in line with other studies where no significant changes in orbital dynamic stability were confirmed when the effect of speed on orbital stability during walking was considered (Dingwell et al., 2007). To our knowledge there have been no previous attempts to investigate orbital dynamic stability in running. Our findings suggest that, along with local dynamic stability, participants were also able to maintain their periodic limit-cycle stability under the influence of changing speeds during the task constraints of running.

Effects of plane of motion on local and orbital dynamic stability

The results of this study showed that in all running patterns, the degree of stability was significantly higher in the secondary, compared to primary plane of progression. The greater value of LyE in the AP direction in forward and backward running (Figure 2 left) implied that local dynamic stability was lower in the primary plane of progression. This was also true for lateral running during which local dynamic stability was lower in the ML direction (primary plane of progression; Figure 2 left). In two studies on forward walking, it was shown that dynamic stability is more sensitive to perturbations in ML compared to AP direction implying that dynamic stability is controlled through increased active mechanisms in ML direction (McAndrew et al., 2010; McAndrew et al., 2011). In a study by Wurdeman and Stergiou (2013) on forward and lateral walking, it was also shown that, in both forward and lateral walking, local dynamic stability was lower in the secondary plane of progression (i.e. ML in forward, and AP in lateral walking). They concluded that this outcome was due to higher active control of stability in secondary plane of progression. The results of our study, which showed that local dynamic stability was greater in the secondary plane of progression, contrasted with data reported in the mentioned studies on walking. This contradiction could be explained by considering differences between the task constraints of walking and running. In particular, walking is usually modeled as an inverted pendulum. A pendulum will oscillate with more predictable dynamics and thus less active control might be needed in the AP during forward walking. Running, unlike walking, is modeled as a mass-spring system, which is more erratic and might require greater active control. Due to this difference, the control of the primary and secondary planes of progression might require different *weightings* with respect to active and passive mechanisms in these two tasks.

The results (Figure 2 right), showed that orbital dynamic stability in the secondary plane of progression (ML in forward/backward and AP in lateral running) was also significantly higher in comparison to that of primary plane of progression (AP in forward and backward and ML in lateral running). This finding indicates that the athletes' ability to maintain periodic limit-cycle stability is greater in the secondary plane of progression. Quantification of orbital and local dynamic stability values demonstrated that both were higher in the secondary plane of progression in all running patterns.

Limitations of the study

There are a number of limitations associated with methods adopted in this study. First, local and orbital dynamic stabilities were quantified under the specific task constraints of treadmill running to enhance experimental control of locomotion speed in participants. Research studies on stability of walking patterns have demonstrated that using a treadmill might affect the observed levels of stability (Dingwell, Cusumano, Cavanagh, & Sternad, 2001). It is important to note that no published results have so far been elicited in studies comparing stability of running in both treadmill and over-ground running, and future research should take this distinction into consideration. In addition, one reason for the difference between the results of the present study and the study of Wurdeman and Stergiou (2013) might be due to the fact that our study consisted of skilled athletes who were exposed to regular running training in different directions. The control mechanisms of maintaining stability adopted by these participants might be different to the less skilled in the study of Wurdeman and Stergiou (2013).

Conclusions

The findings of this study demonstrated that local and orbital dynamic stabilities were not affected by speed in any of the three running patterns. In addition, this study showed that in running, unlike walking, stability in the direction perpendicular to the direction of running is significantly higher. This difference could be interpreted according to the different models of walking and running. In particular, walking is usually modeled as an inverted pendulum. A pendulum will oscillate with more predictable dynamics and thus less active control might be needed in the primary plane of progression. Running on the other hand, is modeled as a mass-spring system, which is more erratic and might require greater active control in the primary plane of progression. The results of this study could be manifested in sports training and rehabilitation programs where developments of integrated exercise protocols that challenge both speed and stability of individuals might produce a tangible enhancement of athletic skill level.

References

Bruijn, S. M . (2010). *Is stability an unstable concept Quantifying dynamic stability of human locomotion.* (Doctoral Dissertation), Vrije Universiteit Amsterdam, Retrieved from http://dare.ubvu.vu.nl/

Bruijn, S. M., van Dieen, J. H., Meijer, O. G., & Beek, P. J. (2009). Statistical precision and sensitivity of measures of dynamic gait stability. *Journal of Neuroscience Methods, 178*, 327-333. doi: 10.1016/j.jneumeth.2008.12.015

Dingwell, J. B., Cusumano, J. P., Cavanagh, P. R., & Sternad, D. (2001). Local Dynamic Stability Versus Kinematic Variability of Continuous Overground and Treadmill Walking. *Journal of Biomechanical Engineering, 123*, 27. doi: 10.1115/1.1336798

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*, 1723-1730. doi: 10.1016/j.jbiomech.2006.08.006

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*, 444-452. doi: 10.1016/j.jbiomech.2004.12.014

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*, 827-835. doi: 10.1016/j.jbiomech.2003.06.002

England, S. A. , & Granata, K. P. (2007). The influence of gait speed on local dynamic stability of walking. *Gait & Posture, 25*, 172–178.

Fraser, A. M. (1986). Using mutual information to estimate metric entropy. In G. Mayer-Kress (Ed.), *Entropies and Dimensions* (Vol. 82-87). Berlin: Springer.

Hurmuzlu, Y., & Basdogan, C. (1994). On the measurement of dynamic stability of human locomotion. *Journal of Biomechanical Engineering, 116*, 30-36.

Jordan, K., Challis, J. H., Cusumano, J. P., & Newell, K. M. (2009). Stability and the time-dependent structure of gait variability in walking and running. *Human Movement Science, 28*, 113-128. doi: 10.1016/j.humov.2008.09.001

Jordan, K., Challis, J. H., & Newell, K. M. (2007). Speed influences on the scaling behavior of gait cycle fluctuations during treadmill running. *Human Movement Science, 26*, 87-102. doi: 10.1016/j.humov.2006.10.001

Kang, H. G., & Dingwell, J. B. (2006). Intra-session reliability of local dynamic stability of walking. *Gait & Posture, 24*, 386-390. doi:10.1016/j.gaitpost.2005.11.004

Kantz, H, & Schreiber, T. (2004). *Nonlinear Time Series Analysis*. Cambridge, UK: Cambridge University Press.

Kennel, M., Brown, R., & Abarbanel, H. (1992). Determining embedding dimension for phase-space reconstruction using a geometrical construction. *Physical Review A, 45*, 3403-3411. doi: 10.1103/PhysRevA.45.3403

Kurz, M. J., Arpin, D. J., & Corr, B. (2012). Differences in the dynamic gait stability of children with cerebral palsy and typically developing children. *Gait & Posture, 36*, 600-604. doi: 10.1016/j.gaitpost.2012.05.029

Look, N., Arellano, C. J., Grabowski, A. M., McDermott, W. J., Kram, R., & Bradley, E. (2013). Dynamic stability of running: The effects of speed and leg amputations on the maximal Lyapunov exponent. *Chaos, 23*, 043131-043131. doi: 10.1063/1.4837095

Manor, B., Wolenski, P., & Li, L. (2008). Faster walking speeds increase local instability among people with peripheral neuropathy. *Journal of Biomechanics, 41,* 2787–2792. doi:10.1016/j.jbiomech.2008.07.006

Manor, B., Wolenski, P., Guevaro, A., & Li, L. (2009). Differential effects of plantar desensitization on locomotion dynamics. *Journal of Electromyography and Kinesiology, 19,* e320–e328. doi:10.1016/j.jelekin.2008.06.006

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,* 1470–1475. doi:10.1016/j.jbiomech.2010.02.003

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,* 644-649. doi: 10.1016/j.jbiomech.2010.11.007

Mehdizadeh, S., Arshi, A. R., & Davids, K. (2014). Effect of speed on local dynamic stability of locomotion under different task constraints in running. *European Journal of Sport Science*. Advance online publication. doi: 10.1080/17461391.2014.905986

O'Connor, S. M., & Kuo, A. D. (2009). Direction-dependent control of balance during walking and standing. *Journal of Neurophysiology, 102*, 1411-1419. doi: 10.1152/jn.00131.2009

Roos, P. E., & Dingwell, J. B. (2013). Influence of neuromuscular noise and walking speed on fall risk and dynamic stability in a 3D dynamic walking model. *Journal of Biomechanics, 46,* 1722–1728. doi: 10.1016/j.jbiomech.2013.03.032

Rosenstein, M. T., Collins, J. J. , & De Luca, C. J. (1993). A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D, 65*, 117-134.

Shelhamer, M. (2006). *Nonlinear dynamics in physiology A state-space approach*. Singapore: World Scientific.

Stergiou, N., Moraiti, C., Giakas, G., Ristanis, S., & Georgoulis, A. D. (2004). The effect of the walking speed on the stability of the anterior cruciate ligament deficient knee. *Clinical Biomechanics, 19*, 957-963. doi: 10.1016/j.clinbiomech.2004.06.008

Takens, F. (1981). Detecting strange attractors in turbulence. In D. Rand & L. S. Young (Eds.), *Dynamical Systems and Turbulence, Warwick 1980* (Vol. 898, pp. 366-381). Berlin Heidelberg: Springer

Wurdeman, S. R., & Stergiou, N. (2013). Temporal structure of variability reveals similar control mechanisms during lateral stepping and forward walking. *Gait & Posture, 38*, 73-78. doi: 10.1016/j.gaitpost.2012.10.017

Table 1: results of two-way ANOVA test for largest finite-time Lyapunov exponent (LyE) and maximum Floquet multiplier (maxFM) of ankle marker.

		Speed			***Plane of progression***			***Interaction***		
		F	***P*-value**	η^2	**F**	***P*-value**	η^2	**F**	***P*-value**	η^2
LyE	**Forward**	0.64	0.53	0.08	38.12	<0.001	0.84	0.28	0.75	0.03
	Backward	0.27	0.76	0.03	242.03	<0.001	0.97	0.11	0.88	0.01
	Lateral	0.23	0.79	0.04	49.33	0.001	0.90	1.95	0.19	0.28
maxFM	**Forward**	0.49	0.67	0.07	69.11	<0.001	0.92	1.96	0.18	0.24
	Backward	2.00	0.17	0.25	91.36	<0.001	0.93	0.19	0.82	0.03
	Lateral	0.65	0.54	0.11	8.32	0.03	0.62	3.39	0.07	0.40

η^2= effect size (partial eta-squared).

Figures captions:

Figure 1: calculation of largest finite-time Lyapunov exponent (LyE), maximum Floquet multiplier (maxFM) and deviation phase (DP). (A) original time series *x(t)* obtained from experiment, (B) 3D representation of state space reconstructed from time series *x(t)* and its time copies $x(t+\tau)$, and $x(t+2\tau)$, where $\tau$is the time delay. To determined time delay and embedding dimension, average mutual information (AMI) and global false nearest neighbours (GFNN) theories were adopted, respectively (Fraser, 1986; Kennel et al., 1992). Note that the dimension of state space is greater than three but cannot be visually observed, (C) the expanded view of a region of the reconstructed state space in which it is schematically shown that initial separation of j^{th} pairs of points, $d_j(0)$, diverge after *i* time steps shown by $d_j(i)$. (D) Average logarithmic divergence of all pairs of neighbouring points plotted over time (shown as stride number) to calculate LyE. (E) the large view of the Poincaré section which was shown in the state space. The big circle is the limit cycle calculated by averaging all points of the Poincaré section. The Jacobian maps the distance between the current state of the system from the limit cycle distance, $[S_k-S^*]$ to the distance between the next state of the system from the limit cycle distance $[S_{k+1}-S^*]$. The maximum Floquet multiplier which is the maximum eigenvalue of the Jacobian matrix determines to what extent each cycle converges or diverges to/from the limit cycle.

Figure 2: Results of largest finite-time Lyapunov exponent (LyE; left) and maximum Floquet multiplier (maxFM; right) for the ankle marker in anterior-posterior (AP) and medial-lateral (ML) planes. Speed is presented as the percent of preferred running speed (% PRS). Error bars are standard deviations of the mean.