Validity of Real-Time Ultra-wideband Global Navigation Satellite System Data Generated by a Wearable Microtechnology Unit

Article *in* The Journal of Strength and Conditioning Research · January 2019

DOI: 10.1519/JSC.0000000000003059

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Submission Type: ORIGINAL INVESTIGATION

Running Head: Real-time validity

Word Count:

Abstract = 217

Manuscript = 2261

Number of Tables = 1

Number of Figures = 0

Abstract

This study aimed to determine the validity of real-time ultra-wideband data generated by a wearable microtechnology unit during rugby league training sessions using a repeated measures crossover study. Twenty-four semi-professional rugby league players wore a commercially available microtechnology device (StatSports Apex) during 10 training sessions. Total distance; moderate-speed running (3.6-4.9 $m \cdot s^{-1}$); high-speed running (5.0-6.9 $m \cdot s^{-1}$); very high-speed running (≥7 $m \cdot s^{-1}$); maximum velocity ($m \cdot s^{-1}$); the number of high-intensity accelerations (≥ 2.78 $m \cdot s^{-2}$) and decelerations (≥ -2.78 $m \cdot s^{-2}$), Dynamic Stress Load (AU) and high metabolic load distance (m) were recorded in real-time via an Apex beacon over a secured wireless network before being exported to a csv file at the end of the session. The data were then downloaded to a computer post-event. To determine the validity of the real-time data, they were compared to the post-event downloaded data using coefficient of variation and Pearson's correlation coefficient. There was almost perfect agreement between real-time and post-event downloaded data for all variables reported. The overall bias effect size scores were all *trivial*, ranging from 0.00 for total distance and high-speed running up to -0.12 for maximal velocity; Pearson's correlations were either *perfect* or *nearly perfect* (r = 0.98-1.00). Irrespective of the movement speed, the data collected by these devices in real-time show excellent levels of agreement with post-event downloaded data.

KEY WORDS: GPS, team sports, MEMS, monitoring, workloads, training

Introduction

The use of wearable microtechnology devices have seen a large growth since their inception into athlete tracking in the early 21st century. The devices incorporate a global navigation system satellite (GNSS) chip and some house other inertial measurement devices such as accelerometers, gyroscopes and magnetometers. This allows various measures of external load to be quantified based on distance, speed and tri-axial accelerometer load in order to measure physical activity performed (6). Over recent years, there has been an exponential growth in publications utilizing GNSS devices (21). Given this proliferation it is important to consider the metrics derived from these devices are reflective of the activities performed.

Given the large volume of metrics available, practitioners need to be cognizant of which variables are reliable and valid when it comes to tracking training loads. The continual development of technology has led to improved accuracy of these devices, however there are still issues in quantifying accelerations, decelerations, particularly when the data are discretized into zones (29, 30). Distance, speed, accelerometer load, average acceleration, and in some cases, collisions appear to be the most reliable metrics to report (4, 13, 29). Furthermore, total, moderate, high-speed distance (5, 14, 24) and exposure to maximal velocity efforts (22) appear to be associated with injury risk by profiling the acute (1 to 10-day average) in comparison to the chronic (14 to 35-day average) load. As well as injury risk, microtechnology workloads are also associated with changes in physical capacities. In particular, distance covered above individualized speed zones have been positively associated with improvements in running capacity in soccer players (8). In addition, microtechnology derived accelerometer load has been used to track neuromuscular status during standardized training drills (27). Given these relationships, practitioners must be able to monitor the training dose applied accurately throughout a training session to prescribe the optimal workloads for each individual. Distances covered, speeds reached, and accelerometer load appear important for tracking injury risk, fatigue, and changes in fitness across team sport players.

The need to track training loads has been shown to be important from the perspectives of injury risk (7), training adaptations (11), and performance (1). As such, a large amount of time is devoted to tracking and monitoring player workloads.

During the pre-season period the aim is to prescribe a training load that improves fitness and technical capabilities (19). A high pre-season load in the form of sessions completed, total distance, and distance covered at high speeds is associated with reduced injury risk and greater match workloads in professional Australian football players throughout a competitive season (19, 23). During the in-season period, the aim shifts to delivering sufficient load to maintain capacities whilst addressing technicaltactical aspects of performance in preparation for the next game. Indeed, excessive load prior to a game may result in increased fatigue, and reductions in performance (1, 16), but this relationship is influenced by individual characteristics of the player (9, 17). As such, practitioners will typically prescribe an external load for a specific session based on numerous factors such as workload ratios (15), fitness of the player (10, 18), chronic training load and player experience (9). Given the relationships between load and training outcomes, it is important that the planned workloads are met. Deviation from the planned load could impact on injury risk (15, 26) and, or, fatigue status (27). During team sport training, meeting the individual needs of each player is often difficult due to the intermittent and sometimes stochastic nature of drills. At the end of sessions, players may be prescribed 'individualized top-ups' to achieve the planned load, commonly in the form of high-speed running. When dealing with players returning from injury they present an increased injury risk (28). As such, the zone for prescribing the appropriate training load is even more narrow. With this in mind, it is clearly important to be able to track loads in real-time to ensure that the planned load is met for each player.

Whilst a large body of work has been done on the reliability and validity of global positioning system microtechnology (6), indicating that sampling rate of the global positioning system (GPS) chip and the metric in question are key (20, 30). Little is known regarding the validity of the real-time data in comparison to the post-event downloaded data following the session. To date, there have been two studies that have assessed the accuracy of real-time data. One study in 2010 using Catapult Sprint (MinimaxX, Team Sport 2.0, Catapult Innovations) showed coefficients of variation of 9.6% for total, 8.2% for jogging (4.2-5.0 $m{\cdot}s^{-1}$), 6.4% for running (5.0-6.9 $m{\cdot}s^{-1}$), and 19.6% for sprint (6.9-10.0 $m{\cdot}s^{-1}$) distance (2). A more recent study using an updated version of Catapult Sprint (Version 5.1.7) found a reduction in the noise of real-time data compared to the previous 2010 study (3), which may have been due to a different software version being used. Specifically, this study reported coefficients of variation of 0.3% for total, 6.8% for high-speed (5.5-7.0 $m{\cdot}s^{-1}$), and 9.7% for sprint (>7.0 $m{\cdot}s^{-1}$) distance. In addition, maximal velocity had a coefficient of variation of 2.6% and 0.6% for accelerometer load. Although these studies suggest that there has been an improvement in the data viewed in real-time and currently the data closely reflect the actual activities performed, other manufacturers using different technology means that further validation is required. As such, the aim of the present investigation was to determine the validity of real-time ultra-wideband data generated by a wearable microtechnology unit.

Methods

Experimental Approach to the Problem

To determine the validity of real-time microtechnology data to post-event downloaded data, player workloads were tracked during rugby league training sessions using a repeated measures crossover design. Real-time data was saved following each training session and subsequently compared to post-event downloaded data.

Subjects

Twenty-four semi-professional rugby league players participated in this study (age = 25.1 ± 3.8 years; height = 185.2 ± 7.3 cm; weight = 95.5 ± 11.9 kg). The study gained ethical approval prior to the start of the study (2016-68E). All data were collected as part of the routine operations of the club. Players signed written informed consent to acknowledge that their training data would be used for research purposes.

Procedures

The microtechnology units used in this study comprised a 10 Hz multi-global navigation satellite system (GNSS) chip, a 100 Hz triaxial accelerometer, 100 Hz gyroscope and 10 Hz magnetometer (StatSports Apex, Newry, Northern Ireland). These units have been shown to have small amounts of bias (1.05-2.3%) for measuring distances up to 400 m and peak speed (0.17%) (4). Approximately 20 min prior to each training session, the microtechnology units were switched on and placed in a tight-fitting vest so that the unit sat between the scapula on the upper back. Each player was assigned a specific unit at the start of the season and this was maintained across all sessions. To receive information from the units in real-time, a customized laptop computer (Dell Latitude 5580, Dell Technologies, NSW, Australia) running Apex software (version 3.0.01191) was synced with a manufacturer designed beacon via an ultra-wideband (UWB) secured wireless network. UWB is a wireless communication technology capable of transmitting large amounts of digital data over a wide frequency spectrum using low powered radio signals. Data is transferred from the Apex units to the live streaming data beacon at a rate of 6.8 $Mbit{\cdot}s^{-1}$ with a communication range of up to 300 m. The beacon was placed 2 m behind the half-way line of the football field, with the laptop located within 2-m of the beacon to maximize the wireless signal. All training was conducted on the same grassed football field, with dimensions of 72 m wide and 116 m in length (including the in-goal area). As such, all players were within a 93-m radius of the beacon at all times. At the start of the warm-up, the live session was started by the sport scientist and then stopped at the cessation of the last drill. When closing the live session in the Apex software, the real-time data was exported to a csv file. Following the session, the files were downloaded using the manufacturer provided software and then exported into a custom Excel spreadsheet. The Apex software can track 26 GNSS metrics in real-time, although some metrics, such as collisions, require post-event processing and are therefore not able to be tracked in real-time. As such, the variables used in the current study were total distance; moderate-speed running (3.6-4.9 $m{\cdot}s^{-1}$); high-speed running (5.0-6.9 $m{\cdot}s^{-1}$); very high-speed running (≥7 $m{\cdot}s^{-1}$); maximum velocity ($m{\cdot}s^{-1}$); the number of high-intensity accelerations (≥ 2.78 $m{\cdot}s^{-2}$) and decelerations (≥ -2.78 $m{\cdot}s^{-2}$), Dynamic Stress Load (AU) and high metabolic load distance (m). Dynamic Stress Load is a manufacturer derived metric of the weighted sum of all impacts ≥2 g; high metabolic load distance is all distance accumulated over 25.5 $W \cdot kg^{-1}$. Only players that completed the whole session and were not in modified training were included for analysis. A total of 10 training sessions were analyzed (184 files) with an average training time of 62.8 ± 24.1 min per session and a total training time of 691 min.

Statistical Analyses

The standard error of estimate and overall bias were used to assess the difference between real-time and post-event downloaded data. First, data were log transformed to control for any non-uniformity of error that may have occurred. Both statistics were presented in their raw units and Cohen's effect size (ES) score with 90% confidence intervals. Thresholds of ≤0.19, *trivial*; 0.20-0.59, *small*; 0.60-1.19, *moderate*; and ≥1.20, *large* were used to determine the magnitude of the ES difference. Pearson's correlation coefficients were also calculated. All statistical procedures were conducted in Excel using a custom designed spreadsheet (12). Descriptive statistics were used and data are displayed as the mean ± standard deviation (SD).

Results

The results of the analysis are shown in Table 1. All reported variables showed a *perfect*, or *near perfect* correlation between real-time and post-event downloaded data. There was a *trivial* underestimation of metrics recorded in real-time compared with post-event downloaded data.

TABLE 1 NEAR HERE

Discussion

The aim of this study was to assess the validity of real-time data obtained via an ultra-wideband wireless network during rugby league training sessions in comparison to post-event downloaded data. The results of this study show that irrespective of movement speed, there were high levels of agreement between real-time and post-event downloaded data. As such, practitioners can have a high level of confidence that the metrics returned live during a training session closely reflect the applied load captured by wearable microtechnology.

The present findings were similar to recent research comparing real-time and post-event downloaded data, in different technology. However, unlike the current study, they reported magnification in error as movement speed increased (3). The current findings actually showed a reduction in the overall bias as movement speed increased across moderate-, high- and very high-speed running zones. Moreover, the results reported currently are significantly better than one using older technology carried out in 2010 (2). This previous study reported coefficients of variation as high as 19.6% for distance over 6.9 $m \cdot s^{-1}$, more than 10 times than found in the current study for the same speed zone (1.5%). As previously stated, the microtechnology units used in this study comprised a 10 Hz GPS chip, (StatSports Apex, Newry, Northern Ireland), whereas the previous study used a 5Hz GPS chip (MinimaXX, Team Sport 2.0, Catapult Innovations) (2) and highlight how well technology has developed and will continue to do so. Errors in the region of 20% would question the utility of real-time to monitor the training dose. For example, if you were planning a session involving 600 m of distance at a running speed above 5 $m \cdot s^{-1}$, devices used in the previous study indicate the player may have actually covered up to 720 m (2). Whereas, with the devices used in this study, the real-time data would only underestimate high speed distance by 6-9 m on average (if the planned load was 600 m). Whilst this discrepancy may not seem to be a large amount, recent research regarding workload ratios show that spikes in load are associated with injury risk (5, 25), and loads that are too high or too low result in maladaptation (11). As such, the ability to closely control loads in real-time is beneficial for practitioners. Despite previous reports, the results of the present study indicate that real-time data closely reflects post-event downloaded data. These disparities between the current study and previous reports is not surprising given the significant advances in technology that have been made over recent years.

Conclusions

Irrespective of movement speed, real-time data obtained during training closely reflects the post-event downloaded data in these specific microtechnology units (StatSports Apex). The trivial underestimations of distances covered, and speeds reached during training indicate there is negligible difference in real-time data. Real-time data can be used to track the progress of each player during training sessions with a high degree of confidence. This means that a player's session can be modified in real-time during the training session so that the planned load can be achieved via (1) cessation of the session or (2) modification of the session or drill to increase or decrease the accumulated load.

Practical Applications

Practitioners can be confident the data collected in real-time using this system closely reflect the post-event data. Distances covered at high speeds can be accurately tracked in real-time.

Acknowledgments

The authors would like to thank the players and staff of the clubs involved for their support of the research. No financial support was provided to this study and the authors have no conflicts of interest to report.

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Table 1. Comparison between real-time and post-event downloaded microtechnology data during rugby league training sessions.

	Real-time data	Downloaded data	Overall bias (raw units)	Overall bias (ES)	SEE (raw units)	SEE (ES)	Pearson's correlation (r)
Total Distance (m)	2362 ± 1210	2363 ± 1210	-0.50 ± 0.73	0.00 ± 0.00	4.15 ± 1.13	0.00 ± 0.00	1.00
Moderate-speed running (m)	309 ± 178	312 ± 181	-3.03 ± 1.69	-0.01 ± 0.01	9.24 ± 1.33	0.03 ± 0.00	1.00
High-speed running (m)	146 ± 130	147 ± 130	-0.56 ± 0.33	0.00 ± 0.00	1.84 ± 0.26	0.01 ± 0.01	1.00
Very high-speed running (m)	13.2 ± 23.2	13.3 ± 23.2	-0.04 ± 0.02	-0.01 ± 0.00	0.11 ± 0.02	0.01 ± 0.01	1.00
Maximum velocity ($m \cdot s^{-1}$)	6.8 ± 1.0	6.9 ± 1.0	-0.11 ± 0.03	-0.12 ± 0.03	0.18 ± 0.03	0.19 ± 0.03	0.98
Accelerations ≥ 2.78 $m \cdot s^{-2}$ (#)	39.2 ± 26.0	39. 2 ± 26.3	-0.06 ± 0.35	0.00 ± 0.01	2.01 ± 0.29	0.08 ± 0.01	1.00
Decelerations ≥ -2.78 $m \cdot s^{-2}$ (#)	21.3 ± 18.8	21.4 ± 19.0	-0.17 ± 0.21	-0.01 ± 0.01	1.16 ± 0.17	0.06 ± 0.01	1.00
Dynamic Stress Load (AU)	121 ± 91	124 ± 91	-2.86 ± 0.55	-0.03 ± 0.01	3.11 ± 0.45	0.03 ± 0.01	1.00
High Metabolic Load Distance (m)	392 ± 246	394 ± 255	-2.56 ± 1.27	-0.01 ± 0.01	6.78 ± 0.99	0.03 ± 0.01	1.00

Aggregated data are presented as means ± SD, whereas validity statistics are presented ± 90% CI. Moderate-speed running (3.6-4.9 $m \cdot s^{-1}$), high-speed running (5.0-6.9 $m \cdot s^{-1}$), and very high-speed running (≥7 $m \cdot s^{-1}$); ES = effect size; SEE = standard error of the estimate; CI = confidence interval.