Quantifying foot placement variability and dynamic stability of movement to assess control mechanisms during forward and lateral running

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Original Article

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Abstract

Research has indicated that human walking is more unstable in the secondary, rather than primary plane of progression. However, the mechanisms of controlling dynamic stability in different planes of progression during running remain unknown. The aim of this study was to compare variability (standard deviation and coefficient of variation) and dynamic stability (sample entropy and local divergence exponent) in anterior-posterior and medio-lateral directions in forward and lateral running patterns. For this purpose, fifteen healthy, male participants ran in a forward and lateral direction on a treadmill at their preferred running speeds. Coordinate data of passive reflective markers attached to body segments were recorded using a motion capture system. Results indicated that: 1) there is lower dynamic stability in the primary plane of progression during both forward and lateral running suggesting that, unlike walking, greater control might be required to regulate dynamic stability in the primary plane of progression during running, 2) as in walking, the control of stability in anterior-posterior and medio-lateral directions of running is dependent on the direction of progression, and 3), quantifying magnitude of variability might not be sufficient to understand control mechanisms in human movement and directly measuring dynamic stability could be an appropriate alternative.

1. Introduction

Studies on walking have indicated that humans are more unstable in the medio-lateral (ML; i.e. frontal plane, secondary plane of progression) compared to anterior-posterior direction (AP; i.e. sagittal plane, primary plane of progression; Bauby & Kuo, 2000; Donelan et al., 2004; Kuo, 1999). The implication is that there might be greater neuromuscular control of ML direction fluctuations through sensory feedback originating from visual, vestibular and proprioceptive systems (Bauby & Kuo, 2000; Wurdeman et al., 2012). A study on lateral stepping gait has also supported the findings that there is greater control in the secondary plane of progression suggesting that control of motion depends on the direction of progression (Wurdeman et al. 2012). These studies, however, have all concentrated on human walking and little is known about the mechanisms of maintaining stability in the AP and ML directions in running gait. Maintaining stability in running is an important factor required to preserve balance, prevent falling and enhance performance in dynamic environments such as sport, e.g., agility (Mehdizadeh et al., 2014). Since running mechanics are different to walking (Cappellini et al., 2006; Dugan & Bhat, 2005; Novacheck, 1998; Sasaki & Neptune, 2006), distinct control strategies might be required to maintain stability in different planes of progression in running.

However, how to characterize the control mechanisms in maintaining stability has been the subject of many studies in human movement science. Examination of movement variability has been suggested as an appropriate method to understand mechanisms of motion control (Collins & Kuo, 2013). Nonetheless, there is an ambiguity surrounding the appropriate method of quantifying variability. While earlier studies tended to focus on the *magnitude* of variability (Bauby & Kuo, 2000; Donelan et al., 2004), in a recent study by Wurdeman et al. (2012), adoption of standard deviation (SD) and coefficient of variation (i.e., SD divided by mean; CoV), as the measures of magnitude of variability, resulted in contradictory findings. That is, while SD was greater in the primary plane of progression, the result for CoV was the opposite. This was argued to be mainly due to significantly different scales of step length and step width. Nevertheless, this outcome led to some confusion in the literature.

An alternative approach to clarify this source of confusion could be to quantify the *structure* of movement system variability (i.e. dynamic stability), instead of simply measuring the magnitude of variability. The implication is that, if dynamic stability is lower in a specific direction, higher control might be required in that direction. In a study by Wurdeman and Stergiou (2013), it was shown that largest Lyapunov exponent (LyE), as a measure of dynamic stability, was greater in the ML direction. This was indicative of lower local dynamic stability in the ML direction, thus requiring increased control. Using LyE to quantify dynamic stability, McAndrew et al. (2010; 2011) demonstrated that there is greater sensitivity of body movements to perturbations in the ML direction during walking, supporting the view that there is a lower level of dynamic stability in the ML direction. Furthermore, using the nonlinear measure of sample entropy (SaEn), Lamoth et al. (2010), showed that increased regularity of kinematic time series is associated with higher stability, and more control in human locomotion. Taken together, the data from these studies suggested that using nonlinear measures to quantify dynamic stability may be an appropriate method to characterize control mechanisms in human locomotion.

In studies of planar running robots, it has been shown that passive running robots are marginally stable, thus requiring control input signals to accelerate recovery from perturbations (Hyon & Emura, 2004; Raibert et al., 1989; McGeer, 1990). These results signify that, in human running, the control of dynamic stability might require additional control signals in the direction of progression to prevent perturbations from hindering displacement.

The aims of this study were, therefore, to compare variability and dynamic stability in both the AP and ML directions and to determine whether they differed in forward and lateral running patterns. Variability was quantified using linear measures of standard deviation and coefficient of variation. In addition, nonlinear measures of sample entropy and the local divergence exponent were adopted to quantify dynamic stability. It was hypothesized that lower levels of dynamic stability might be observed in the primary plane of progression in both forward and lateral running. Furthermore, it was hypothesized that, as in walking, control of dynamic stability in running depends on the direction of progression.

2. Methods

2.1. *Participants*

15 healthy male participants were investigated in this study. Their average age was 24.1±1.0 years with average mass and height of 68.8±3.8 kg and 1.76±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.

2.2. *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). For the purpose of this study, only foot and C7 markers were used for further analyses.

2.3. *Task*

Before starting the experiment, participants were given time to familiarize themselves with running in a forward, and also in their own lateral direction, on the treadmill. During the actual tests, all participants ran on a motorized treadmill (Cosmed® T150, Rome, Italy) at their preferred running speeds (PRS). PRS in each direction was recorded following approaches similar to protocols described in previous works by Dingwell and Marin (2006), Jordan et al. (2009) and Jordan et al.(2007). Each participant was asked to run for 2 minutes in each direction. 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. Sufficient rest periods were allocated between the tests to allow participants to recover. All participants wore their own comfortable running shoes.

2.4. *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).

2.5. Data analysis

2.5.1. Linear measures of foot placement variability

For both running patterns, the variability was quantified for the foot placement variables introduced in Table 1. To calculate the linear measures of foot placement variability, position data werefirst filtered using a fourth-order low-pass Butterworth filter with 10 Hz cutoff frequency. Position data for individual strides were time-normalized to 100 data points for all participants. For forward running, each stride cycle was determined from point of heel contact to heel contact of the same foot. Heel contacts were identified as the minima in the ankle vertical time series (Li et al., 1999). For lateral running, however, since participants ran on their forefoot and had toe strikes instead of heel strikes, this algorithm was operated using toe markers. Foot center of mass (COM) was determined as the midpoint of the heel and toe markers during foot contact with the treadmill surface (Wurdeman et al., 2012). The calculation of variables was based on the work of Balasubramanian et al. (2010) and Wurdeman et al. (2012) and modified for analysis of running patterns. For forward running, the introduced variables were calculated for both right and left legs. However, due to the similarity of the results, we report the results of right leg here. For lateral running however, the foot placement variables were calculated and reported for both lead and lag legs. The standard deviation (SD) of foot placement variables and coefficient of variation (i.e. SD divided by the mean; CoV) were calculated over 100 strides as the linear measures of foot placement variability.

2.5.2. Nonlinear measure of dynamic stability

Sample entropy (SaEn) and the Local divergence exponent (LDE) were calculated as nonlinear measures of dynamic stability. Details on the calculation of SaEn and LDE already exist in the literature (Bruijn et al., 2013; Bruijn et al., 2009; Dingwell & Marin, 2006; Lamoth et al., 2010; Yentes et al., 2013).

SaEn quantifies the degree of predictability or regularity of a time series (Lamoth et al., 2010), and is defined as the probability that a sequence of data points, having repeated itself within a tolerance r for a window length m, will also repeat itself for $m+1$ points, without allowing self-matches (Lamoth et al., 2009). Smaller SaEn value indicates greater regularity and predictability of the time series. Greater regularity of the kinematic time series in human movement has been reported as an indication of higher stability and more control (Lamoth et al., 2010). To calculate SaEn, two input parameters m, the window length that will be compared, and r, the similarity criterion, are needed. To determine these parameters, the approach suggested by Yentes et al. (2013) was applied in the present study. That is, a range of m (m=2 and m=3) and r (r=0.1 and r=0.2 times the standard deviation of the time series) were used. However, since the results were consistent between all combinations of m and r, m=2 *and* r=0.2 were used in this study. SaEn was calculated based on the foot placement variables introduced in Table 1.

The LDE measures the exponential rate of divergence of neighbouring trajectories in the state space (Rosenstein et al., 1993). Since LDE measures the rate of divergence of the trajectories, a greater LDE value is indicative of lower levels of local dynamic stability of a system. To calculate the LDE first, a state space with appropriate dimension and time delay was reconstructed based on Takens's (1981) theory (Kantz & Schreiber, 2004; Takens, 1981). Time delay is determined as the first local minimum of average mutual information (AMI) function (Fraser, 1986). A time delay of 10 samples was found to be appropriate for data associated with the AP and ML directions. In addition, a Global False Nearest Neighbors (GFNN) measure was used to determine embedding dimension (Kennel, et al., 1992). For the purpose of this study, an embedding dimension of 5 was calculated for data associated with AP and ML directions. All time series were time-normalized to an equal length of 10000 points. A total number of 100 consecutive strides were analyzed. The approach implemented in this study was introduced by Rosenstein et al. (1993), which is most suitable for a finite time series. The LDE was determined from the slopes of a linear fit in the divergence diagrams in the range of 0 to 0.5 stride (approximately 0 to 50 samples) (Bruijn et al., 2009). In the present study, all LDE values were presented as the rate of divergence/stride. Since the priority of the motor control system is maintaining stability of the upper body (Kang, & Dingwell, 2009), we quantified the LDE of trunk (C7 marker) motion (Dingwell & Marin, 2006).

Due to possible loss of information at critical points, non-filtered time-series were used to calculate both LDE and SaEn (Dingwell & Marin, 2006). For SaEn, the time series were also normalized to unit variance which results in the outcome being scale-independent (Lamoth et al., 2010). In addition, due to the nonstationarities encountered in the biological time series, differenced time series were used to calculate the LDE and SaEn (Yentes et al., 2013).

Statistical analyses

Data associated with forward and lateral running were analyzed separately. Separate two-way repeated measure analyses of variance (ANOVA) were performed to determine the effect of plane of progression (AP or ML) and gait event (foot contact and foot off) on SD, CoV and SaEn. In addition, separate independent t-test analyses were performed to determine the difference in the LDE between AP and ML directions. Statistical significance was set at $P<0.05$.

3. Results

3.1. Standard deviation (SD)

The results of ANOVAs for SD values are presented in Table 2 and Figure 1. For forward running, only the plane factor displayed a statistically significant effect on SD (F=54.72, $P<0.001$), with the AP direction exhibiting higher SD values (Figure 1, top left). For lateral running, the results indicated that interaction effects were statistically significant for the lead leg (F= 8.40, *P*=0.01). Simple main effect analyses revealed that SD was significantly greater in the ML direction at foot contact (Figure 1, down left; *P*<0.05). For lag leg, however, only the plane factor significantly affected SD values (F= 9.66, *P*=0.009), withthe ML direction exhibiting higher SDs (Figure 1, down left).

3.2. *Coefficient of variation (CoV)*

The results of ANOVAs for CoV are presented in Table 3 and Figure 1. For forward running, only the plane factor displayed a statistically significant effect on CoV (F=25.46, *P*<0.001), with ML direction exhibiting higher CoV values (Figure 1, top right). For lateral running, the results also indicated that interaction effects were statistically significant for both lead (F= 29.07, *P*<0.001) and lag legs (F= 27.93, *P*<0.001). The results of simple effects analyses revealed that while for the lead leg, AP direction had significantly greater CoV at foot contact, for the lag leg, this was the case at foot off (Figure 1, down right; *P*<0.05).

3.3. *Sample entropy (SaEn)*

According to the results presented in Table 4 and Figure 2, for forward running, only the interaction effect was statistically significant for SaEn (*P*=0.02). Simple effects analyses revealed that the value of SaEn was greater in the AP direction at heel strike (*P*<0.05). For lateral running, there was a significant interaction effect for the lead leg (F=7.35, *P*=0.01). Simple effects analyses indicated that SaEn was significantly higher in the ML direction at foot contact (*P*<0.05). For the lag leg on the other hand, no significant effects of plane, gait event, or their interactions were found (*P*>0.05).

3.4. *Local divergence exponent (LDE)*

The results of LDE for C7 marker are shown in Figure 3. For forward running, the value of LDE was significantly higher in the AP direction (*P*<0.001), indicative of lower local dynamic stability in the AP direction. For lateral running, the results showed that the LDE was significantly higher in the ML direction ($P<0.001$).

4. Discussion

This study sought to compare variability, as well as dynamic stability, in running patterns in AP and ML directions. The results appeared to confirm the initial hypotheses. That is, there was evidence of lower dynamic stability in the primary plane of progression in both forward and lateral running. Results implied that greater control might be required to maintain dynamic stability in the primary plane of progression in running gait.

4.1. Linear measures of variability

The results of our study revealed that measurement of foot placement variability using linear methods (SD and CoV) led to some contradictory outcomes. That is, while the results of SD analyses showed that foot placement variability was greater in the primary plane of progression (Table 2 and Figure 1), the results of CoV measures indicated that foot placement variability was higher in the secondary plane of progression (Table 3 and Figure 1). Similar cases were encountered in the study of Wurdeman et al. (2012) on walking.They reported that this outcome might be primarily due to the significantly different scales of step length and step width in running. Arellano and Kram (2011) reported that there is minimal variability of step width in forward running, suggesting that there might be little need for active control in the ML direction. However, greater magnitude of variability could also be interpreted as the result of poor system control. In other words, higher magnitude of variability could signify that it might be unnecessary for a system to control movement in that direction (see the study of Rosenblatt et al., 2014 on walking). Therefore, it could be argued that measuring magnitude of variability might not be an appropriate approach to understand control mechanisms in human locomotion.

4.2. Dynamic stability in primary versus secondary planes of progression

Our results on quantifying dynamic stability using both SaEn and LDE suggest that there are lower levels of dynamic stability in the primary plane of progression in running. That is, our observations of greater values of SaEn in the primary plane of progression (Table 4 and Figure 2) demonstrate that the foot placement time series were less regular in the primary plane of progression. Greater regularity of the kinematic time series in human movement has been reported as an indication of higher stability and more control (Lamoth et al., 2010). Therefore, our results on SaEn suggest that dynamic stability was lower in the primary plane of progression which requires increased control to regulate dynamic stability. Our findings also indicated that local dynamic stability was lower in the primary plane of progression in both running patterns (Figure 3). The lower levels of dynamic stability in the primary plane of progression could imply that more control might be required to maintain system dynamic stability in this direction. Taken together, these results imply that, since nonlinear measures quantify dynamic stability of locomotion directly, they might be more appropriate to investigate the mechanisms of control in human locomotion.

Studies on designing running robots, has shown that active control input is required to facilitate any recovery from perturbations (Hyon & Emura, 2004; McGeer, 1990; Raibert et al., 1989). These findings are therefore, aligned with the results of our study where participants tried to functionally respond to inherent local perturbations (for a study on the stability of running in the ML direction, see Seipel & Holmes, 2005).

Furthermore, the lower dynamic stability in the primary plane of progression in both forward and lateral running implies that, as in walking (Wurdeman et al., 2012), the control of stability in AP and ML directions of running, is also dependent on the direction of progression, and is not set *a priori*, based on anatomical planes of the human body.

4.3. Differences between walking and running in controlling stability

The findings of this study imply that the mechanisms of controlling stability differ between walking and running. That is, while previous studies on walking have indicated that there is higher dynamic stability in the primary plane of progression (Bauby & Kuo, 2000; Donelan et al., 2004), our data suggested that dynamic stability is lower in the primary plane of progression in running. This distinction might be caused by differences in the mechanics of walking and running. That is, since there is a flight phase in running where both feet are off the ground, increased sensory feedback might be required to control foot placement adaptation in the primary plane of progression.

4.4. Limitations

Calculation of SaEn is highly sensitive to the window length, *m*, and the similarity criterion, *r*. Therefore, extensive effort should be assigned to the appropriate choice of *m*, and *r*. For the purpose of this study, the results were consistent over all pairs of *m*, and *r* that we investigated in our study.

5. Conclusions

There are three main conclusions associated with this study. First, our findings indicated that there is lower dynamic stability, in the primary plane of progression during both forward and lateral running. These data suggested that, unlike walking, greater control might be required to regulate system stability in the primary plane of progression during running. Second, results demonstrated that as in walking, control of stability in AP and ML directions of running, is dependent on the direction of progression. Finally, our data indicated that measuring the magnitude of movement variability might not be sufficient to understand control mechanisms in human movement, and quantifying system dynamic stability could serve as an appropriate alternative.

6. Acknowledgment

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Conflict of Interest: None

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Tables:

Table 1: foot placement variables and their definitions. Pelvis center of mass (COM) was calculated as the centroid of the three S1 and right and left anterior superior iliac spine markers in the horizontal plane. In forward running, the variables were calculated for right leg. In lateral running, the variables were calculated for both lead and lag legs.

Variable name	**Definition**
Forward running	
AP-HS	Distance in AP direction between foot COM and pelvis COM at heel strike
AP-TO	Distance in AP direction between foot COM and pelvis COM at toe off
ML-HS	Distance in ML direction between foot COM and pelvis COM at heel strike
ML-TO	Distance in ML direction between foot COM and pelvis COM at toe off
Lateral running	
AP-FC	Distance in AP direction between foot COM and pelvis COM at foot contact
AP-FO	Distance in AP direction between foot COM and pelvis COM at foot off
ML-FC	Distance in ML direction between foot COM and pelvis COM at foot contact
ML-FO	Distance in ML direction between foot COM and pelvis COM at foot off

Table 2: results of two-way ANOVA test for standard deviation (SD) of foot placement in forward and lateral running.

		Plane			**Gait event**			**Interaction**		
		F	***P*-value**	η^2	**F**	***P*-value**	η^2	**F**	***P*-value**	η^2
Forward		54.72	<0.001	0.82	4.64	0.05	0.27	0.05	0.82	0.004
Lateral	**Lead**	10.79	0.007	0.47	4.17	0.06	0.25	8.40	0.01	0.41
	lag	9.66	0.009	0.44	2.08	0.17	0.14	0.01	0.90	0.001

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

Table 3: results of two-way ANOVA test for coefficient of variation (CoV) of foot placement in forward and lateral running.

		Plane			**Gait event**			**Interaction**		
		F	***P*-value**	η^2	**F**	***P*-value**	η^2	**F**	***P*-value**	η^2
Forward		25.46	<0.001	0.68	0.02	0.87	.002	2.24	0.16	0.15
Lateral	**Lead**	8.71	0.01	0.42	20.82	0.001	0.63	29.07	<0.001	0.70
	lag	41.59	<0.001	0.77	29.89	<0.001	0.71	27.93	<0.001	0.70

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

Table 4: results of two-way ANOVA test for sample entropy (SaEn) of foot placement in forward and lateral running.

		Plane			**Gait event**			**Interaction**		
		F	***P*-value**	η^2	**F**	***P*-value**	η^2	**F**	***P*-value**	η^2
Forward		3.48	0.08	0.18	2.11	0.16	0.12	6.35	0.02	0.29
Lateral	**Lead**	4.54	0.05	0.23	0.27	0.60	0.01	7.35	0.01	0.32
	lag	1.23	0.28	0.07	0.04	0.82	0.003	0.005	0.94	0.00

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

Figure captions:

Figure 1: results of standard deviation (SD) and coefficient of variation (CoV) for forward (top) and lateral (down) running patterns. For lateral running, the results for lead and lag legs are shown in separate columns. Error bar represent standard deviations.

Figure 2: results of sample entropy (SaEn) for forward (top) and lateral (down) running patterns. For lateral running, the results for lead and lag legs are shown in separate columns. Error bars represent standard deviations.

Figure 3: results of local divergence exponent (LDE) calculated for C7 marker for forward and lateral running patterns. Error bars represent standard deviations. Note that in forward running, AP is the primary plane of progression whereas in lateral running, ML is the primary plane of progression.