Journal of Sports Sciences

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rjsp20

The development and validation of an open-source accelerometery algorithm for measuring jump height and frequency in ballet

Joseph W. Shaw, Brian Maloney, Adam M. Mattiussi, Derrick D. Brown, Matthew Springham, Charles R. Pedlar & Jamie Tallent

JOURNAL OF SPORTS SCIENCES
https://doi.org/10.1080/02640414.2023.2223048

SPORTS MEDICINE AND BIOMECHANICS

The development and validation of an open-source accelerometery algorithm for measuring jump height and frequency in ballet

Joseph W. Shaw [a,b], Brian Maloney [a,b], Adam M. Mattiussi [a,b], Derrick D. Brown [c], Matthew Springham [a,b], Charles R. Pedlar [a,d] and Jamie Tallent [e,f]

[a]Faculty of Sport, Allied Health and Performance Science, St Mary's University, Twickenham, UK; [b]Ballet Healthcare, The Royal Ballet, London, UK; [c]Institute of Sport Science, Dance Science, University of Bern, Bern, Switzerland; [d]Institute of Sport, Exercise, and Health, Division of Surgery and Interventional Science, University College London, London, UK; [e]School of Sport, Rehabilitation and Exercise Sciences, University of Essex, Colchester, UK; [f]Department of Physiotherapy, School of Primary and Allied Health Care, Faculty of Medicine, Nursing and Health Science, Monash University, Melbourne, Australia

ABSTRACT
The aim was to determine the validity of an open-source algorithm for measuring jump height and frequency in ballet using a wearable accelerometer. Nine professional ballet dancers completed a routine ballet class whilst wearing an accelerometer positioned at the waist. Two investigators independently conducted time-motion analysis to identify time-points at which jumps occurred. Accelerometer data were cross-referenced with time-motion data to determine classification accuracy. To determine the validity of the measurement of jump height, five participants completed nine *jetés*, nine *sautés* and three double *tour en l'air* from a force plate. The jump height predicted by the accelerometer algorithm was compared to the force plate jump height to determine agreement. Across 1440 jumps observed in time-motion analysis, 1371 true positives, 34 false positives and 69 false negatives were identified by the algorithm, resulting in a sensitivity of 0.98, a precision of 0.95 and a miss rate of 0.05. For all jump types, mean absolute error was 2.6 cm and the repeated measures correlation coefficient was 0.97. Bias was 1.2 cm and 95% limits of agreement were −4.9 to 7.2 cm. The algorithm may be used to manage jump load, implement periodization strategies, or plan return-to-jump pathways for rehabilitating athletes.

ARTICLE HISTORY
Received 29 November 2022
Accepted 17 May 2023

KEYWORDS
inertial measurement unit; sensor; rehabilitation; training load; dance; athlete monitoring

Introduction

In professional ballet, jumping and landing movements are the most common mechanism of time-loss injury (27% and 38% of time-loss injuries in women and men, respectively) (A. M. Mattiussi et al., 2021). During a professional ballet performance, dancers jump at a rate of 4.99 ± 4.93 jumps·min^{-1} (Wyon et al., 2011), exceeding rates observed in sports such as volleyball (Bahr & Bahr, 2014) and basketball (Scanlan et al., 2011). In these sports, jump load has been associated with changes in injury risk and performance (Bahr & Bahr, 2014; Benson et al., 2021; Sanders et al., 2018). As a result, jump load has been suggested to be "the next great injury analytic" in sports medicine research (Moran et al., 2019). Although jump load is increasingly recognised as an important variable for ballet dancers, it is not yet routinely collected. The monitoring and management of jump load may therefore be a method by which the risk of maladaptive responses to ballet training may be attenuated (Moran et al., 2019; Shaw, Mattiussi, Brown, Springham, et al., 2021).

The monitoring of jump load has been facilitated by the development of algorithms that can identify jumping actions from wearable accelerometer signals. In athletic settings, several commercial wearable devices have been validated for the identification of jumping actions and the measurement of their height (Benson et al., 2020; Jaitner et al., 2017; MacDonald et al., 2017; Skazalski et al., 2018). However, financial barriers make investment in high-end wearable technology unrealistic for many ballet healthcare departments, and rarely are the details of these algorithms shared publicly. Furthermore, the majority of studies validating jump algorithms have been conducted in volleyball players (Charlton et al., 2017; Skazalski et al., 2018) or in non-sport-specific individuals (Monnet et al., 2014); the extent to which these results can be extrapolated to ballet is unknown given the large repertoire of jump types observed (A. Mattiussi et al., 2021).

Only one study has investigated the use of wearable sensor algorithms for activity recognition in ballet, using convolutional neural networks, and between 1–6 wearable inertial measurement units (IMUs), to identify jumps and leg lifts (Hendry et al., 2020). Though activity recognition was high with multiple sensors, and when the movements were analysed in isolation (98.0–98.5%), accuracy decreased when transition movements were introduced, and only a single sensor was used (78.0–81.6%). Furthermore, implementation of this method is impractical, given that considerable data science expertise is required, and the data and algorithms are not published open-source. In sporting research, several studies have validated proprietary algorithms (Benson et al., 2020; Charlton et al., 2017; Sadi & Klukas, 2011), whilst some have validated more complex machine learning approaches (Kautz et al., 2017). Though feasibility studies

CONTACT Joseph W. Shaw joseph.shaw@stmarys.ac.uk Mason Healthcare Suite, Royal Opera House, Bow St, Covent Garden, London WC2E 9DD
Supplemental data for this article can be accessed online https://doi.org/10.1080/02640414.2023.2223048

have been conducted on rule-based algorithms, such studies suffer from small jump counts (Bruening et al., 2018; Jaitner et al., 2017), overlapping of training and testing data (Bruening et al., 2018) and inadequate detail/no open-source code (Bruening et al., 2018; Jaitner et al., 2017).

The aim of the current study was to investigate the validity of an algorithm for measuring the height and frequency of jumps in professional ballet. To maximise the ease of implementation, we used a simple rule-based algorithm requiring only one sensor, and share the algorithm in several formats.

Materials and methods

Design

A cross-sectional study design was employed to investigate the validity of measuring jump frequency and height using an accelerometer and a rule-based algorithm. The investigation was comprised of two sub-studies. Firstly, the accelerometer measurement of jump frequency was validated against time-motion analysis during ballet class. Participants were nine professional ballet dancers (four men: age 25.6 ± 3.1 y; height 177.0 ± 6.0 cm; mass 70.4 ± 6.3 kg; five women: age 30.4 ± 5.4 y, height 164.4 ± 4.2 cm; mass 52.0 ± 3.2 kg). Secondly, the accelerometer measurement of jump height was validated against a force plate measurement. Participants were five male professional ballet dancers (age 24.7 ± 1.2 y; height 180.8 ± 2.5 cm; mass 73.0 ± 5.1 kg). Following a full explanation of the study protocol, participants gave written informed consent. Ethical approval was granted by the local board of ethics in accordance with the Declaration of Helsinki.

Materials and measures

A nine-axis IMU (LSM9DS1, STMicroelectronics, Geneva, Switzerland), housing a tri-axial 100 Hz accelerometer was used, mounted to a processor board (ASM2021-R, TinyCircuits, Akron, Ohio), SD card writer (ASD2201-R, TinyCircuits, Akron, Ohio), and lithium-ion battery (ASR00007, TinyCircuits, Akron, Ohio). The device was 8 mm × 20 mm × 42 mm and weighed 8.7 g. Participants wore a tightly fitting elasticated strap housing the device in a pouch situated anteriorly in line with the apex of the iliac crest, such that the accelerometer axes were roughly aligned with the anatomical axes of the participant (Figure 1). This position was chosen to reflect the acceleration of the participant's centre of mass, whilst minimizing obstruction of the participant's movement during ballet. A posteriorly worn device was not viable in ballet given the requirement for floor-based movements, during which the device may be pressed between the dancer and the floor. Data were recorded to a secure digital card and uploaded following completion of each protocol.

For the reference measurement of jump height, force plates (ForceDecks FDLite, Vald Performance, Newstead, Queensland, Australia; or Kistler type 9268A, Kistler AG, Winterthur, Switzerland) sampling at 1000 Hz were used. For the time-motion analysis, ballet classes were filmed using a Sonycam DCR-SX33E (Sony Group Corporation, Tokyo, Japan).

Figure 1. The position of the belt housing the accelerometer.

Protocol

Jump frequency

Participants each completed one of three unaltered ballet classes, delivered as part of a normal working day at The Royal Opera House. Each participant wore an accelerometer for the full duration of class. The video camera was placed in an elevated position in a front corner of the studio. Two investigators (JS, BM) reviewed the footage to identify timestamps at which dancers performed a jump. In line with previous research of this nature (MacDonald et al., 2017; Twitchett, Angioi, et al., 2009; Wyon et al., 2011), jumping events were determined subjectively by the reviewers. To ensure accuracy, any discrepancies in time-motion analysis were settled by a third investigator (AM). Where the view of the movement was obscured (e.g., by another dancer), the movement was excluded from the analysis. Timestamps identified through time-motion analysis were then cross-referenced with timestamps identified by the accelerometer algorithm.

Jump height

Participants completed three sets of jumps on a force platform. Set one consisted of nine *sautés* (a two-to-two foot vertical jump), set two consisted of nine unilateral *jetés* (an anterior leap from one leg to the other), and set three consisted of three double *tour en l'air* (a two-to-two foot vertical jump with 720° of rotation). A total of 105 jumps were therefore observed (45 *sautés*, 45 *jetés*, 15 double *tour en l'air*). Fewer double *tour en l'air* were recorded due to the greater physical and technical complexity of the movement. To ensure a range of jump heights were measured, *sautés* and *jetés* were manipulated through the participants' effort levels ($3 \times 30\%$, $3 \times 60\%$ and $3 \times 90\%$ of maximum effort). Participants began each trial with a three second stationary period during which body weight was recorded. For the *sautés* and double *tour en l'air*, participants jumped from, and landed in the same location. For the *jetés*, participants initiated the jump from a stationary position on the force plate, and jumped unilaterally and anteriorly to land at a self-determined distance. Reference jump height was calculated from raw force-time data using the take-off velocity method detailed in Moir (Moir, 2008), whereby jump height is calculated as: take-off velocity (Wyon et al., 2011)/2 g.

Data analysis

Following the completion of each protocol, data were uploaded from the accelerometer. Tri-axial acceleration data were filtered using a fourth-order zero-lag low-pass Butterworth filter with a cut-off frequency of 12 Hz (Wundersitz et al., 2013) and processed using a rule-based algorithm. The algorithm was hand-crafted and created prior to this study based on data collected as part of routine monitoring at a professional ballet company between April 2019 and December 2020.

Algorithm overview

The algorithm used was a rule-based classifier, developed using a trial-and-error process during routine data collection prior to this study. The exact steps completed by the algorithm are detailed explicitly in the R code presented in Appendix 1. A broad overview of the process is outlined below and visualised in Figure 2:

(1) The accelerometry time series is filtered and cleaned, with the primary purpose of identifying data points during which the participant may be airborne. This stage operates on the principal that an accelerometer in freefall will read zero g; these rules therefore seek to remove unwanted signal noise whilst the participant is airborne (e.g., airborne movement, skin movement, etc.)
(2) Identify key features of a vertical jump trace (acceleration peaks, points of take-off, and points of landing) and their temporal interrelationships.
(3) Identify jumps when conditions are met (a point of take-off is present, and is preceded – within 0.40 s – by an acceleration peak >1.65 g; a point of landing is present, and is followed – within 0.38 s – by a resultant acceleration peak >1.65 g, and a vertical acceleration peak >1.35 g; and the points of take-off and landing are separated by between 0.22 and 0.80 s).
(4) When all conditions are met, estimate jump height based on the measured flight time.

An R Shiny web application housing an interactive user interface to the algorithm is provided in Appendix 2; a Microsoft Excel spreadsheet containing the algorithm can be found in Appendix 3.

Statistical analysis

Mean absolute error (MAE), repeated-measures Bland-Altman plots with 95% limits of agreement (LoA), Pearson's correlations and repeated measures correlations (r_{rm}) were used to measure the agreement and correlation between accelerometer-derived jump height and the criterion measure of jump height. For the validation of jump frequency during ballet class, the count of true positives (TP), false positives (FP) and false negatives (FN), and subsequently the sensitivity:

$$\frac{TP}{TP + FN}$$

precision:

$$\frac{TP}{TP + FP}$$

miss rate:

$$\frac{\mathrm{FN}}{\mathrm{FN} + \mathrm{TP}}$$

and critical success index:

$$\frac{TP}{TP + FN + FP}$$

were calculated. Accuracy and specificity were not calculated based on the absence of a true negative measure. All analysis took place in R v.4.0.4 (R Foundation for Statistical Computing, Vienna, Austria).

Results

For the comparison of predicted jump height and reference jump height, the Pearson's correlation was 0.96, and the r_{rm} was 0.97 (Figure 3A). The MAE was 2.58 cm, with 95% LoA of –6.7 to 5.7 cm, and a mean bias of –0.47 cm. Figure 3B shows the Bland-Altman plots presenting the mean bias, 95% LoA, and their 95% confidence intervals for each jump type.

For the validation of jump frequency, a total of 1440 jumps were observed across the nine classes. Eleven observations were removed from the study as both reviewers, or one reviewer and the third reviewer, agreed that a jump could not be reliably determined due to an obstructed view. Agreement between the two primary reviewers was 93.6%. Sensitivity, precision, and miss rate values were 0.95, 0.95 and 0.05, respectively. Full results and summary statistics of the IMU and video analysis for each participant are presented in Table 1.

Discussion

This study demonstrated the validity of a hand-crafted rule-based algorithm for measuring jump height and frequency in professional ballet. Unlike previous studies validating the use of wearable technology to measure jump-load, the present algorithm is open-source, does not require data science expertise, and is shared alongside R code, an R Shiny application, and an Excel spreadsheet, which can be used to facilitate implementation. This study therefore provides healthcare practitioners working in ballet companies and

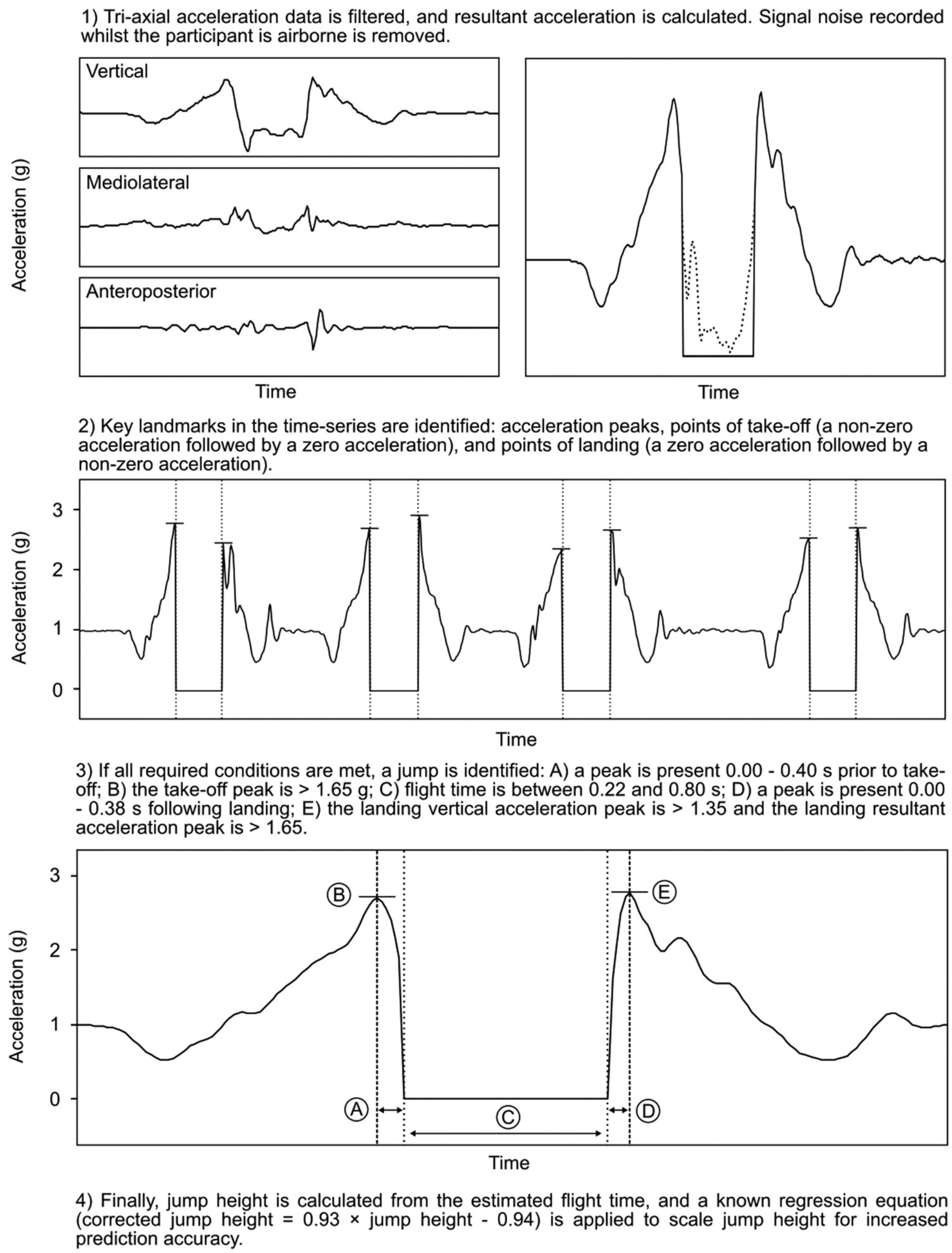

Figure 2. Schematic illustrating the simplified steps involved in the algorithm to identify jumps and calculate jump height.

schools with a practical open-source tool for monitoring the jump load experienced by dancers.

The present validation of jump count revealed sensitivity, precision, and miss rate values of 0.95, 0.95 and 0.05, respectively. These values are comparable to similar studies investigating the validity of commercial wearable devices in sports such as volleyball (MacDonald et al., 2017; Skazalski et al., 2018) and snowboarding (Sadi & Klukas, 2011), and provide a basis for the use of this algorithm in practice. Similarly, a high level of agreement was observed between the estimated jump height and the reference measure ($r_{rm} = 0.97$, bias = +1.2 cm, 95% LoA: −4.9 to 7.2 cm, MAE: 2.6 cm). These values are more accurate than those that have been reported in validation studies of commercial accelerometers (MacDonald et al. (MacDonald et al., 2017): $r = 0.91$, bias = 2.5 cm, 95% LoA −6.1 to 9.8 cm; Skazalski et al. (Skazalski et al., 2018): bias = 9.1 cm, intra-class correlation = 0.93). The mean absolute error of the jump height estimation was greater during double *tour en l'air* than during *sautés* or *jetés*. This may reflect the increased complexity of the movement (and subsequently a greater inaccuracy in the identification of take-off and landing) or the greater jump heights that are required (such that the same percentage error results in a larger absolute error). Readers should note that the present algorithm appears to slightly overestimate large jumps; though this small bias is unlikely to be clinically relevant for load management, practitioners should note that the algorithm is not appropriate for the measurement of maximal jump height in isolation.

The present algorithm is practical and straightforward to implement into rehearsals. Firstly, only a single sensor is

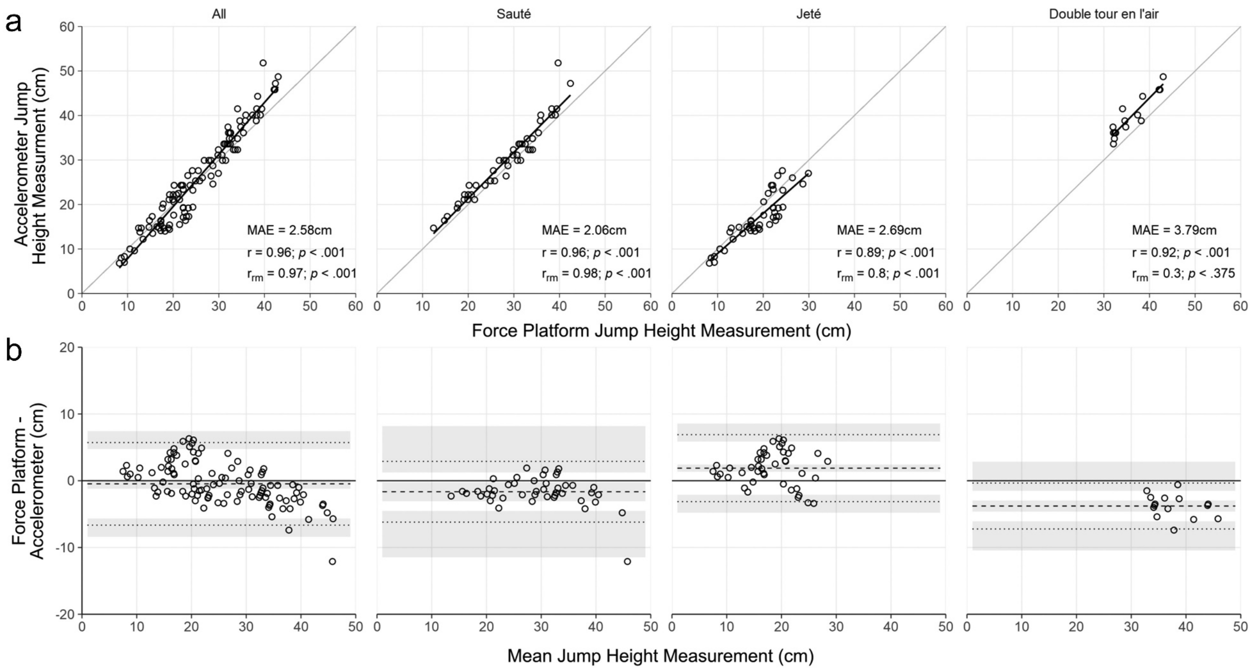

Figure 3. a) Correlation and b) Bland-Altman plots illustrating the relationship and agreement between accelerometer-derived and force platform-derived measurements of jump height. Grey areas represent 95% CIs for the mean bias, and upper and lower confidence intervals. MAE = Mean absolute error.

Table 1. Results of the validation of jump frequency.

Participant	Sex	Rank	Video Count	Wearable Count	TP	FP	FN	Sensitivity	Precision	Miss Rate	CSI
1	M	A	191	196	187	7	4	0.98	.96	0.02	0.94
2	M	FA	200	201	188	11	12	0.94	.94	0.06	0.89
3	M	FS	211	207	204	3	7	0.97	.99	0.03	0.95
4	M	P	242	243	232	7	10	0.96	.97	0.04	0.93
5	F	A	103	102	101	1	2	0.98	.99	0.02	0.97
6	F	FA	154	148	144	3	10	0.94	.98	0.06	0.92
7	F	S	131	124	124	0	7	0.95	1.00	0.05	0.95
8	F	P	118	110	108	1	10	0.92	.99	0.08	0.91
9	F	P	90	85	83	1	7	0.92	.99	0.08	0.91
Total	-	-	1440	1416	1371	34	69	0.95	.98	0.05	0.93
Mean	-	-	169	166	161	4	8	0.95	.98	0.05	0.93
SD	-	-	53	56	52	4	3	0.02	.02	0.02	0.03

Note: TP – True positives; FP – False positives; FN – False negatives; CSI – Critical success index; SD – Standard deviation; F – Female; M – Male; A – Artist; FA – First Artist; S – Soloist; FS – First Soloist; P – Principal.

required to calculate jump load, which is likely to be better received by dancers than multi-sensor approaches. Additionally, a waist-worn device is easily hidden, and does not obstruct the dancer's movement. A tri-axial accelerometer – rather than a nine-axis IMU – is used; this is advantageous both in terms of cost and signal processing requirements. However, the use of more signals may facilitate a greater measurement accuracy, and is a potential avenue for future research. The algorithm used is simpler than machine learning approaches that have been used previously (Hendry et al., 2020). This is beneficial for several reasons. Firstly, the user is not required to have data science expertise; users with only basic data handling experience can implement the algorithm using the spreadsheet contained in Appendix 3. Similarly, this method is therefore more interpretable, and does not come in a black box, as would many machine learning models.

Jump load has previously been demonstrated to be a useful metric for understanding injury risk in basketball (Benson et al., 2021) and volleyball (García de Alcaraz et al., 2020). However, whilst the present algorithm provides a valid means of measuring jump height and frequency during ballet, it is important that healthcare practitioners understand that jump load is not a direct measure of physiological tissue damage (Edwards, 2018; Kalkhoven et al., 2021). Jump load may provide a means through which load can be managed (e.g., ensuring gradual progression following injury, identifying rapid increases in load) (Shaw, Mattiussi, Brown, Williams, et al., 2021), but users should be cautious not to over-rely on jump load as an injury metric, and instead consider it only one part of a larger puzzle. The ability to measure jump load provides benefits beyond injury risk management. Understanding the jumping demands experienced during rehearsals and performances may be beneficial for strength and conditioning coaches designing supplementary training programmes (Shaw, Mattiussi, Brown, Springham, et al., 2021; Twitchett, Koutedakis, et al., 2009). Similarly, for physiotherapists and strength and conditioning coaches involved in the rehabilitation of a dancer, understanding the demands of a given ballet may aid in the planning and management of a return-to-jumping pathway (Taberner et al., 2020). Finally, the measurement of jump load may facilitate discussions with artistic staff around load and season periodisation through objective data (Wyon, 2010).

Whilst this algorithm was designed and tested on balletic jumps, we suggest that given the methodological steps taken by the algorithm, the results would be comparable for non-balletic jumps. There may therefore be considerable use for this algorithm in other sporting populations; for example, in jumping sports such as basketball or volleyball or for managing plyometric load during more general training (Allerheiligen & Rogers, 1995).

Strengths and limitations

The key strength of this work is its accessibility: unlike previous research, the present algorithm is open-source and does not require data science expertise. Another strength is that unlike some studies of this nature (MacDonald et al., 2017), we have validated the measurement of jump frequency in an unaltered ballet class *in situ* (as opposed to creating an arbitrary set of movements) adding to the ecological validity of the present algorithm. In contrast, the validation of jump height during jetés from a force plate required the dancer to jump from a stationary position, ex situ. It is possible that this artificially increased the accuracy, as the identification of the exact point of take-off may have been improved in the absence of preceding movement, as might be the case during rehearsal or performance. Another limitation of the current study is that the algorithm used does not differentiate between one-legged and two-legged take-offs and landings. Whilst this is possible using wearable technology, the aim of the present study was to provide a method requiring limited equipment (i.e., a single accelerometer) and only a basic level of data handling. The comparison of the present algorithm to previously validated algorithms would have been beneficial for contextualising and assessing the quality of the current results. Finally, we have mounted the device such that it does not inhibit balletic movement, though this position is on soft tissue. The use of this algorithm on populations with greater abdominal adipose tissue should, therefore, be approached with caution.

Conclusion

The present study investigated the validity of a rule-based algorithm for the measurement of jump height and count in professional ballet and demonstrated comparable accuracy to commercial systems. Unlike commercial products common in sport and exercise science, this algorithm has been designed to increase accessibility: open-source software is provided; the algorithm does not require data science expertise to use; and only a single sensor is required. The ease of use and low-cost of applying this method provides a solution to the management of jump load in ballet companies and schools.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

Joseph Shaw received PhD funding from The Royal Ballet for the completion of this project.

ORCID

Joseph W. Shaw http://orcid.org/0000-0002-1538-9966

Data availability statement

No data are available.

References

Allerheiligen, B., & Rogers, R. (1995). Plyometrics program design. *Strength & Conditioning Journal*, *17*(4), 26–31. https://doi.org/10.1519/1073-6840(1995)017<0026:PPD>2.3.CO;2

Bahr, M. A., & Bahr, R. (2014). Jump frequency may contribute to risk of jumper's knee: A study of interindividual and sex differences in a total of 11 943 jumps video recorded during training and matches in young elite volleyball players. *British Journal of Sports Medicine*, *48*(17), 1322–1326. https://doi.org/10.1136/bjsports-2014-093593

Benson, L. C., Owoeye, O. B. A., Räisänen, A. M., Stilling, C., Edwards, W. B., & Emery, C. A. (2021). Magnitude, frequency, and accumulation: Workload among injured and uninjured youth basketball players. *Frontiers in Sports and Active Living*, *3*(April), 1–18. https://doi.org/10.3389/fspor.2021.607205

Benson, L. C., Tait, T. J., Befus, K., Choi, J., Hillson, C., Stilling, C., Grewal, S., MacDonald, K., Pasanen, K., & Emery, C. A. (2020). Validation of a commercially available inertial measurement unit for recording jump load in youth basketball players. *Journal of Sports Sciences*, *38*(8), 928–936. https://doi.org/10.1080/02640414.2020.1737360

Bruening, D. A., Reynolds, R. E., Adair, C. W., Zapalo, P., Ridge, S. T., & Najafi, B. (2018). A sport-specific wearable jump monitor for figure skating. *PLoS One*, *13*(11), 1–13. https://doi.org/10.1371/journal.pone.0206162

Charlton, P. C., Kenneally Dabrowski, C., Sheppard, J., & Spratford, W. (2017). A simple method for quantifying jump loads in volleyball athletes. *Journal of Science & Medicine in Sport / Sports Medicine Australia*, *20*(3), 241–245. https://doi.org/10.1016/j.jsams.2016.07.007

Edwards, W. B. (2018). Modeling overuse injuries in sport as a mechanical fatigue phenomenon. *Exercise and Sport Sciences Reviews*, *46*(4), 224–231. https://doi.org/10.1249/JES.0000000000000163

García de Alcaraz, A., Ramírez-Campillo, R., Rivera-Rodríguez, M., & Romero-Moraleda, B. (2020). Analysis of jump load during a volleyball season in terms of player role. *Journal of Science & Medicine in Sport / Sports Medicine Australia*, *23*(10), 973–978. https://doi.org/10.1016/j.jsams.2020.03.002

Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P., & Straker, L. (2020). Development of a human activity recognition system for ballet tasks. *Sports Medicine - Open*, *6*(1). https://doi.org/10.1186/s40798-020-0237-5

Jaitner, T., Ebker, G., Schmidt, M. (2017). Estimation of the jump height for the volleyball spike by a mobile imu unit. In: *35th Conference of the International Society of Biomechanics in Sports*. Cologne, 222–225.

Kalkhoven, J. T., Watsford, M. L., Coutts, A. J., Brent Edwards, W., & Impellizzeri, F. M. (2021). Training load and injury: Causal pathways and future directions. *Sports Medicine*, *51*(6), 1137–1150. https://doi.org/10.1007/s40279-020-01413-6

Kautz, T., Groh, B. H., Hannink, J., Jensen, U., Strubberg, H., & Eskofier, B. M. (2017). Activity recognition in beach volleyball using a deep convolutional neural network: Leveraging the potential of deep learning in sports. *Data Mining and Knowledge Discovery*, *31*(6), 1678–1705. https://doi.org/10.1007/s10618-017-0495-0

MacDonald, K., Bahr, R., Baltich, J., Whittaker, J. L., & Meeuwisse, W. H. (2017). Validation of an inertial measurement unit for the measurement of jump count and height. *Physical Therapy in Sport: Official Journal of the Association of Chartered Physiotherapists in Sports Medicine*, *25*, 15–19. https://doi.org/10.1016/j.ptsp.2016.12.001

Mattiussi, A., Shaw, J. W., Brown, D. D., Price, P., Cohen, D. D., Pedlar, C. R., & Tallent, J. (2021). Jumping in ballet: A systematic review of kinetic and kinematic parameters. *Medical Problems of Performing Artists*, *36*(2), 108–128. https://doi.org/10.21091/mppa.2021.2011

Mattiussi, A. M., Shaw, J. W., Williams, S., Price, P. D., Brown, D. D., Cohen, D. D., Clark, R., Kelly, S., Retter, G., Pedlar, C., & Tallent, J. (2021). Injury epidemiology in professional ballet: A five-season prospective study of 1596 medical attention injuries and 543 time-loss injuries. *British Journal of Sports Medicine*, *55*(15), 843–850. https://doi.org/10.1136/bjsports-2020-103817

Moir, G. L. (2008). Three different methods of calculating vertical jump height from force platform data in men and women. *Measurement in Physical Education and Exercise Science*, *12*(4), 207–218. https://doi.org/10.1080/10913670802349766

Monnet, T., Decatoire, A., & Lacouture, P. (2014). Comparison of algorithms to determine jump height and flight time from body mounted accelerometers. *Sports Engineering*, *17*(4), 249–259. https://doi.org/10.1007/s12283-014-0155-1

Moran, L. R., Hegedus, E. J., Bleakley, C. M., & Taylor, J. B. (2019). Jump load: Capturing the next great injury analytic. *British Journal of Sports Medicine*, *53*(1), 8–9. https://doi.org/10.1136/bjsports-2018-099103

Sadi, F., & Klukas, R. (2011). Reliable jump detection for snow sports with low-cost mems inertial sensors. *Sports Technology*, *4*(1–2), 88–105. https://doi.org/10.1080/19346182.2012.708974

Sanders, G. J., Boos, B., Shipley, F. M., Scheadler, C. A., & Peacock, C. (2018). An accelerometer-based training load analysis to assess volleyball an accelerometer-based training load analysis to assess volleyball performance. *Journal of Exercise and Nutrition*, *1*(1), 3–8. https://doi.org/10.53520/jen2018.1034

Scanlan, A., Dascombe, B., & Reaburn, P. (2011). A comparison of the activity demands of elite and sub-elite Australian men's basketball competition. *Journal of Sports Sciences*, *29*(11), 1153–1160. https://doi.org/10.1080/02640414.2011.582509

Shaw, J. W., Mattiussi, A. M., Brown, D. D., Springham, M., Pedlar, C. R., & Tallent, J. (2021). The activity demands and physiological responses observed in professional ballet: A systematic review. *Journal of Science in Sport and Exercise*, *5*(4), 254–269. https://doi.org/10.36905/jses.2021.04.04

Shaw, J. W., Mattiussi, A. M., Brown, D. D., Williams, S., Kelly, S., Springham, M., Pedlar, C. R., & Tallent, J. (2021). Dance exposure, individual characteristics, and injury risk over five seasons in a professional ballet company. *Medicine & Science in Sports and Exercise*, *Publish Ahead of Print*. https://doi.org/10.1249/MSS.0000000000002725

Skazalski, C. M., Whiteley, R., Hansen, C., & Bahr, R. (2018). A valid and reliable method to measure jump-specific training and competition load in elite volleyball players. *Scandinavian Journal of Medicine & Science in Sports*, *28*(5), 1578–1585. https://doi.org/10.1111/sms.13052

Taberner, M., Allen, T., & Cohen, D. D. (2020). Infographic. Progressing rehabilitation after injury: Consider the 'control-chaos continuum'. *British Journal of Sports Medicine*, *54*(2), 116–117. https://doi.org/10.1136/bjsports-2019-100936

Twitchett, E., Angioi, M., Koutedakis, Y., & Wyon, M. (2009). Video analysis of classical ballet performance. *Journal of Dance Medicine & Science: Official Publication of the International Association for Dance Medicine & Science*, *13*(4), 124–128. https://doi.org/10.1177/1089313X0901300405

Twitchett, E., Koutedakis, Y., & Wyon, M. (2009). Physiological fitness and professional classical ballet performance: A brief review. *Journal of Strength & Conditioning Research*, *23*(9), 2732–2740. https://doi.org/10.1519/JSC.0b013e3181bc1749

Wundersitz, D. W. T., Netto, K. J., Aisbett, B., & Gastin, P. B. (2013). Validity of an upper-body-mounted accelerometer to measure peak vertical and resultant force during running and change-of-direction tasks. *Sports Biomechanics*, *12*(4), 403–412. https://doi.org/10.1080/14763141.2013.811284

Wyon, M. (2010). Preparing to perform: Periodization and dance. *Journal of Dance Medicine & Science*, *14*(2), 67–72. https://doi.org/10.1177/1089313X1001400205

Wyon, M., Twitchett, E., Angioi, M., Clarke, F., Metsios, G., & Koutedakis, Y. (2011). Time motion and video analysis of classical ballet and contemporary dance performance. *International Journal of Sports Medicine*, *32*(11), 851–855. https://doi.org/10.1055/s-0031-1279718