

Medicine & Science IN Sports & Exercise

The Official Journal of the American College of Sports Medicine

www.acsm-msse.org

... Published ahead of Print

Wrist-worn Accelerometry for Runners: Objective Quantification of Training Load

Victoria H Stiles¹, Matthew Pearce¹, Isabel S Moore², Joss Langford³, and Alex V Rowlands^{4,5,6}

¹Sport and Health Sciences, College of Life and Environmental Sciences, University of Exeter, Exeter, United Kingdom; ²Cardiff School of Sport and Health Sciences, Cardiff Metropolitan University, Cardiff, United Kingdom; ³GENEActiv, Activinsights, Cambridgeshire, United Kingdom; ⁴Diabetes Research Centre, University of Leicester, Leicester, United Kingdom; ⁵National Institute for Health Research (NIHR) Leicester Biomedical Research Centre, United Kingdom; ⁶Alliance for Research in Exercise, Nutrition and Activity (ARENA), Sansom Institute for Health Research, Division of Health Sciences, University of South Australia, Adelaide, Australia

Accepted for Publication: 15 June 2018

Medicine & Science in Sports & Exercise® Published ahead of Print contains articles in unedited manuscript form that have been peer reviewed and accepted for publication. This manuscript will undergo copyediting, page composition, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered that could affect the content.

Copyright © 2018 the Author(s). Published by Wolters Kluwer Health on behalf of the American College of Sports Medicine

Wrist-worn Accelerometry for Runners: Objective Quantification of Training Load

Victoria H. Stiles¹, Matthew Pearce¹, Isabel S. Moore², Joss Langford³,
and Alex V. Rowlands^{4,5,6}

¹Sport and Health Sciences, College of Life and Environmental Sciences, University of Exeter, Exeter, United Kingdom; ²Cardiff School of Sport and Health Sciences, Cardiff Metropolitan University, Cardiff, United Kingdom; ³GENEActiv, Activinsights, Cambridgeshire, United Kingdom; ⁴Diabetes Research Centre. University of Leicester, Leicester, United Kingdom; ⁵National Institute for Health Research (NIHR) Leicester Biomedical Research Centre, United Kingdom; ⁶Alliance for Research in Exercise, Nutrition and Activity (ARENA), Sansom Institute for Health Research, Division of Health Sciences, University of South Australia, Adelaide, Australia

Corresponding author contact details:

Corresponding author

Dr Victoria Stiles, Sport and Health Sciences, College of Life and Environmental Sciences, University of Exeter, Exeter, UK; Tel: +44(0)1392 722885; Fax: +44(0)1392 724726; email: v.h.stiles@exeter.ac.uk

This project was supported by Medical Research Council Proximity to Discover funding (Reference: MC_PC_14127) in collaboration with Activinsights Ltd, UK. AR is with the National Institute for Health Research (NIHR) Biomedical Research Centre based at University Hospitals of Leicester and Loughborough University, the National Institute for Health Research Collaboration for Leadership in Applied Health Research and Care – East Midlands (NIHR CLAHRC – EM) and the Leicester Clinical Trials Unit. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health.

Conflicts of Interest

As a collaborative study with industry supported by MRC Proximity to Discover funding, the industry partner may potentially benefit from the outcomes from the research. However, the open-source analysis procedures employed in the current study impose no restriction for other members of the activity monitoring industry to also benefit. There are no other competing interests. The results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation and do not constitute endorsement by ACSM.

Copyright © 2018 The Author(s). Published by Wolters Kluwer Health, Inc. on behalf of the American College of Sports Medicine. This is an open access article distributed under the Creative Commons Attribution License 4.0 (CCBY), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Abstract

Purpose: This study aimed to apply open-source analysis code to raw habitual physical activity data from wrist-worn monitors to: 1) objectively, unobtrusively and accurately discriminate between ‘running’ and ‘non-running’ days; and 2) develop and compare simple accelerometer-derived metrics of external training load with existing self-report measures. **Methods:** Seven-day wrist-worn accelerometer (GENEActiv, Activinsights Ltd, Kimbolton, UK) data obtained from 35 experienced runners (age, 41.9 ± 11.4 years; height 1.72 ± 0.08 m; mass 68.5 ± 9.7 kg; Body Mass Index, 23.2 ± 2.2 kg.m²; 19 [54%] women) every other week over 9-18 weeks were date-matched with self-reported training log data. Receiver-Operating-Characteristic analyses were applied to accelerometer metrics (‘Average Acceleration’, ‘Most Active-30mins’, ‘Mins \geq 400mg’) to discriminate between ‘running’ and ‘non-running’ days and cross-validated (leave one out cross-validation; LOOCV). Variance explained in training log criterion metrics (Miles, Duration, Training Load) by accelerometer metrics (‘Mins \geq 400mg’, ‘WL(workload)400-4000mg’) was examined using linear regression with LOOCV. **Results:** ‘Most Active-30mins’ and ‘Mins \geq 400mg’ had >94% accuracy for correctly classifying ‘running’ and ‘non-running’ days, with validation indicating robustness. Variance explained in Miles, Duration and Training Load by ‘Mins \geq 400mg’ (67-76%) and ‘WL400-4000mg’ (55-69%) was high, with validation indicating robustness. **Conclusion:** Wrist-worn accelerometer metrics can be used to objectively, unobtrusively and accurately identify running training days in runners, reducing the need for training logs or user input in future prospective research or commercial activity tracking. The high percentage of variance explained in existing self-reported measures of training load by

simple, accelerometer-derived metrics of external training load supports the future use of accelerometry for prospective, preventative and prescriptive monitoring purposes in runners.

Keywords: workload, training exposure, training programmes, athlete monitoring, injury prevention, performance

ACCEPTED

Introduction

Runners are suggested to be particularly at risk of developing a running related injury (RRI) if they have one or a combination of the following: a history of injury, low or high running experience (high indicates that long distances have been run for many years), a low (women) or high (men) weekly training frequency, a low or high overall weekly running mileage or a sudden increase in training load (1-3). Characteristics of external training load (work done) typically described as the distance, frequency, intensity and duration of running per day/week or month are therefore highly modifiable risk factors for RRI (1-4). Optimal patterns of training load relative to rest and sleep (recovery) are also important in the prevention of RRI and illness (5-7). However a single validated method enabling longitudinal training patterns to be objectively, accurately and unobtrusively quantified in runners is unavailable. A more detailed understanding of the influence of training load on RRI and performance could be enhanced by an improved ability to objectively monitor simple, yet meaningful characteristics of external training load in runners on a large population scale (5,8,9).

Within research and applied settings, characteristics of external training load such as miles and duration, are typically recorded using a training log (self-reported or coach-reported), global navigational satellite system (GNSS), or prescribed within a training programme. To avoid inaccuracies from self-reported data due to recall bias (over/under-reported training/activity), characteristics of external training load can be more accurately quantified using objective measurements (9,10). For example, initial findings from the use of pedometers in military recruits to estimate distances covered over consecutive weeks of training, have highlighted the importance of capturing evidence of previously unreported additional training and habitual

physical activity (PA) associated with stress fractures (9). In addition to pedometers, there has been a vast increase in the use of more sophisticated, commercial, consumer-focused wrist-worn activity trackers that are worn 24/7 to monitor habitual PA (11). These usually incorporate accelerometers that sample at various frequencies and/or GNSS. With or without additional user input to improve the accuracy of identifying training events, the external training characteristics objectively recorded by the majority of these devices seem only to replicate those captured in a training log, e.g. distance and duration. Restricting objective quantification of training characteristics to the replication of existing metrics, may limit insight into the possible effects of accelerometer-derived metrics of external training load on performance and injury outcomes in runners.

Accelerometer-derived measures of load, if available, tend to input accelerations to 'black-box' on-board processors and produce manufacturer-specific, proprietary metrics that appear difficult to interpret (5). For example, in team sports (12-15) there has been some development with the use of vest-/back-mounted tri-axial accelerometers to provide a proprietary measure termed PlayerLoad™ (modified vector magnitude in arbitrary units representing rates of change in instantaneous acceleration (16)). Proprietary metrics limit comparisons with data recorded by other devices. The wear location and limited battery life in these devices also limits their ability to monitor other important training or non-training activity outside of training sessions. These aspects, alongside other practical issues related to access to longitudinal data, limit the use of accelerometry in running-related research that seeks to develop new measures of external training load that might help reduce RRI and improve performance. The ability to objectively, unobtrusively and accurately quantify external training load without user input using high

resolution, tri-axial, open source (non-proprietary) acceleration data from a single wearable device over weeks at a time, is therefore attractive.

Wrist-worn accelerometers are now widely used in very large research cohorts to measure characteristics of habitual PA (17) including sleep without the need for a sleep diary (18). These research-grade monitors generate high-resolution raw data, which can be processed using open-source software, facilitating the development of metrics most appropriate for a specific research question. For example, outputs from these monitors have been validated with ground reaction force data (19,20) enabling metrics indicative of external mechanical loading relative to bone health to be established (21). A similar approach could therefore be developed to provide a field-based proxy measure of external mechanical load (biomechanical risk factor) relevant to injury. Example metrics in PA and health research include ‘Average Acceleration’, ‘Most Active-30mins’ or ‘Mins \geq 400mg’ (Table 1) which describe the intensity of activity in different user-defined time periods or time spent above user-defined intensities of activity (e.g. 400 mg is a validated vigorous activity threshold in adults (22)). While these wrist-worn tri-axial accelerometer-derived metrics are validated for use in large-scale population PA research, it is not yet known whether they can be used to accurately and unobtrusively measure external training load in runners in the field. The application of these sample metrics provides a justifiable starting point for objectively classifying and quantifying an alternative measure of external training load in runners. Further experimentation with the creation of a composite metric of workload (‘WL400-4000mg’; Table 1) from intensity multiplied by duration (23), may also provide a possible accelerometer-derived alternative to Foster’s (24) composite measure of Training Load (rating of perceived exertion x duration). Embedding a procedure for classifying

running and non-running training days from accelerometer data and accurately obtaining accelerometer-derived metrics of external training load within existing, validated protocols for accurately monitoring habitual activity (25, 26) including those used to derive accurate measures of sleep (18), would benefit subsequent analysis of patterns of training relative to rest and recovery (6,7). The benefits of high wear compliance and increased measurement reliability associated with the use of wrist-worn monitors (27) would also support this future analysis.

Insert Table 1 near here

The aims of this study are to assess whether simple PA metrics derived from the application of open-source analysis code to repeated week-long raw habitual PA data from wrist-worn tri-axial accelerometers in runners can be used to; 1) objectively, unobtrusively and accurately discriminate between running training days and non-running days; and 2) quantify external training load on running training days. It was hypothesised that the ‘Most Active 30-mins’ metric (Table 1) would be the best discriminator for classifying running and non-running days as it focuses on a single continuous period of activity rather than an average derived from the entire day. It was also hypothesised that ‘Mins \geq 400mg’ and ‘WL400-4000mg’ would demonstrate at least a moderate level of correspondence (variance explained) with existing self-reported measures of training load (criterion measures) from a training log.

Methods

Participants

41 runners (22 women) with >2 years running experience who were training for an event (e.g.

10K, half/full marathon) were recruited. An early attrition rate (14.6%) due to injury or withdrawal resulted in 35 runners (19 women [54%]; Table 2) monitoring their training load for at least nine consecutive weeks (mean 12.6 ± 2.3 weeks) between December 2015-June 2016, to obtain a range of training intensities prior to their target event. Variations in average weekly running mileage, duration and pace (minutes/mile) averaged over the monitoring period indicate heterogeneous characteristics of training in this sample of runners (Table 2). The Sport and Health Sciences Ethics Committee at the University of Exeter approved this study and all participants provided written informed consent.

Insert Table 2 near here

Self-monitoring of training load

For the duration of the monitoring period, after each activity, runners were required to record the following data as soon as possible in a training log: date of session; start/end times (session duration calculated); activity/training type (e.g. road/off-road/track/treadmill run or other (e.g. gym, swimming, cycling, circuits or yoga)); running miles covered; an overall session RPE after consulting a visual scale, regardless of session type. Training logs were returned every two weeks (mail) for manual input into a database. A composite measure of running Training Load (session RPE x session duration) in arbitrary units was subsequently calculated (7,24). Using activity/training type data, each day was classified as either a 'running' (all surface types) or 'non-running' day, with the latter further classified as either 'other training' (e.g. gym, swimming, cycling, circuits or yoga) or a 'rest' day. Where running training occurred twice on one day, running miles and duration were summed, a mean running RPE was calculated and

Training Load was recalculated. If different types of training including running occurred on the same day, that day was labelled as a 'running' day. Average self-reported weekly training load characteristics for the sample of runners are presented in Table 2.

Accelerometer monitoring of training load

Runners were issued with a GENEActiv accelerometer (100 Hz, tri-axial, $\pm 8g$; Activinsights Ltd, Kimbolton UK) every other week to wear on their non-dominant wrist to collect seven days of data. Monitoring on alternate weeks allowed monitors to be refreshed and reduced participant burden to help maximise wear compliance during test weeks. Participants were requested to wear the monitor 24-hours a day. As minimal differences exist in accelerometer output between monitors worn on dominant and non-dominant wrists during higher intensity activity, (28) runners were permitted to swap the wear location of the GENEActiv to their dominant wrist for the duration of a run if the wear location clashed with the preferred placement of another personal wearable device. Raw acceleration files were extracted and processed through an open-source package (GGIR Version 1.2-8, (25)) in R (<http://cran.r-project.org>) for auto-calibration and calculation of the dynamic acceleration in milli-gravitational units (mg) averaged over 5-second epochs (the resultant vector magnitude corrected for gravity, ENMO, as described previously,(26)). A total of 1532 days were obtained from which 1494 (97.5%) accelerometer days with at least 10 hours of wear per waking day, (29) were analysed. Time accumulated in bins spanning 50 mg intervals between 50 and 4000 mg (50-99.99 mg; 100-149.99 mg; 150-199.99 mg etc) were obtained with activity <50 mg considered non-meaningful,(21,30) and the incidence of time accumulated >4000 mg extremely brief and rare.

Accelerometer metrics and statistical analysis

Discriminating between 'running' and 'non-running' days (Aim 1)

Accelerometer data were time-matched with training log data for each calendar day in STATA (Version 15). 'Average Acceleration', 'Most Active 30-mins' and 'Mins \geq 400mg', which are typical metrics used to describe characteristics of habitual PA, were considered candidates for discriminating between 'running', 'other training' and 'rest' days (Table 1). Receiver-Operating-Characteristic (ROC) analyses were carried out for these metrics to derive the optimum thresholds for discrimination between 'running' and 'non-running' training days. Performances were summarised by calculating the area under the ROC curves (AUROC). Similar to the methods by Evenson et al,(31) thresholds were selected that optimised the balance between sensitivity ('running' classified as 'running') and specificity ('non-running' classified as 'non-running'). Optimal thresholds were applied to the data and the percentage of days correctly classified as 'running' and 'non-running' calculated. The percentage of days correctly classified as 'non-running' was further broken down according to whether the day was a 'other training' or 'rest' day. The percentage of misclassification for each type of 'other training' misclassified as 'running' was also identified. To detect a medium effect size with power of 80% and alpha of 0.05 (AUROC of 0.6 as significantly different from an AUROC of 0.5, no association), a total sample of at least 258 days (sample ratio of 1:1 with 129 positive days and 129 negative days) was required. The generalisability and performance of the ROC models on unseen data was assessed using leave-one-out-cross-validations (LOOCV) (32).

Estimation of external training load on accelerometer-classified 'running' days (Aim 2)

From training log data, Miles, Duration and Training Load, which are frequently monitored to

understand the influence of training load on performance, injury and illness,(1,3,6,7,24,33) were used to represent external and composite criterion measures of training load (criterion measures). On running training days that were classified using cut points from accelerometer metrics which demonstrated the highest levels of accuracy for correctly classifying running days (see Aim 1), accelerometer-derived metrics of training load ('Mins \geq 400mg' and 'WL400-4000mg'; Table 1) were examined to see how closely they corresponded to criterion measures. On each set of classified days, variances explained in training log criterion measures (Miles, Duration and Training Load) by 'Mins \geq 400mg' and 'WL400-4000mg' were examined using linear regression analysis. The generalisability and performance of the model on unseen data was assessed using LOOCV. Statistical analyses were carried out in STATA (Version 15) with an alpha level set at 0.05.

Results

Discriminating between 'running' and 'non-running' days (Aim 1)

From 35 participants, a total of 1494 days with >10-hours wear were analysed, of which 694 were 'running' days, 641 were 'rest' days and 159 were 'other training' days. Each participant contributed 18-56 days [mean(SD) = 42.7(8.8)]. Of these, 2-42 [19.8(10)] were 'running' days, 0-37 [18.3(9.0)] were 'rest' days, and 0-23 [4.5(6.0)] were 'other training' days.

Cut-points for identifying 'running days' from habitual PA using respective accelerometer metrics with AUC significant at $p < 0.05$ are presented in Table 3. Discrimination between 'running' and 'rest' days was excellent (88-94% agreement; Table 3). Both the 'Most Active-30mins' and 'Mins \geq 400mg' had >94% accuracy for classifying 'running' as 'running' and 'non-

running' as 'non-running' and were subsequently used to separately classify running days for Aim 2. 'Average Acceleration' performed similarly for correctly classifying 'non-running' days (93%), but was weaker at correctly classifying 'running' days (88%). Irrespective of the metric, the greatest inaccuracy was from misclassifying 'other training' days as 'running' days, ranging from 14% misclassification for 'Most Active-30mins' to 33% misclassification for 'Average Acceleration'. The LOOCV procedure indicated robustness and stability as the high performance was maintained ($AUC \geq 0.93$).

Insert Table 3 Here

The rate of misclassification of 'other training' activities as 'running' is shown in Table 4. The most frequent 'other training' activities undertaken were cycling (47 occurrences) and gym/exercise classes (45 occurrences). The most likely activities to be misclassified by the 'Average Acceleration' metric were field/racket sport (95%), circuit training (57%) and then cycling (53%). A similar pattern was found when using 'Mins \geq 400mg', except circuit training was not misclassified. The 'Most Active-30mins' metric performed better for field or racket sports (25% misclassification) and generally across the board, but still misclassified nearly a third of cycling occurrences.

Insert Table 4 Here

Estimation of external training load on accelerometer-classified ‘running’ days (Aim 2)

On running days classified using ‘Mins \geq 400mg’ or using ‘Most Active-30mins’ (accelerometer metrics most successful at classifying running days from Aim 1), the accelerometer-derived training load metric ‘Mins \geq 400mg’ explained approximately 75-76% and 74% of the variance in Miles and Duration, respectively, and 67% and 71% of the variance in Training Load (Table 5). The variance explained by ‘WL400-4000mg’ in Miles, Duration and Training Load was slightly lower at 63-69% on running days classified using either ‘Mins \geq 400mg’ or ‘Most Active-30mins’, except for Training Load when running days were classified using ‘Mins \geq 400mg’, which was much lower (55%). The LOOCV procedure indicated robustness and stability as the high performance was maintained in all cases.

Insert Table 5 Here

Discussion

Raw acceleration data from wrist-worn accelerometers widely used in research can be used to objectively, unobtrusively and accurately identify running training days and quantify external training load in runners. Importantly, the accelerometer metrics used are embedded within existing, validated open-source software for processing and analysing accelerometer data for accurate quantification of habitual PA (25,26). As a field-based proxy measure of external mechanical load, (19,20) use of these accelerometer-derived metrics will enhance future research that seeks to further understand the influence of objectively measured modifiable patterns of external training load relative to rest and sleep on RRI and performance outcomes (1-8).

Discriminating between ‘running’ and ‘non-running’ days

The high degree of accuracy for correctly classifying running days and days with no training indicates that wrist-worn accelerometer metrics can be used to objectively and unobtrusively discriminate between ‘running’ and ‘non-running’ days. While each accelerometer metric was able to discriminate between these days, the mean acceleration recorded during ‘Most Active-30mins’ was the best discriminator. As running is characterised by high accelerations,(22) that incorporate an impact peak, (19,20) high accelerations for the most active continuous 30-minutes of the day likely reflects the deliberate inclusion of a running session. The length of the training session may not match 30-minutes, but the elevation of the acceleration alone is sufficient to simply differentiate between running and non-running days. In contrast, metrics that sum time spent at high accelerations across the day (‘Mins \geq 400mg’), or the average accelerations across the day, can be elevated due to short activity bursts spread across the day which may or may not be part of a training session.

Even for the ‘Most Active-30mins’, a degree of misclassification in ‘field or racket sports’ and ‘circuits’ is likely due to these activities including aspects of running or lunging and jumping, which could elevate average acceleration to exceed magnitudes typically found during running (19,20). For cycling, road or track vibration also has the potential to elevate this average acceleration to similar levels found when running. Post-hoc analysis of demographic and training data indicated that very short runs may be a potential source of misclassification. However, we are also cognisant that validation of accelerometer data in the field is complicated by the use of potentially inaccurate self-reported training log or training programme information (under and over-reported training activity; 9,10). If using this simple metric to identify running training days

in future studies, any accepted level of misclassification will depend on the nature of the activity misclassified relative to the research question.

Estimation of external training load on 'running' days

When 'running' days were classified using 'Most Active-30mins', approximately 71-76% of the variance in Miles, Duration or Training Load was explained by the accelerometer-derived training load metric 'Mins \geq 400mg', which was approximately 7-13% more than the variance explained by the composite workload metric 'WL400-4000mg' on these days. When running days were classified using 'Mins \geq 400mg', similarly high levels of variance in Miles and Duration were explained by the accelerometer-derived training load metrics 'Mins \geq 400mg' and 'WL400-4000mg' compared to when days were classified using 'Most Active-30mins' but 4% and 9% less variance was explained in Training Load by respective metrics on these days. Despite differences, these accelerometer-derived metrics correspond highly with criterion measures, especially Miles and Duration, which suggests a high degree of convergent validity with existing training log methods for quantifying external training load. 'Mins \geq 400mg' in particular appears to be a good measure of external training load and can be easily obtained from longitudinal monitoring of habitual PA. For comparison, fast walking at 5 km/hr in adults yields approximately 170 ± 56 mg from a wrist-worn accelerometer, whilst running at 8 km/hr yields approximately 760 ± 200 mg (22). A threshold of 400 mg, which is also validated to quantify vigorous activity equivalent to 6 METS, (22; Table 1) therefore provides sufficient margins to avoid capturing lower-intensity walking-type activity whilst capturing lower accelerations introduced by large variability when running at 8 km/hr and lower accelerations from slower speed running. For comparison, additional analysis of accelerometer-derived metrics of external

training load on days classified using training log information, indicated that 'Mins \geq 400mg' (75%, 75% and 72% respectively) and 'WL400-4000mg' (65%, 60% and 62% respectively) explained similar variation in Miles, Duration and Training Load when days were classified using either 'Mins \geq 400mg' or 'Most Active-30mins'. An ability to use a single simple accelerometer-derived metric (e.g. 'Mins \geq 400mg') to accurately classify running days and provide a valid measure of external training load, lays the foundation for overcoming challenges such as ease of use and data interpretation described by Bourdon and colleagues,(5) for accelerometry to be used in training programme prescription. Further, it would be possible to use the regression analyses to predict outcomes familiar to runners (e.g. miles), but for analytical purposes we believe it preferable to use the directly measured metrics.

Accelerometer metrics are also highly correlated with lab-based measures of ground reaction force, (19,20) which suggests that accelerometer-derived metrics of external training load may add more value to models of RRI and performance than existing training log-based measures. Further research to determine whether 'Mins \geq 400mg' and/or 'WL400-4000mg' translate into meaningful measures of external training load in relation to injury and performance would be beneficial.

Implications of this study

The ability to obtain accurate, objective training records without the need for user input removes the reliance on the creation of a subjective training log, reduces participant burden, avoids bias and other reporting inaccuracies associated with logging or marking data on paper or a device, (9,10) and facilitates the accurate monitoring of runners' training behaviour in future prospective

studies. It also removes the need to match training log data, sometimes with multiple entries, with accelerometer data across days. A high monitor wear compliance (90% of days >16hrs; 76% of days >22 hrs) in this population also supports its inclusion in the future analysis of patterns of training relative to rest and sleep. In contrast to GNSS devices which are reliant on tracking a physical change in position in an outdoor environment, (5) accelerometers also have the advantage of being able to be used anywhere, even to monitor external load when running on the spot. Developing accelerometer-derived measures of external training load provides a natural extension of an accelerometer's existing ability to accurately measure all aspects of habitual PA including rest and sleep longitudinally.

Further developments

Streamlining methods for collecting, generating and visualising simple accelerometer-derived training load metrics, (5) could facilitate their inclusion in commercial activity trackers and healthcare monitors for training programme monitoring, prescription and injury prevention purposes. It would also be beneficial to examine time spent at higher intensities of acceleration (e.g. >1000 mg approximating 10 Km/hr; 28) to separately analyse higher and lower intensity running. In an effort to avoid bias from self-reported measures of Miles and Duration (10), further comparison of accelerometer-derived metrics with objectively measured criterion measures (e.g. GPS) might be beneficial, however it would be important to avoid over-burdening the runner with a requirement to wear multiple monitoring devices. To improve the classification of 'running' from 'other training' activities, alternative analysis methods such as those used in the Sedentary Sphere, (34,35) which consider the orientation of the monitor due to wrist position to estimate upright, sitting and lying down postures, could also be explored to distinguish

running from other activities, such as cycling. Analysis of the frequency compositions of the raw acceleration signal from different activities may also allow the selection of suitable filters to improve classification performance or enable metrics to be developed that allow cycling and racket sports to be identified explicitly. Whilst the high performance from the LOOCVs carried out in this study demonstrate the robustness of using accelerometer metrics to classify running days, further validation of the method in an independent sample would also be beneficial.

Strengths and Limitations

We employed longitudinal methods for objectively monitoring habitual PA in runners every other week and obtained written self-reported training logs every week over at least a nine-week period. The incorporation of runners leading up to events of differing lengths ensured a wide range of training patterns for testing. The results were robust across this range. During this period, runners remained motivated to complete training logs and were familiar with wearable devices yielding a large number of matched training log and accelerometer days with the added benefit of high accelerometer wear compliance. A rich bank of data was therefore obtained allowing robust statistical methods to be employed with cross-validations to address each research question. However, the nature of the sample does limit the generalisability of the results. All participants were self-identified runners who were training for an event. Most did undertake some form of cross-training, but the degree of engagement in other activities may be greater in people who do not identify as runners, or runners when they are not leading up to an event. Further research should investigate the degree of misclassification of 'other training' as 'running' in other populations.

Conclusions

Wrist-worn accelerometer metrics can be used to objectively, unobtrusively and accurately identify running training days in runners, reducing the need for training logs or user input in future prospective research or commercial activity tracking. A high percentage of the variance explained in existing metrics by new, simple, accelerometer-derived metrics of external training load supports the development and future use of accelerometry for prospective, preventative and prescriptive monitoring purposes in runners.

ACCEPTED

Acknowledgements

This project was supported by Medical Research Council Proximity to Discover funding (Reference: MC_PC_14127) in collaboration with Activinsights Ltd, UK.

The authors would like to thank the runners who volunteered their time and committed to having their training load monitored over multiple weeks.

AR is with the National Institute for Health Research (NIHR) Biomedical Research Centre based at University Hospitals of Leicester and Loughborough University, the National Institute for Health Research Collaboration for Leadership in Applied Health Research and Care – East Midlands (NIHR CLAHRC – EM) and the Leicester Clinical Trials Unit. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health.

Conflicts of Interest

As a collaborative study with industry supported by MRC Proximity to Discover funding, the industry partner may potentially benefit from the outcomes from the research. However, the open-source analysis procedures employed in the current study impose no restriction for other members of the activity monitoring industry to also benefit. There are no other competing interests. The results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation and do not constitute endorsement by ACSM.

References

1. van Gent RN, Siem D, van Middelkoop M, Bierma-Zeinstra SMA, Koes, BW. Incidence and determinants of lower extremity running injuries in long distance runners: a systematic review. *Br J Sports Med.* 2007;41(8):469–80.
2. Nielsen, RO, Buist I, Sørensen H, Lind M, Rasmussen S. Training errors and running related injuries: A systematic review. *Int J of Sports Physical Therapy.* 2012;7(1):58–75.
3. van der Worp MP, ten Haaf DSM, van Cingel R, de Wijer A, Nijhuis-van der Sanden MWG, Staal JB. Injuries in Runners; A Systematic Review on Risk Factors and Sex Differences. *PLoS One* [Internet]. 2015 [cited 2015 February 23];10(2) e0114937. Available from: <https://doi.org/10.1371/journal.pone.0114937>. doi: 10.1371/journal.pone.0114937.
4. Hreljac A. Etiology, prevention and early intervention of overuse injuries in runners: A biomechanical perspective. *Phys Med Rehabil Clin N Am.* 2005;16(3):651-67.
5. Bourdon PC, Cardinale M, Murray A, et al. Monitoring athlete training loads: consensus statement. *Int J of Sp Phys and Perf.* 2017;12(S2):161-70.
6. Schwellnus M, Soligard T, Alonso J, et al. How much is too much? (Part 2) International Olympic Committee consensus statement on load in sport and risk of illness. *Br J Sports Med.* 2016;50(17):1043-52.

7. Soligard T, Schweltnus M, Alonso J, et al. How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *Br J Sports Med.* 2016;50(17):1030-41.
8. Willy RW. Innovations and pitfalls in the use of wearable devices in the prevention and rehabilitation of running related injuries. *Physical Therapy in Sport.* 2018;29:26-33.
9. Moran DS, Evans R, Arbel Y, Luia O, Hadid A, Yanovich R, Milgrom C, Finestone AS. Physical and psychological stressors linked with stress fractures in recruit training. *Scand J Med Sci Sports.* 2013;23(4):443-450.
10. Nielsen, RO, Nohr EA, Rasmussen S, Sørensen H. Classifying running-related injuries based upon etiology, with emphasis on volume and pace. *Int J of Sports Physical Therapy.* 2013;8(2):172-79.
11. Geib RW, Swink PJ, Vorel AJ, Waite GN. The bioengineering of changing lifestyle and wearable technology: A mini review. *Biomed Sci Instrum.* 2015;51:69-76.
12. Casamichana D, Castellano J, Calleja-Gonzalez J, San Román J, Castagna C. Relationship between indicators or training load in soccer players. *J of Strength and Conditioning Res.* 2013;27(2):369-74

13. Scott BR, Lockie RG, Knight TJ, Clark AC, Janse de Jonge XA. A comparison of methods to quantify the in-season training load of professional soccer players. *Int J of Sports Phys and Perf.* 2013;8(2):195-202.
14. Scanlan AT, Wen N, Tucker PS, Dalbo VJ. The relationships between internal and external training load models during basketball training. *J of Strength and Conditioning Res.* 2014;28(9):2397-405.
15. Murray NB, Gabbett TJ, Townshend AD, Blanch P. Calculating acute:chronic workload ratios using exponentially weighted moving averages provides a more sensitive indicator of injury likelihood than rolling averages. *Br J Sports Med.* 2017;51(9):749-54.
16. Boyd LJ, Ball K, Aughey RJ. The reliability of Minimax X accelerometers for measuring physical activity in Australian Football. *Int J of Sp Phys and Perf.* 2011;6(3):311-21
17. Doherty A, Jackson D, Hammerla N, et al. Large Scale Population Assessment of Physical Activity Using Wrist Worn Accelerometers: The UK Biobank Study. *PLoS One* [Internet]. 2017 [cited 2017 February 1];12(2) e0169649. Available from <https://doi.org/10.1371/journal.pone.0169649>. doi:10.1371/journal.pone.0169649.
18. Van Hees VT, Sabia S, Jones SE, Wood AR, Anderson KN, Kivimaki M, Frayling TM, Pack AI, Bucan M, Mazzotti DR, Gehrman PR, Singh-Manoux A, Weedon MN. Estimating sleep parameters using an accelerometer without sleep diary. *bioRxiv* [Internet]. 2018 [cited 2018

February 1]. Available from: <https://www.biorxiv.org/content/early/2018/02/01/257972>. doi: 10.1101/257972.

19. Rowlands AV, Stiles VH. Accelerometer counts and raw acceleration output in relation to mechanical loading. *J Biomech*. 2012;45(3):448-54.

20. Stiles VH, Griew PJ, Rowlands AV. Use of accelerometry to classify activity beneficial to bone in premenopausal women. *Med Sci Sports Exerc*. 2013;45(12):2353-61.

21. Stiles VH, Metcalf BS, Knapp KM, Rowlands, AV. A small amount of precisely measured high-intensity habitual physical activity predicts bone health in pre- and post-menopausal women in UK Biobank. *Int J Epidemiol* 2017;46(6):1847-56

22. Hildebrand M, van Hees VT, Hansen BH, Ekelund U. Age group comparability of raw accelerometer output from wrist- and hip-worn monitors. *Med Sci Sports Exerc*. 2014;46(9):1816-24.

23. van der Ploeg H, Hillsdon M. Is sedentary behaviour just physical inactivity by another name? *Int J of Behav Nutr Phys Act* [Internet]. 2017 [cited 2017 October 23];14(1):142. Available from: <https://doi.org/10.1186/s12966-017-0601-0>. doi:10.1186/s12966-017-0601-0.

24. Foster C. Monitoring training in athletes with reference to overtraining syndrome. *Med Sci Sports Ex*. 1998;30(7):1164-8.

25. van Hees VT, Fang Z, Langford J, et al. Auto-calibration of accelerometer data for free-living physical activity assessment using local gravity and temperature: an evaluation on four continents. *J Appl Physiol*. 2014;117(7):738-44.
26. van Hees VT, Gorzelniak L, Dean Leon EC et al. Separating movement and gravity components in an acceleration signal and implications for the assessment of human daily physical activity. *PLoS One* [Internet]. 2013 [cited 2013 April 23];8(4). Available from: <https://doi.org/10.1371/journal.pone.0061691>. doi:10.1371/journal.pone.0061691.
27. van Hees VT, Renström F, Wright A et al. Estimation of daily energy expenditure in pregnant and non-pregnant women using a wrist-worn tri-axial accelerometer. *PLoS One* (Internet). 2011 [cited 2011 July 29];6(7). Available from: <https://doi.org/10.1371/journal.pone.0022922>. doi:10.1371/journal.pone.0022922.
28. Esliger DW, Rowlands AV, Hurst TL, Catt M, Murray P, Eston RG. Validation of the GENE Accelerometer. *Med Sci Sports Exerc*. 2011;43(6): 1085–93.
29. Sievänen H, Kujala UM. Accelerometry – simple but challenging. *Scand J Med Sci Sports*. 2017;27(6):574-78.
30. Bakrania K, Yates T, Rowlands AV, et al. Intensity Thresholds on Raw Acceleration Data: Euclidean Norm Minus One (ENMO) and Mean Amplitude Deviation (MAD) Approaches.

PLoS One [Internet]. 2016 [cited 2016 October 5];11(10): Available from: <https://doi.org/10.1371/journal.pone.0164045>. doi:10.1371/journal.pone.0164045.

31. Evenson KR, Catellier DJ, Gill K, Ondrak KS, McMurray RG. Calibration of two objective measures of physical activity for children. *J Sports Sci*. 2008;26(14):1557–65.

32. Efron B, Tibshirani RJ. *An introduction to the bootstrap*. 1st ed (Hardback). Dordrecht (Netherlands): Chapman & Hall Inc, Springer Science+Business Media; 1994. 240-1 p.

33. Gordon D, Wightman S, Basevitch I, et al. Physiological and training characteristics of recreational marathon runners. *Open Access J Sports Med* [Internet]. 2017 [cited 2017 November 24];8:231–41. Available from: <http://doi.org/10.2147/OAJSM.S141657/> doi:10.2147/OAJSM.S141657.

34. Rowlands AV, Olds TS, Hillsdon M, et al. Assessing sedentary behaviour with the GENEActiv: Introducing the Sedentary Sphere. *Med Sci Sports Exerc*. 2014;46(6):1235-47

35. Rowlands AV, Yates T, Olds TS, Davies M, Khunti K, Edwardson CL. Wrist-worn accelerometer-brand independent posture classification. *Med Sci Sports Exerc*. 2016;48(4):748-54.

Table 1. Acceleration metrics considered* for discriminating between ‘running’ and ‘non-running’ days and used[†] to quantify external training load on ‘running’ training days

Acceleration Metric	Description	Rationale
Average Acceleration *	Average daily dynamic acceleration in mg	<p>This metric (also known as ENMO) has previously been used to quantify levels of habitual physical activity (PA).(17, 27) The inclusion of running activity within a day was assumed to lead to higher average acceleration for that day.</p> <p>This metric was not used to quantify external training load on running training days as average acceleration reflects the whole day and not just higher intensity accelerations reflective of training.</p>
Most Active-30mins *	Average acceleration in mg for the most active continuous 30-minute period of the day	<p>This metric identifies the single most active 30-minute period of activity within a day and not the entire day. By looking at a single continuous period of activity, it has the potential to discriminate well between a day including a running training session (regardless of length of run) compared to the</p>

		<p>most active 30-minute period on ‘other training‘ and ‘rest‘ (non-running) days.</p> <p>This metric was not used to quantify training load on running days as it only corresponds to 30 minutes of the day.</p>
Mins \geq 400mg ^{*Ψ}	<p>Time in minutes accumulated throughout the day at or greater than an intensity of 400 mg</p>	<p>An intensity of 400 mg is a validated threshold of activity used to estimate time spent at vigorous (six times the rate of energy expenditure at rest; 6 METS [metabolic equivalents]) levels of habitual PA in population research.(22)</p> <p>All high intensity activity is summed, wherever it occurs within a day, which means this metric may be useful for both discrimination of days and quantification of external training load.</p>
¹ WL400-4000mg ^{Ψ}	<p>Time in minutes accumulated in 50 mg bins \geq400 mg was multiplied by the average intensity of the bin (e.g. 425 mg was the average intensity of</p>	<p>Similar to methods presented by Foster,(24) for calculating session rating of perceived effort as a composite measure of training load (RPE x duration), this acceleration metric multiplies intensity by duration to give value to short but potentially meaningful amounts of high-intensity</p>

	<p>the 400-450 mg bin) to create individual workload (WL) bins in mg-minutes (mgmins). WL bins between 400 and 4000 mg were summed to create a total WL metric in mgmins.</p>	<p>activity that may be particularly relevant in new models relating accelerometer-derived metrics of external training load with RRI and performance outcomes. The lower and upper accelerations (400 and 4000 mg) border the zone where accelerations typical of running fall.(22) This metric was considered for quantifying external training load only.</p>
--	---	--

¹ As recently proposed by Hillsdon.(23)

Table 2. Summary characteristics for runners including self-reported weekly training volume metrics

	Average	Range (min-max)
Age (years)	41.9 (11.4)	23 - 63
Height (m)	1.72 (0.08)	1.60 - 1.86
Mass (kg)	68.5 (9.7)	54.1 – 93.8
BMI (kg.m ²)	23.2 (2.2)	18.8 – 27.7
*Miles/week (miles)	22.1 (12.4 – 34.1)	1 – 149.5
*Total duration/week (minutes)	208.0 (124 – 323)	10 – 1048
*Minutes/mile (minutes)	9.3 (8.2 – 10.6)	6.2 – 41.6
*Running sessions/week	3 (1 – 4)	0 - 13

All values are means (standard deviations) unless indicated otherwise. * Median (inter quartile range). Ranges for training volume metrics represent minimum-maximum volumes from individual weeks.

Table 3. Optimum accelerometer cut-points for differentiation between ‘running’ and ‘non-running’ days [includes rest days (no training) and ‘other-training’ days (days with a different type of training)]

	Accelerometer metrics		
	Average Acceleration	Mins \geq 400mg	Most Active-30mins
Cut-point	40.9 mg	22.4 min	525.3 mg
AUC (95% CI)	*0.93 (0.92-0.95)	*0.95 (0.94-0.96)	*0.97 (0.96-0.98)
Agreement (%)	88	92	94
‘Running’ correctly classified as ‘running’ (%)	88	94	94
‘Rest’ correctly classified as ‘non-running’ (%)	93	95	95
‘Other training’ correctly classified as ‘non-running’ (%)	67	72	86
LOOCV AUC (95% CI)	0.93 (0.92-0.95)	0.95 (0.94-0.96)	0.97(0.96-0.98)

AUC, Area Under Curve; * significantly different ($p < 0.05$) to the null hypothesis of an AUC of 0.5; CI, Confidence Interval; LOOCV, leave one out cross validation.

Table 4. Percentage of ‘other training’ activities misclassified as ‘running’ when using ‘Average Acceleration’, ‘Mins \geq 400mg’ and ‘Most Active-30mins’ to discriminate between ‘running’ and ‘non-running’ days

Other training	Actual number of occurrences	% misclassified as ‘running’ by accelerometer metrics		
		Average Acceleration	Mins \geq 400mg	Most Active- 30 min
Field or racket sport	20	95.0	90.0	25.0
Circuit training	7	57.1	0	14.3
Cycling	47	53.2	53.2	31.9
Walk	6	16.7	0	0
Gym/exercise class	45	4.5	4.4	2.2
Swimming	32	0	0	0
Sailing	2	0	0	0

Table 5. Percentage of the variance explained in Miles, Duration and Training Load when using ‘Mins \geq 400mg’ and ‘WL400-4000mg’ to quantify external training load on ‘running’ days classified using ‘Mins \geq 400mg’ and ‘Most Active-30mins’

	Miles		Duration		Training Load	
	R ²	LOOCV R ²	R ²	LOOCV R ²	R ²	LOOCV R ²
Training load on ‘running’ days classified using ‘Mins\geq400mg’						
Mins \geq 400mg	74.8	74.6	73.7	73.4	66.9	70.0
WL400-4000mg	69.2	68.9	63.5	63.2	54.8	64.2
Training load on ‘running’ classified using ‘Most Active-30mins’						
Mins \geq 400mg	76.2	76.0	74.6	74.4	70.8	70.4
WL400-4000mg	69.0	68.7	62.9	62.5	64.0	63.5

R², coefficient of determination from linear regression; LOOCV R², coefficient of determination for leave one out cross validations