Journal of Biomechanics 85 (2019) 187–192

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Short communication

New considerations for collecting biomechanical data using wearable sensors: Number of level runs to define a stable running pattern with a single IMU

Lauren C. Benson [a,*], Nizam U. Ahamed [a], Dylan Kobsar [a], Reed Ferber [a,b,c]

[a] University of Calgary, Faculty of Kinesiology, 2500 University Dr. NW, Calgary, AB T2N 1N4, Canada
[b] Running Injury Clinic, Calgary, AB T2N 1N4, Canada
[c] University of Calgary, Faculty of Nursing, 2500 University Dr. NW, Calgary, AB T2N 1N4, Canada

A R T I C L E I N F O

Article history:
Accepted 2 January 2019

Keywords:
Running
Outdoor surfaces
Inertial measurement unit
Wearable technology

A B S T R A C T

Wearable technology can be used to quantify running biomechanical patterns in a runner's natural environment, however, changes in external factors during outdoor running may influence a runner's typical gait pattern. Therefore, the purpose of this study was to determine how many runs are needed to define a stable or typical running pattern. Six biomechanical variables were recorded using a single wearable sensor placed on the lower back during ten outdoor runs for twelve runners. Univariate and multivariate distributions were created and based on the probability density function, the percent of similar data points (within 95%) from each unique run for the same runner were determined. Stability was defined when the addition of data from a new run resulted in less than a 5% change in the probability density function. To cross-validate, the percent of similar data points at stability was compared between the same and different runners using a repeated-measures MANOVA (Bonferroni-corrected $\alpha = 0.007$). The maximum number of runs needed to reach stability for univariate and multivariate analyses was four and five, respectively. There was a significant overall effect on similar data points between the same and different runners ($p = 0.001$), with a greater percent of similar data points for the same runner compared to other runners ($p < 0.007$). Based on biomechanical data collected using a single wearable sensor placed on the lower back, this is the first study to show that four (univariate) to five (multivariate) runs are needed to establish a stable running pattern in real-world settings.

1. Introduction

Inertial measurement units (IMUs) can be used to quantify running biomechanical patterns in a runner's natural environment (Reenalda et al., 2016), which is ideal considering most runners complete their runs outdoors (Taunton et al., 2003). However, guidelines for the use of IMUs during longitudinal monitoring of running have yet to be established (Benson et al., 2018). Thus, a challenge for recording running biomechanics in real-world settings, and over the course of several training runs, is the ability to identify when observed changes in running patterns are due to intrinsic factors (e.g. fatigue or injury development) rather than external factors that are a part of a runner's natural environment (e.g. changes in clothing, weather, running surface, etc.).

While very little research in this area exists, it has been suggested that "a few days" of recorded data are needed to construct a "relatively stable" gait pattern (Cola et al., 2015). However, an actual measure of stability across multiple days has not been defined, nor has the number of runs needed to reach the point of stability been established. Furthermore, the individual variables or combination of variables used to represent the running pattern could influence running pattern stability. Therefore, the purpose of this study was to determine the number of runs needed to establish a stable running pattern for runners in their natural running conditions based on both univariate and multivariate analyses of running biomechanical data. It was hypothesized that multiple runs would be needed to establish a stable running pattern, and due to the added complexity of relationships between variables, more runs would be needed for multivariate compared to univariate analyses.

* Corresponding author.
E-mail addresses: lauren.benson@ucalgary.ca (L.C. Benson), nizam.ahamed1@ucalgary.ca (N.U. Ahamed), drjkobsa@ucalgary.ca (D. Kobsar), rferber@ucalgary.ca (R. Ferber).

https://doi.org/10.1016/j.jbiomech.2019.01.004
0021-9290/

2. Methods

2.1. Procedures

Twelve recreational runners (9F, 3M; 48.5 (12.0) yr; 166.8 (7.9) cm; 68.7 (11.2) kg) provided informed consent to participate in this study approved by the Ethics Board at the University of Calgary (REB16-2035). A GPS watch (Garmin vívoactive® HR, recording rate 1 Hz; Garmin International Inc., KS, USA) was attached to each runner's preferred wrist, and a commercially-available IMU (Lumo Run®, sampling rate 100 Hz, recording rate every five strides; Lumo Bodytech Inc., Mountain View, CA, USA) was attached to the back of the shorts near the individual's center of mass (Table 1). Participants wore both the IMU and the GPS watch during all training runs over the course of a marathon training program. Clothes, shoes, device placement, pace and running route were not controlled. The first five minutes of each run were considered warmup and those data were excluded. Altitude was filtered using a moving average of 10 s. Similar sections of running were identified based on the following criterion: running speed greater than 1.8 m/s (Diedrich and Warren, 1995), the section being longer than 100 m, and an elevation between +/−2% grade until 2.5 km for each run were available for analysis. The first 10 runs that were reported to be pain-free were used (Table 2).

2.2. Analyses

Sets consisting of increasing numbers of runs were created as training datasets, and individual runs that were not part of the training dataset were used as testing datasets. Specifically, each runner's 10 runs were grouped into unique sets with all combinations of 1–10 runs included in a set. A leave-one-out approach was used to determine the level of similarity between all combinations of a training dataset and a test dataset for each runner (Table 3). For each unique training dataset, the probability density function of the univariate or multivariate normal distribution (Eq. (1)) was determined using the MATLAB *mvnpdf* function for each of the IMU variables individually (univariate), and for all of the IMU variables together (multivariate) (MathWorks, 2018).

$$P = \frac{1}{\sqrt{|\Sigma|(2\pi)^d}} \exp\left(-\frac{1}{2}(x-\mu)\Sigma^{-1}(x-\mu)'\right) \quad (1)$$

where d is the number of variables, x is a 1-by-d vector representing a single observation, μ is a 1-by-d vector representing the mean of all observations, and $\sum$ is the covariance matrix.

A threshold, epsilon, of the resulting probability density function was determined such that 95% of the training data had a probability greater than or equal to epsilon. Next, the probability density function of the testing dataset was determined from the mean and covariance matrix of the training dataset. Data points in the testing dataset with probability greater than or equal to epsilon were considered similar to the training dataset, and the percent of similar data points in the testing dataset was recorded (Fig. 1).

The percent of similar data points was averaged across all pairs of training and testing datasets with the same number of runs per set, giving a singular value for each runner, number of runs, and each IMU variable individually (univariate) and together (multivariate). The running pattern was considered stable when the addition of one more run to the training dataset resulted in less than a 5% increase of percent of similar data points. This stability point was determined separately for each runner and each IMU variable (univariate and multivariate). The overall stability point for each

Table 1
Variables recorded by the IMU and GPS watch during each run.

Device	Variable	Description	Units
IMU	Cadence	Number of bilateral steps per minute	steps/min
	Bounce	Vertical displacement of center of mass	cm
	Braking	Reduction in forward velocity following foot strike	m/s
	Pelvic drop	Frontal plane motion of pelvis	deg
	Pelvic rotation	Transverse plane motion of pelvis	deg
	Ground contact Time	Time of foot contact with the ground	ms
GPS watch	Speed	–	m/s
	Distance	–	km
	Altitude	–	m

Table 2
The mean and standard deviation of run characteristics for the retained sections across all 10 runs for each runner.

Runner	Time (s)		Flat distance (m)		Elevation gain (m)		Elevation loss (m)		Speed (m/s)		Total distance (m)		Time between runs (days)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	875.1	28.5	2538.8	7.8	12.5	4.8	−11.1	1.3	2.89	0.10	4279.0	1514.8	5	11
2	885.1	31.6	2535.0	4.4	13.1	5.1	−12.2	2.3	2.86	0.11	3870.4	936.6	6	10
3	1182.6	48.6	2527.3	3.9	12.2	5.0	−13.4	5.1	2.14	0.10	3959.8	1253.6	5	5
4	927.7	39.1	2535.1	3.6	18.4	4.8	−17.0	4.1	2.71	0.10	4455.2	1339.5	3	1
5	899.4	97.5	2535.2	6.9	12.5	4.9	−12.8	2.7	2.83	0.31	3328.7	468.3	7	5
6	1049.4	66.2	2530.9	5.1	13.0	3.8	−13.5	2.7	2.41	0.16	3822.9	985.7	7	6
7	1021.5	60.7	2531.0	3.8	14.3	4.0	−13.7	5.0	2.47	0.15	4206.1	1224.0	7	6
8	1156.4	39.5	2713.9	31.7	8.5	2.0	−12.5	3.1	2.34	0.07	4230.8	570.0	4	4
9	1091.2	32.7	2528.1	3.5	12.4	3.9	−14.5	3.2	2.32	0.07	4155.8	924.0	4	5
10	1009.3	70.1	2717.9	34.1	9.5	3.5	−8.2	2.6	2.69	0.18	3886.4	717.4	11	10
11	952.3	38.5	2534.2	2.0	11.1	4.3	−14.1	4.3	2.66	0.11	3746.0	971.0	4	3
12	910.6	83.4	2534.5	6.2	13.0	6.4	−12.2	4.2	2.79	0.26	4072.1	2070.9	6	3

Table 3
Unique training datasets of runs based on number of runs included in each set. Testing datasets for each training dataset were all individual runs not included in the training dataset. The number of subject-specific train-test pairs is indicated.

Number of runs per set	Number of unique sets	Training datasets	Number of subject-specific train-test pairs
1	10	{Run 1}, {Run 2}, ...	90
2	45	{Run 1 + 2}, {Run 1 + 3}, ...	360
3	120	{Run 1 + 2 + 3}, {Run 1 + 2 + 4}, ...	840
4	210	{Run 1 + 2 + 3 + 4}, {Run 1 + 2 + 3 + 5}, ...	1260
5	252	{Run 1 + 2 + 3 + 4 + 5}, {Run 1 + 2 + 3 + 4 + 6}, ...	1260
6	210	{Run 1 + 2 + 3 + 4 + 5 + 6}, {Run 1 + 2 + 3 + 4 + 5 + 7}, ...	840
7	120	{Run 1 + 2 + 3 + 4 + 5 + 6 + 7}, {Run 1 + 2 + 3 + 4 + 5 + 6 + 8}, ...	360
8	45	{Run 1 + 2 + 3 + 4 + 5 + 6 + 7 + 8}, {Run 1 + 2 + 3 + 4 + 5 + 6 + 7 + 9}, ...	90
9	10	{Run 1 + 2 + 3 + 4 + 5 + 6 + 7 + 8 + 9}, {Run 1 + 2 + 3 + 4 + 5 + 6 + 7 + 8 + 10}, ...	10
10	1	{Run 1 + 2 + 3 + 4 + 5 + 6 + 7 + 8 + 9 + 10}	0

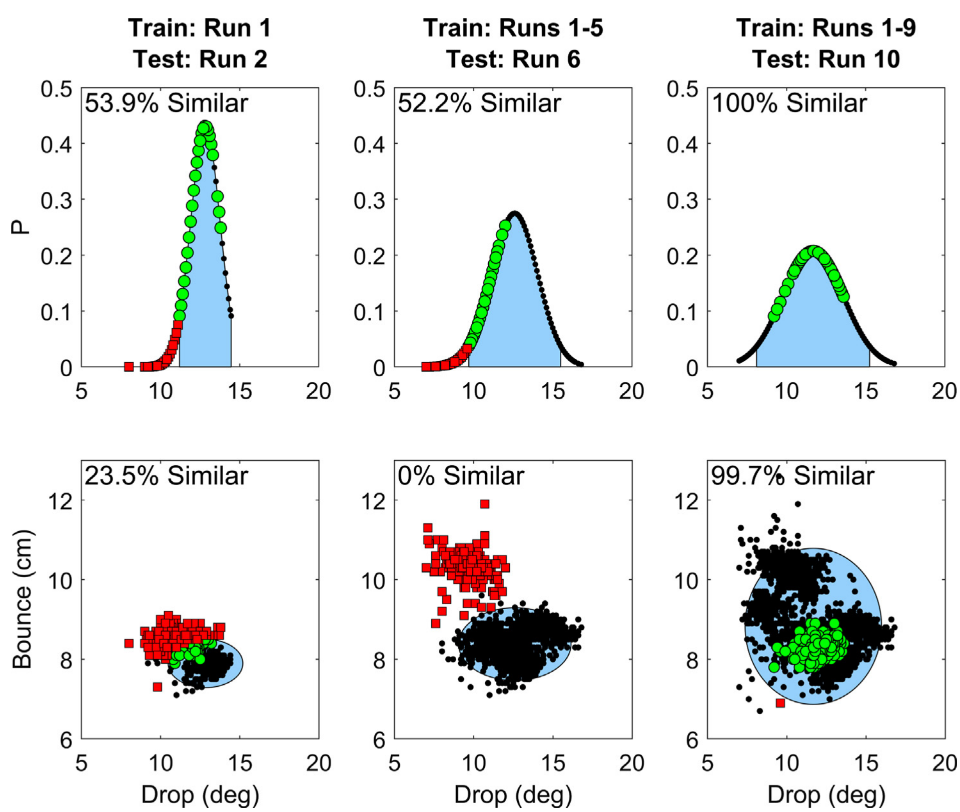

Fig. 1. Determination of the percent of similar data points for a representative runner and representative training and testing datasets. Top row: Univariate analysis for pelvic drop. The probability density function (P) is plotted against the values for pelvic drop in the training dataset (small dots). The shaded area under the curve represents 95% of the probability density function. A testing dataset of a run from the same runner but different from the run(s) included in the training dataset is applied to the same probability density function. The data points in the testing dataset are plotted depending on if they fall inside (circles) or outside (squares) 95% of the distribution of the training dataset, and the percent of similar data points is indicated. Bottom row: Two-dimensional example of the multivariate analysis, using pelvic drop and bounce. The two variables from the training set are plotted against each other (small dots), and the shaded area represents 95% of the probability density function. A testing dataset of a run from the same runner but different from the run(s) included in the training dataset is applied to the same probability density function. The data points in the testing dataset are plotted depending on if they fall inside (circles) or outside (squares) 95% of the distribution of the training dataset, and the percent of similar data points is indicated. Note: The two-dimensional multivariate analysis in this example is for visualization purposes only; six-dimensional multivariate analyses were used in this investigation.

IMU variable (univariate and multivariate) was determined as the maximum number of runs to reach stability across the 12 runners.

To ensure that the runner's stable running pattern – defined by the number of runs at the stability point – was unique to each runner, and to cross-validate this approach, an additional group of testing datasets was generated using the runs by all other runners. Only the number of runs at the overall stability point for each variable were used for this analysis. Each unique combination of runs at the overall stability point was a training dataset, and there were 110 testing datasets (10 runs for 11 other runners). Following the steps above, the probability density function of the univariate and multivariate normal distributions was determined for the training datasets, and the percent of similar data points was averaged across all pairs of training-testing datasets for each runner. A repeated-measures MANOVA was used to determine overall differences between the percent of similar data points for the subject-specific testing datasets and all other runners testing datasets across all univariate and multivariate analyses. In the case of a sig-

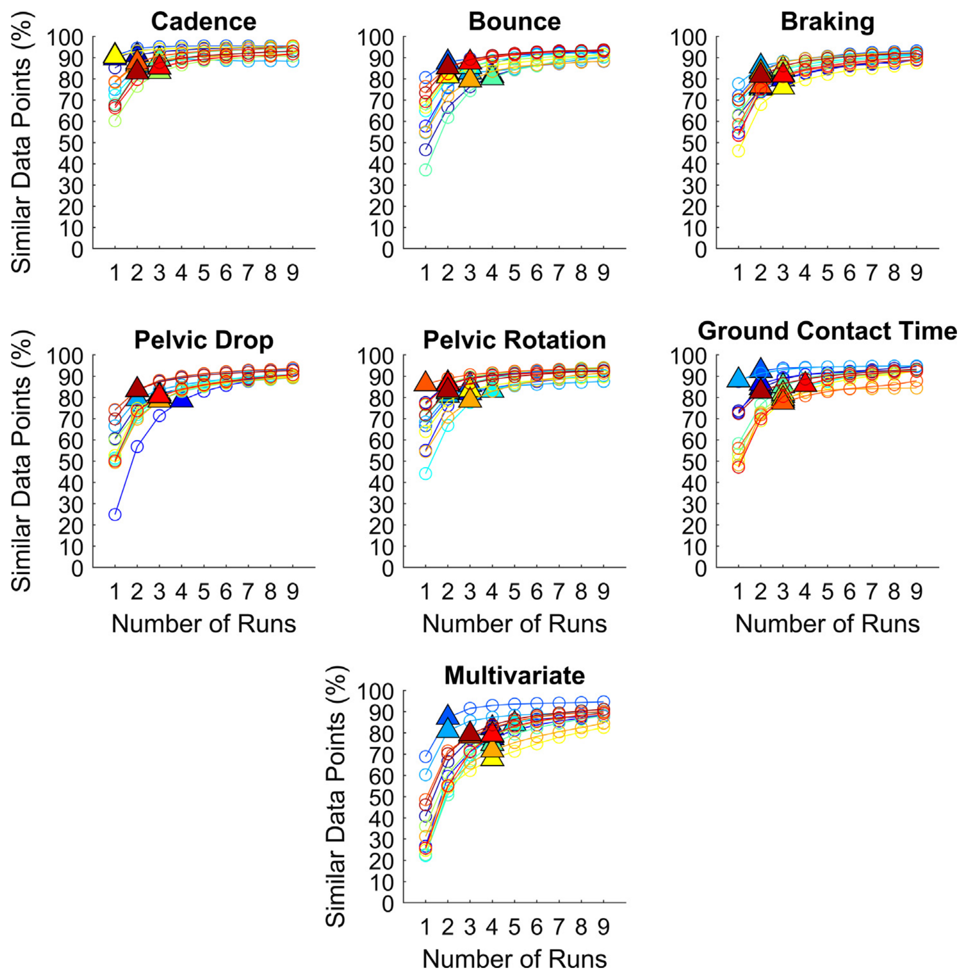

Fig. 2. The percent of similar data points in subject-specific testing datasets for training datasets of between one and nine runs, averaged across all pairs of training and testing datasets for each number of runs and all univariate and multivariate analyses. Each line/color represents one runner. The stability point for each runner, defined as the number of runs where the addition of one more run to the training dataset resulted in less than a 5% increase of percent of similar data points, is indicated with a triangle.

Table 4
Number of runs needed to define a stable running pattern for each runner and each univariate and multivariate analysis. Each individual runner's maximum number of runs is highlighted in **bold**. The mean (SD) and maximum number of runs is also determined across all runners, with the overall stability point for each variable defined as the maximum number of runs across all runners.

Runner	Stability point (number of runs)						
	Cadence	Bounce	Braking	Drop	Rotation	GCT	Multivariate
1	2	**4**	2	3	2	2	**4**
2	1	3	3	**4**	3	2	**4**
3	1	2	2	2	**3**	2	2
4	2	**3**	2	2	2	1	2
5	2	3	3	3	4	3	**5**
6	3	**4**	3	3	2	3	**4**
7	3	2	3	3	2	3	**4**
8	1	2	3	3	3	3	**4**
9	2	3	2	3	3	3	**4**
10	2	2	2	2	1	**3**	**3**
11	3	3	3	3	2	**4**	**4**
12	2	2	2	2	2	2	**3**
Mean (SD)	2.0 (0.7)	2.8 (0.8)	2.5 (0.5)	2.8 (0.6)	2.4 (0.8)	2.6 (0.8)	3.6 (0.9)
Maximum	3	4	3	4	4	4	5

Note: GCT = ground contact time.

nificant ($p < 0.05$) omnibus test, all pairwise comparisons (subject-specific vs. all other runners for each univariate and multivariate analysis) were evaluated at a Bonferroni-corrected $\alpha = 0.007$. Effect size was reported as Cohen's d. All statistical tests were conducted in SPSS (v24.0.0.1, SPSS, Inc., Chicago, IL).

3. Results

The percent of similar data points for subject-specific testing datasets increased with the number of runs in the training dataset (Fig. 2). For most runners, the number of runs at the stability point

Table 5
Percent of similar data points and results of the pairwise comparisons between the subject-specific testing datasets and the testing datasets from all other runners for each univariate and multivariate analysis.

Variable	Subject-specific		All other runners		P	d
	Mean	SD	Mean	SD		
Cadence	89.7	3.7	49.8	26.6	<0.001*	2.10
Bounce	86.7	3.7	43.3	32.0	0.001*	1.90
Braking	83.3	3.9	45.1	33.0	0.002*	1.63
Drop	85.0	3.3	74.2	28.2	0.218	0.54
Rotation	87.6	3.2	51.0	28.3	0.001*	1.82
Ground contact time	87.6	4.3	62.1	24.8	0.006*	1.43
Multivariate	83.0	5.8	22.7	20.8	<0.001*	3.95

* Significant at the Bonferroni-adjusted $\alpha = 0.007$.

for the multivariate analysis was five, which was greater than or equal to the number of runs at the stability point for all univariate analyses (Table 4).

There was a significant overall effect of testing dataset type on the percent of similar data points across all univariate and multivariate analyses, $F_{(5,7)} = 25.578$, $p = 0.001$. Pairwise comparisons indicated that the percent of similar data points in the subject-specific testing datasets was greater than the percent of similar data points in the testing datasets for all other runners for the multivariate analysis and all univariate analyses ($p < 0.007$), except for pelvic drop (Table 5).

4. Discussion

The purpose of this study was to determine the number of runs needed to establish a stable running pattern for runners in their natural running conditions based on both univariate and multivariate analyses of running biomechanical data. Overall, and in support of the hypotheses, the results of the current study show that four runs are needed to establish a stable gait pattern for univariate analyses, while five runs are needed to reach the stability point for multivariate analyses. Moreover, support for selecting these values as the overall stability point comes from the cross-validation approach, where the number of similar data points in a subject-specific testing dataset was significantly greater than testing datasets of runs from all other runners for all but one univariate analysis.

This is the first study to define a stable running pattern using data from multiple runs, a novel statistical approach, and the inclusion of multivariate analyses. The strength of this approach is that differences from the stable running pattern may provide real-world indications of alterations in running biomechanics, due to factors such as fatigue, performance, and/or injury status. This study improves upon previous research which sought to monitor changes in biomechanical data from just one run (Norris et al., 2016), averaged univariate metrics across all runs (Kiernan et al., 2018), or did not define a stable pattern before attempting to detect abnormal patterns (Cola et al., 2015). Similarly, studies investigating changes within a run have compared the mean of individual variables between pre-defined stages (Reenalda et al., 2016; Schütte et al., 2016), whereas the current approach suggests a multivariate representation of a stable running pattern could be used to identify atypical biomechanical data throughout the run. Thus, future research should consider the translation of this approach into real time data processing.

The results of this study indicate that individual or combinations of biomechanical variables can be used to identify unique running patterns for individual runners, except for pelvic drop alone. The lone non-significant finding suggests that the recorded distribution of pelvic drop is similar among all runners. In contrast, the multivariate analysis accounts for relationships between variables (Fukuchi et al., 2011), so while the distribution of certain variables (e.g. pelvic drop) may overlap between runners, the combination of many variables provides a smaller distribution and a more reliable (consistent) representation of an individual's running pattern than separate univariate distributions.

Limitations to this study are acknowledged. First, the similar distribution of pelvic drop may represent a consistent biological pattern among all healthy runners in this study, however, previous research has shown differences in pelvic drop between healthy and injured runners (Dierks et al., 2008; Nakagawa et al., 2012; Willson and Davis, 2008; Willy et al., 2012). Thus, the current result could be due to an inability to reliably determine pelvic drop from a single IMU. Likewise, other common variables in running biomechanics analyses (e.g. joint kinematics and kinetics) that cannot be recorded from a single IMU might be relevant when defining a stable running pattern. Future research using IMUs placed on multiple locations and a broader representation of commonly used biomechanical variables is therefore necessary to further define a stable running pattern. Second, this study represents one possible way to define the number of runs needed to establish a stable running pattern and other definitions of stability (e.g. a set percentage of similar data points) may be relevant. However, a set percentage may be difficult to achieve for all runners, as this study showed not all individuals reached the same percent of similar data points. Furthermore, the definition of a stability point may depend on similarities between runners (Clermont et al., 2018), and the research question. Therefore, it is likely that a subject-specific or research question-specific definition of stability is better than an overall stability point. The third limitation is that the runners had no restrictions on running route or clothing, yet the data included in the analysis were constrained to level sections of the recorded runs. It has been shown that uphill and downhill running routes (Giandolini et al., 2016; 2015), variations in speed (Benson et al., 2018), or environmental factors (Ahamed et al., 2018) can influence running biomechanics. Future analyses should consider the effect of these factors on the ability to define a stable running pattern.

5. Conclusion

In conclusion, based on longitudinal biomechanical data collected using a single IMU placed on the lower back, this is the first study to define an approach for establishing a stable running pattern in real-world settings. As biomechanical research moves outside of the traditional laboratory setting, this novel methodological approach is recommended to better understand and define day-to-day changes in gait patterns and the influence of ever-changing extrinsic factors.

Conflict of interest

None.

Acknowledgements

This study was partially funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) Idea-2-Innovation Award (grant #I2IPJ 493875-16), a University of Calgary Eyes High Postdoctoral Research award, and a Strategic Research Grant from the Vice-President (Research) at the University of Calgary. The funding sources did not have a role in the design, analysis or presentation of findings related to this study.

References

Ahamed, N.U., Kobsar, D., Benson, L.C., Clermont, C.A., Kohrs, R., Osis, S.T., Ferber, R., 2018. Using an accelerometer to classify subject-specific running biomechanical gait patterns based on changes in environmental weather conditions. Plos One in press.

Benson, L.C., Clermont, C.A., Bosnjak, E., Ferber, R., 2018a. The use of wearable devices for walking and running gait analysis outside of the lab: a systematic review. Gait Posture 63, 124–138.

Benson, L.C., Clermont, C.A., Osis, S.T., Kobsar, D., Ferber, R., 2018b. Classifying running speed conditions using a single wearable sensor: optimal segmentation and feature extraction methods. J. Biomech. 71, 94–99.

Clermont, C.A., Benson, L.C., Osis, S.T., Kobsar, D., Ferber, R., 2018. Running patterns for male and female competitive and recreational runners based on accelerometer data. J. Sports Sci., 1–8

Cola, G., Avvenuti, M., Vecchio, A., Yang, G., Lo, B., 2015. An on-node processing approach for anomaly detection in gait. IEEE Sens. J. 15, 6640–6649.

Diedrich, F.J., Warren, W.H., 1995. Why change gaits?: Dynamics of the walk-run transition. J. Exp. Psychol. Hum. Percept. Perform. 21, 183–202.

Dierks, T.A., Manal, K.T., Hamill, J., Davis, I.S., 2008. Proximal and distal influences on hip and knee kinematics in runners with patellofemoral pain during a prolonged run. J. Orthop. Sports Phys. Ther. 38, 448–456.

Fukuchi, R.K., Eskofier, B.M., Duarte, M., Ferber, R., 2011. Support vector machines for detecting age-related changes in running kinematics. J. Biomech. 44, 540–542.

Giandolini, M., Horvais, N., Rossi, J., Millet, G.Y., Samozino, P., Morin, J.B., 2016. Foot strike pattern differently affects the axial and transverse components of shock acceleration and attenuation in downhill trail running. J. Biomech. 49, 1765–1771.

Giandolini, M., Pavailler, S., Samozino, P., Morin, J., Horvais, N., 2015. Foot strike pattern and impact continuous measurements during a trail running race: proof of concept in a world-class athlete. Footwear Sci. 7, 127–137.

Kiernan, D., Hawkins, D.A., Manoukian, A.C., McKallip, M., Oelsner, M., Caskey, L., Coolbaugh, C.F., 2018. Accelerometer-based prediction of running injury in national collegiate athletic association track athletes. J. Biomech. 73, 201–209.

MathWorks, 2018. Multivariate Normal Distribution. 2018.

Nakagawa, T.H., Moriya, É.T.U., Maciel, C.D., Serrão, F.V., 2012. Trunk, pelvis, hip, and knee kinematics, hip strength, and gluteal muscle activation during a single-leg squat in males and females with and without Patellofemoral pain syndrome. J. Orthop. Sports Phys. Ther. 42, 491–501.

Norris, M., Kenny, I.C., Anderson, R., 2016. Comparison of accelerometry stride time calculation methods. J. Biomech. 49, 3031–3034.

Reenalda, J., Maartens, E., Homan, L., Buurke, J.J., 2016. Continuous three dimensional analysis of running mechanics during a marathon by means of inertial magnetic measurement units to objectify changes in running mechanics. J. Biomech. 49, 3362–3367.

Schütte, K.H., Seerden, S., Venter, R., Vanwanseele, B., 2016. Fatigue-related asymmetry and instability during a 3200-m time-trial performance in healthy runners. In ISBS-Conference Proceedings Archive.

Taunton, J.E., Ryan, M.B., Clement, D.B., McKenzie, D.C., Lloyd-Smith, D.R., Zumbo, B. D., 2003. A prospective study of running injuries: the Vancouver sun run "In Training" clinics. Br. J. Sports Med. 37, 239–244.

Willson, J.D., Davis, I.S., 2008. Lower extremity mechanics of females with and without patellofemoral pain across activities with progressively greater task demands. Clin. Biomech. 23, 203–211.

Willy, R.W., Manal, K.T., Witvrouw, E.E., Davis, I.S., 2012. Are mechanics different between male and female runners with Patellofemoral pain? Med. Sci. Sports Exerc. 44, 2165–2171.