Detecting Structured Variability in the Running Gait Using a GPS-Embedded, Trunk-Mounted Accelerometer. Part 1: Method Description

Jay H. Williams [1], **Daniel J. Jaskowak** [1], **David P. Tegarden** [2]

[1] Department of Human Nutrition, Foods, and Exercise, and [2] Department of Accounting and Information Systems, Virginia Polytechnic Institute and State University, Blacksburg, VA 24060 USA

Gait pattern | Variability | GPS | Machine Learning

Headline

Trunk-mounted (TM) devices incorporating a global positioning system (GPS) antenna, tri-axial accelerometer, gyroscope and/or magnetometer are now widely used to monitor player movements during training and competition (1, 3) as well as evaluate gait characteristics (2). Recently continuous wavelet transform (CWT) and detrended fluctuation analysis (DFA) have been used independently to evaluate and detect altered gait (5, 8, 10, 13). However, these two techniques have not been applied sequentially to analyze gait complexity nor have they been applied to TM accelerometer data.

Aim. The purpose of this study was to develop an approach for determining spatiotemporal gait characteristics and the structure of their variability using TM accelerometer signals processed via CWT and DFA.

Methods

Athletes. Twelve female intercollegiate soccer players (167.7 ± 1.4 cm, 63.4 ± 8.7 kg) participated in this study. Human subjects use approval and informed consent was obtained prior to data collection.

Data Collection. During a training session, subjects ran at a comfortable pace, for 3200m around adjacent practice fields. All subjects wore a GPSports® SPI HPU unit, positioned between the scapulae and fitted per GPSports recommendations. The units contain a 15 Hz GPS receiver, a 100Hz, 16g tri-axial accelerometer and 50Hz magnetometer.

Signal Pre-Processing. Raw accelerometer and speed data were downloaded using the manufacturer's proprietary software (Team AMS®) and exported to Excel files. As speed data are computed at 15Hz, the TeamAMS software "fills in" missing values such that ten identical speed values are provided for each 0.1 sec to match to 100Hz accelerometer signal.

All signal processing routines were performed by customized Matlab® programming. Accelerometer signals were bandpass filtered at 1-40Hz to remove noise and eliminate drift. Next, correction for offset and alignment (i.e. tilt) of the tri-axial data was performed as previously described (17, 18). This procedure estimates the gravitational acceleration components in the anteroposterior and mediolateral directions and transforms the data to a horizontal-vertical coordinate system.

Spatiotemporal Events. Gaussian CWT was employed to detect foot contact events (6, 10, 15). This procedure convolutes the accelerometer data with an analyzing function (e.g. Gaussian wavelet) to remove signal noise while preserving the underlying variations in signal frequency (15). Foot contact events contained within the original signal can be extracted from the reconstructed signal. Vertical accelerations were integrated then differentiated using Gaussian CWT with a scale of 10. The resulting acceleration signal was differentiated again to obtain a jerk signal. Local minima of the transformed acceleration signal were identified as foot strike (initial contact, IC) and the local maxima of the jerk signal were identified as toe off (final contact, FC).

Right and left foot values were determined from the filtered mediolateral acceleration signal (3 Hz low pass). The sign of the signal (positive or negative) at the IC and FC points was used to identify left and right foot contact values. Contact times (CT) were calculated as the difference between IC and the subsequent FC times of the same foot. Step times (StpT) were computed as the difference between successive IC times of the right and left feet. Stride times (StrT) were determined as the difference between IC's of the same foot.

The speed variable was used to calculate step and stride lengths (StpL, StrL). For StpL, average speed during each StpT was multiplied by the StpT. StrL was computed the same way except that average speeds during each StrT were used.

Detrended Fluctuation Analysis. DFA was used to assess the complexity and structure of gait variability for each spatiotemporal variable. DFA is an adapted root mean square analysis of a "random walk" that generates a self-similarity parameter, the fractal scaling index (FSI, also referred to as α) (12, 13). FSI values of 0.5 represent random variability whereas values between 0.5 and 1.0 indicate the presence of persistent long-range correlations or structured variability (4, 12). The procedures followed those of Hausdorff et al. (12) using the WaveForm DataBase toolbox for MatLab (11, 22, 23). Signal

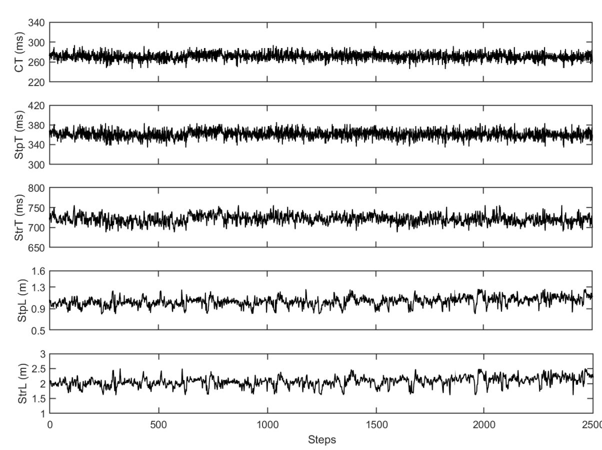

Fig. 1. Gait parameters derived from the CWT analyses for a single subject. Shown are data for 3000 steps, from a single trial.

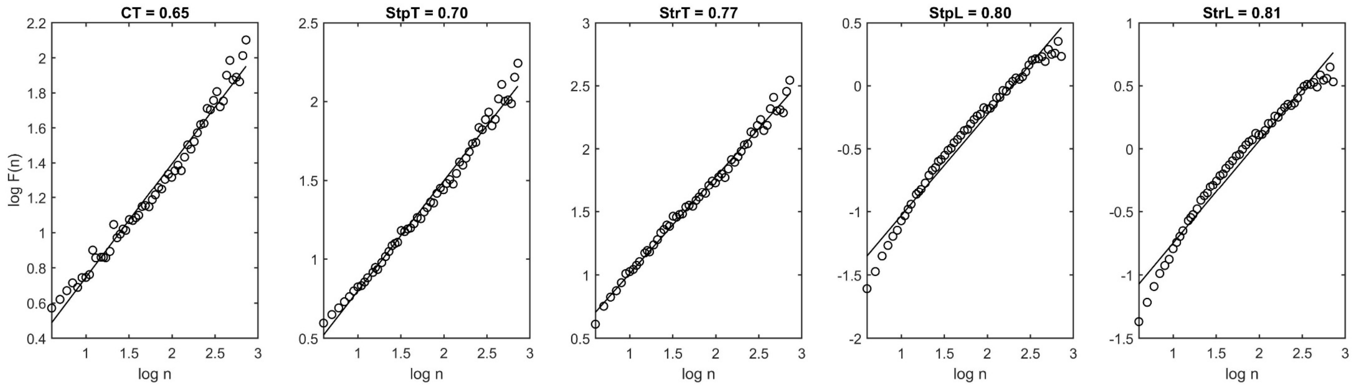

Fig. 2. Plots of DFA window size (log (n)) and average fluctuation (log (F(n)) for spatiotemporal variables, from a single trial.

Table 1. Variables derived from the CWT analysis

Variable	Magnitude	CV (%)	FSI
Contact Time	267.3 ± 2.80 ms	3.32 ± 1.12	0.682 ± 0.082
Step Time	359.56 ± 0.98 ms	4.35 ± 1.21	0.702 ± 0.027
Stride Time	719.20 ± 2.07 ms	3.28 ± 1.46	0.802 ± 0.034
Step Length	1.00 ± 0.07 m	2.82 ± 0.98	0.851 ± 0.084
Stride Length	1.99 ± 0.16 m	3.04 ± 1.27	0.875 ± 0.105

Values are Mean ± SD.

segments or boxes consisting of N data points were analyzed using box sizes of 4 to $\frac{1}{4}$ of the signal length and detrended using a first order polynomial. The log of N (box size) was plotted against the log of the root mean squared error or fluctuation for the given box size (F(N)). The slope of this relationship was used as the FSI (12).

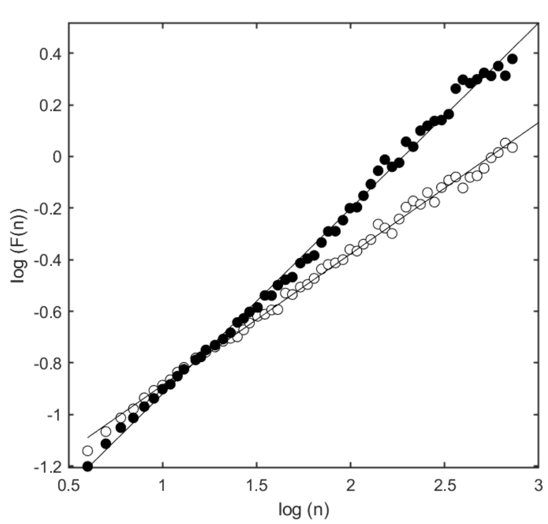

Fig. 3. Plots of DFA window size (log (n)) and average fluctuation (log (F(n)) for CT from a single trial. Filled circles = raw data (FSI=0.719); open circles = shuffled data (FSI = 0.502).

Results

An average of 3169.0 ± 45.5 (x ± SD) steps was detected and analyzed per trial. Average speed was 9.95 ± 0.79 km·hr^{-1} with slight variations during the effort (CV = 7.9 ± 2.3 %).

Figure 1 shows an example of the spatiotemporal variables during the 400m run. As can be seen, there is noticeable variability in all variables within the trial. Magnitudes and coefficients of variation of the spatiotemporal variables are shown in Table 1.

The results of the DFA for a single trial is show in Figure 2 along with the calculated FSI. In all cases, a linear fit to the log F(N) vs log N was found (r2 values, 0.95-0.99) Mean FSI values for each spatiotemporal variable are also shown in Table 1. For all subjects across all variables, FSI values ranged from 0.612 to 0.934 with spatial variables showing the largest and the temporal the smallest FSI. Effect sizes (Cohen's d) between individual variables were all large.

To confirm the use of DFA as a measure of structured variability, spatiotemporal data within each trial were randomly shuffled 5 times and FSI recomputed. Random shuffling retains the mean and standard deviation of the original data but destroys any long-range correlation, complexity and structured variability. The mean FSI for 84 sets of shuffled data (7 variables x 12 subjects) was 0.501 ± 0.003 (Figure 3). This indicates random variability of the shuffled data and emphasizes the structured variability of the original data.

Discussion

This is the first study to combine the previously developed techniques of CWT and DFA to examine the structure of gait variability. In addition, it is the first study to apply this approach to TM accelerometer signals obtained during running. Previous studies have studied the FSI using temporal variables derived from foot strike measures using footswitches, peak detection of ground reaction forces or vertical acceleration signals (8, 12, 16, 20, 21). In general, these studies were limited to DFA analysis of step or stride times. By using multiple spatiotemporal parameters derived using CWT, a more comprehensive examination of gait variability can be carried out. Further, GPS-embedded accelerometers also provide running speed data. This allows investigators to examine gait complexity as a function of speed (14) and/or to use speed as a covariate when comparing alterations in gait variability due to fatigue, overtraining and injury.

Magnitudes of the spatiotemporal variables are similar to those reported by others for similar running speeds (19, 24) and FSI values are in line with previous reports (8, 14, 16, 20, 21). Further, the finding that shuffled data resulted in FSI values near 0.5 indicates that our approach was able to detect structured variability in the running gait. Based on this, it appears that our approach for examining the structure of gait variability during running is feasible.

Additional studies are warranted to understand if and how spatiotemporal variables and FSI might be altered with exercise. For example, FSI values are altered with fatigue, overtraining and injury (8, 16). Gait asymmetry is observed in patients following anterior cruciate ligament (ACL) reconstruction (7, 9). It is not known if ACL injury also affects gait variability and/or if such changes persist during rehabilitation. Thus, the method described here could prove useful in evaluating fatigue and injury and aiding in return-to-play decisions.

Practical Applications

The advantages of TM accelerometers for analyzing gait are that they have become widely available, are able to generate very reliable and valid data and are currently utilized by a number of sport teams (1, 3). As such, it is relatively easy to routinely collect gait data on a large group of subjects. This raises the possibility of identifying abnormal gait structure that might result from injury, fatigue or overtraining.

Limitations

- This study used an athletic cohort of young adults as subjects. Thus, the approach described my not be feasible for other populations (e.g. injured, diseased).
- Only a single running speed was used. Also, the running speed was not self-selected by each subject.

Acknowledgments. The authors thank the players and staff of Virginia Tech Women's Soccer program for their cooperation and assistance with this study.

Dataset

Dataset available on SportPerfSci.com

References

1. Aughey RJ. Applications of GPS technologies to field sports. Int J Sports Physiol Perf, 2011; 6: 295-310.
2. Buchheit M, Gray A, Morin JB. Assessing stride variables and vertical stiffness with GPS-embedded accelerometers: preliminary insights for the monitoring of neuromuscular fatigue on the field. J Sports Sci Med, 2015; 14: 698-701.
3. Cummins C, Orr R, O'Connor H, West C. Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. Sports Med, 2013; 43: 1025-1042.
4. Decker LM, Cignetti F, Stergiou N. Complexity and human gait. Rev Andal Med Deporte, 2010; 3: 2-12.
5. Del Din S, Hickey A, Hurwitz N, Mathers JC, Rochester L, Godfrey A. Measuring gait with an accelerometer-based wearable: influence of device location, testing protocol and age. Physiol Meas, 2016; 37: 17851797.
6. Del Din S, Hickey A, Ladha C, Stuart S, Bourke AK, Esser P, Rochester L, Godfrey A. Instrumented gait assessment with a single wearable: an introductory tutorial. F1000Research, 2016; 5: 2323.
7. Di Stasi SL, Logerstedt D, Gardinier ES, Snyder-Mackler L. Gait patterns differ between ACL-reconstructed athletes who pass return-to-sport criteria and those who fail. The American journal of sports medicine, 2013; 41: 1310-1318.
8. Fuller JT, Bellenger CR, Thewlis D, Arnold J, Thomson RL, Tsiros MD, Robertson EY, Buckley JD. Tracking performance changes with running-stride variability when athletes are functionally overreached. Int J Sports Physiol Perf, 2017; 12: 357-363.
9. Gardinier ES, Manal K, Buchanan TS, Snyder-Mackler L. Gait and neuromuscular asymmetries after acute ACL rupture. Med Sci Sports Exer, 2012; 44: 1490-1496.
10. Godfrey A, Del Din S, Barry G, Mathers JC, Rochester L. Instrumenting gait with and accelerometer: A system and algorithm examination. Med Engr Phys, 2015; 37: 400-407.
11. Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation, 2000; 101: e215-e220.
12. Hausdorff JM, Peng C-K, Ladin Z, Wei J, Goldberger AL Is walking a random walk? Evidence for long-range correlations in stride interval of human gait J Appl Physiol, 1995; 78: 349-358.
13. Hausdorff JM, Purdon PL, Peng C-K, Ladin Z, Wei JY, Goldberger AL. Fractal dynamics of human gait: stability of long-range correlations in stride interval fluctuations. J Appl Physiol, 1996; 80: 1448-1457.
14. Jordan K, Challis JH, Newell KM. Walking speed influences on gait cycle variability. Gait Posture, 2007; 36: 128-134.
15. McCamley J, Donati M, Grimpampi E, Mazzà. An enhanced estimate of initial contract and final contact instants of time using lower trunk inertial sensor data. Gait Posture, 2012; 36: 316-318.
16. Meardon SA, Hamill J, Derrick TR. Running injury and stride time variability over a prolonged run. Gait Posture, 2011; 33: 36-40.
17. Millecamps A, Lowry KA, Brach JS, Perera S, Redfern MS, Sejdić E. Understanding the effects of pre-processing on extracted signal features from gait accelerometry signals. Comp Biol Med, 2015; 62: 164-174.
18. Moe-Nilssen R. A new method for evaluating motor control in gait under real-life environmental conditions. Part 1: The instrument. Clin Biomech, 1998; 13: 320-327.
19. Morin JB, Tomazin K, Samozino P, Edouard P, Millet GY. High-intensity sprint fatigue does not alter constant-submaximal velocity running mechanics and sprint-mass behavior. Eur J Appl Physiol, 2012; 112: 1419-1428.
20. Nakayama Y, Kudo K, Ohtsuki T. Variability and fluctuation in running gait cycle of trained runners and non-runners. Gait Posture, 2010; 31: 331-335.
21. Newell D, van der Laan M. Measures of complexity during walking in chronic non-specific low back pain patients. Clin Chiropractic, 2010; 13: 8-14.

22. Peng C-K, Havlin S, Stanley HE, Goldberger AL Quantification of scaling exponents and cross over phenomena in nonstationary heartbeat time series. CHAOS, 1995; 5: 82-87.
23. Silva I, Moody G. An Open-source Toolbox for Analysing and Processing PhysioNet Databases in MATLAB and Octave. J Open Res Software, 2014; 2: e27.
24. Weyand PG, Sternlight DB, Bellizzi MJ, Wright S. Faster top running speeds are achieved with greater ground reaction forces not more rapid leg movements. J Appl Physiol, 2000; 89: 1991-1999.