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Accelerometry and Global Navigation Satellite Systems Derived Training Loads

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Accelerometry and Global Navigation Satellite Systems Derived Training Loads

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ABSTRACT

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The objectives of this dissertation include 1) to review accelerometry and Global Navigation Satellite System (GNSS) derived measures used to monitor training load, 2) to investigate the validity and reliability of accelerometers (ACCs) to identify stepping events and quantify training load, 3) to assess the relationship between accelerometry and Global Navigation Satellite Systems (GNSS) derived measures in quantifying training load. In Study I, acceleration data was collected via two tri-axial ACC (Device A and Device B) sampling at 100Hz mounted closely together at the xiphoid process level. Each participant (*n*=30) performed two trials of straight-line walking, running, and sprinting on a 20m course. Device A was used to assess ACC validity to identify steps and the test-retest reliability of the instrument to quantify the external load. Device A and Device B were used to assess inter-device reliability. The reliability of accelerometry derived metrics Impulse Load (IL) and Magnitude *g* (MAG) were assessed. In Study II, known distance (DIST) was predicted via acceleration data collected by a tri-axial ACC sampling at 100Hz mounted at the xiphoid process level, simultaneously positional data collected using a triple GNSS unit sampling at 10Hz placed between scapulae. Each participant (*n*=30) walked different DIST around various movement constraints (small and large circles). Thirty distances were completed around each circle and ranged from 12.57–376.99m. In Study I, the instrument demonstrated a positive predictive value (PPV) of 96.98-99.41% and an agreement of 93.08-96.29% for step detection during all conditions. Good test-retest reliability was found with a coefficient of variation (CV) < 5% for IL and MAG during all locomotor

conditions. Good inter-device reliability was also found for all locomotor conditions (IL and MAG CV < 5%). These results indicated that tri-axial ACCs are a valid and reliable tool used to identify steps and quantify external load when movement is completed at a range of speeds. In Study 2, all linear regression models performed well for both movement constraints (R^2=0.922-0.999; RMSE=0.047-0.242, p<0.001). The correlation between all training load measures and the DIST illustrates that both technologies may be used to indicate a total distance completed while walking.

DEDICATION

This dissertation is dedicated to the two individuals who I could never repay their favors as long as I live, my Mother and my Father.

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Chapter 1. Introduction

Training load is a term used to describe the physical effort athletes perform during sport-related training, practice, and competition (Quarrie et al., 2016). To better understand the training process and predict the response of those training loads, practitioners often apply various methods to quantify the training load athletes perform (Bourdon et al., 2017; Gabbett et al., 2017; Halson, 2014; Impellizzeri et al., 2019). Training load is generally categorized as external load or internal load. External loads refer to the physical work athletes engage in during training, practice and competitions. In contrast, internal load represents the physical and psychological response induced by the external load (Impellizzeri et al., 2019). Therefore, knowing the external training load and understanding the internal response will help practitioners optimize their practice.

Objective measures such as total distance performed, number of accelerations and decelerations, mean power output, and amount of weight lifted during training or competition are examples of external load. Objective measures such as heart rate, blood lactate, oxygen consumption, and subjective measures such as the rating of perceived exertion (RPE) are examples of internal load. Additionally, response measures such as wellness questionnaires (Saw et al., 2017), heart rate measures (Botek et al., 2014), jumping tests (Sams et al., 2018) have also been used to assess the training's psychological, physiological, and performance response. Depending on the tools' availability and validity, practitioners choose one or more variables or methods to monitor training load. Due to the advancement of wearable technologies nowadays (particularly GNSS and microtechnology), coaches and sports scientists often estimate players' psychophysiological responses based on monitoring the external load (Impellizzeri et al., 2019).

However, directly assessing the internal load is recommended as players might respond differently to an equivalent training load (Bourdon et al., 2017).

Accelerometer (ACC) and Global Navigation Satellite Systems (GNSS) sensors are two of the most common tools used measure external loads in team, court and field sports (Colby et al., 2014). Although those technologies' capability to assess sports-related events during training or competitions has not received consensus. ACCs and GNSS are used separately or interchangeably to assess training load; however, both technologies' relationship to the same training load has not been well established. Therefore, there are two primary aims of this dissertation: 1. to investigate ACC validity and reliability when identifying sport related events and measuring training load, 2. to evaluate the relationship between different accelerometry derived metrics and GNSS to assess external load. Such information may provide sports scientists and researchers with new insights into the applicability and usefulness of modern technology used in the sports industry.

Research Questions

1. Can Accelerometry data be used accurately to detect steps during various locomotor conditions including walking, running, and sprinting?
2. Can ACC be used to reliably quantify external load during various locomotor conditions including walking, running, and sprinting?
3. Is there a relationship between accelerometry and GNSS derived measures of external load used to quantify the same task?
4. How well can accelerometry and GNSS derived measures predict a known distance?

Hypotheses

1. Steps will accurately be identified during various sport-related activities using accelerometry data.
2. Training load will reliably be quantified by accelerometry derived measures while performing various sport-related activities.
3. A strong relationship will be found between accelerometry and GNSS derived measures to quantify the same task.
4. Known distance covered will be predicted by accelerometry and GNSS derived measures with different levels of predictivity.

Chapter 2. Review of Literature

Introduction

Identifying and monitoring human physical activity has been of interest to scientists for a variety of reasons, including health, fall prevention and sport performance (Bourke et al., 2007; Chambers et al., 2015; Mackintosh et al., 2016; Zhang et al., 2018). Both vision-based (Barris & Button, 2008) and wearable technologies (Aroganam et al., 2019) have been used to track human movements, however, vision-based systems may be prohibitively time consuming and costly to deploy when compared to the host of wearable technologies that have been developed. As wearables have become easier to deploy and costs have decreased, wearables have become essential tools used to track athlete activity and manage training loads in many different sports (Akenhead & Nassis, 2016).

Training load is a term used to describe the physical effort athletes perform during sport related training, practice, and competition (Quarrie et al., 2016). The training loads athletes complete produce the physiological adaptations required to perform in sport. To optimize specific physiological adaptations, coaches and sport scientists not only plan or prescribe training loads, but use various monitoring strategies to quantify athlete training loads and responses to those training loads (Bourdon et al., 2017; Gabbett et al., 2017; Halson, 2014; Impellizzeri et al., 2019). A considerable body of literature supports the use of load monitoring and suggests that training load monitoring and subsequent training modifications may enhance outcomes (e.g., performance, fitness, and readiness) and mitigate negative influences (e.g., excessive fatigue, illness, and injury) of training (Andrade et al., 2020; Bourdon et al., 2017; Gabbett et al., 2017; Halson, 2014; Impellizzeri et al., 2019).

Training load is generally categorized as external load or internal load. This concept was initially presented at the 8th Annual Congress of the European College of Sport Science in 2003 by Impellizzeri et al. (2019). External loads refer to the physical work athletes are exposed to in practice or competitions. In contrast, internal load represents the physical and psychological response induced by the external load (Impellizzeri et al., 2019). Objective measures such as total distance covered, number of acceleration and deceleration, mean power output, and amount of weight lifted during training or competition are examples of external load. Objective measures such as heart rate, blood lactate, oxygen consumption, and subjective measures such as the rating of perceived exertion (RPE) are examples of internal load. Depending on the tools' availability and validity to a sport, practitioners choose one or more variables or methods to monitor training load.

Due to technological advancement in recent years, various wearable devices have been developed to monitor training load (Borges & Driller, 2016; Chambers et al., 2015; Colby et al., 2014; Cummins et al., 2013; Ferrari et al., 2011). Heart rate measures (HR) and near-infrared spectroscopy (NIRS) are examples of wearable instruments used to assess athletes' internal load. HR measures one of the earlier standards used to assess training load. Variables such as HR (Hopkins, 1991), HR recovery (Daanen et al., 2012), HR variability (Plews et al., 2013), and Training Impulse (TRIMP) (Banister & Calvert, 1980) are examples of HR variables evaluated during or after training or competitions to assess internal load. HR-based assessments are common and easy to use but might not be applicable in some sports (Impellizzeri et al., 2019). NIRS measures local muscle oxidative metabolism at rest or during exercise (Ferrari et al., 2011). Recently, NIRS devices were embedded in sports garments which may extend the application of NIRS in the future (Borges & Driller, 2016). However, this technology's validity to assess internal load during various sports is not well established yet.

Nevertheless, an indirect measure such as the session rating of perceived exertion (sRPE), can also estimate internal load. sRPE is obtained by multiplying the athlete's perceived effort of training load (on a 1–10 scale) over the session duration (in minutes) (Foster, 1998). sRPE is a sensitive measure for training load and strongly correlated to internal load measures such as HR-based assessments (Borresen & Lambert, 2008; Foster, 1998; Lovell et al., 2013). sRPE has also correlated to external load measures such as acceleration-based assessments (Casamichana et al., 2013; Gaudino et al., 2015; J. Gentles et al., 2018; Lovell et al., 2013). Despite the promising performance of sRPE to assess training load, coupling an objective assessment along sRPE is highly recommended as some players might unreliably assess their own training load perception (Bourdon et al., 2017).

Furthermore, accelerometry and GNSS derived load have become some of the dominant objective measures to monitor external load in sport (Colby et al., 2014). These wearable technologies can be integrated or used separately to provide an indicator of the external work performed by athletes; consequently, practitioners may be better able to manage fatigue and direct adaptation. The role of ACC and GNSS in load monitoring has received increased attention across a number of sports in recent years (Chambers et al., 2015; Cummins et al., 2013) and will be the primary focus of this dissertation.

Accelerometers

ACCs are responsive motion sensors that measure the magnitude of acceleration in single or multiple axes, generally expressed as the change in velocity every second ($m \cdot s^{-2}$) or gravitational equivalents (g; where 1 g = 9.81 $m \cdot s^{-2}$). ACCs are often combined with gyroscopes and magnetometers which are used as an inertial measurement unit (IMU). IMUs can measure velocity, orientation, and gravitational force, often in the three axes (*x = anterior-posterior, y = medial-lateral, z = vertical*). As described above, ACCs measure acceleration, while gyroscopes measure angular rotation, and magnetometers assess the bearing magnetic direction (Ahmad et al., 2013). ACCs are often used to estimate the intensity of human movement, but may also be used to identify specific types of movement or positions such as locomotor activities and posture (Fortune, Lugade, Morrow, et al., 2014; Lugade et al., 2013). Moreover, the combination of these three sensors has improved the event detection precision such as tennis strokes by 10%, as IMU reported 90% accuracy while ACCs alone reported 80% (Connaghan et al., 2011). In fact, ACCs have been used since the 1950s to monitor human movement (Saunders et al., 1953) and a growing body of literature points to the utility of ACCs to assess human motion in a variety of settings (Moe-Nilssen & Helbostad, 2004; Sant'Anna & Wickström, 2010).

Locomotion and Locomotor Events

Illustrating the range of activities that can be identified via accelerometry, Lugade et al. (2013) demonstrated two triaxial ACC mounted at the waist and thigh can be used identify the static posture orientations of standing, sitting, and laying down as well as differentiate between a range of gait velocities. Much of the literature concerns gait velocities conducted in a clinical setting. Matsushima et al. (2015) found postural sway, gait velocity, cadence, and step length were significantly different between patients and control subjects, showing triaxial ACC positioned at the lower back could be used to assess the gait of ataxic patients. Regarding ACCs placement during movement analysis, various accelerometry techniques can be used to assess gait symmetry. Using two sensors on the feet, accelerometry can assess symmetry by measuring the gait cycle based on the timing of two consecutive foot-flats, or measuring the angular velocity of feet on each gait cycle (Mariani et al., 2013). A single triaxial ACC sensor mounted at the lower trunk can also be used to measure symmetry by analyzing the repetitive movement pattern of the center of mass on each gait cycle (Moe-Nilssen & Helbostad, 2004). Concerning sensors position and the number of sensors used, researchers have found good consistency and correlations between gait symmetry measured with a single 3D ACC attached at the low back and a sensor of each foot (Spearman correlation: $|\rho| = [0.82, 0.88]$, $p < 0.05$) during a straight walk condition (Zhang et al., 2018). This suggests that a single sensor mounted at the low back may be more sensitive and practical to use compared to a sensor on each foot for gait symmetry assessments.

Events such as steps (Pham et al., 2017), falls (Bourke et al., 2007) and jumps (Choukou et al., 2014) can be identified using specific algorithms. Steps are often counted based on toe-off, heel-strike, and/or mid-swing identification with established acceleration thresholds and timespan between sequential gait events to determine valid steps (Salarian et al., 2004). Algorithms that use vertical acceleration (Din et al., 2016) or anterior-posterior acceleration (Micó-Amigo et al., 2016) have been validated to identify steps. For instance, using accelerometry data, Pham et al. (2017) reported an accuracy of 88% with a positive predictive value of 94% when detecting steps in a home-like environment that included turning events, and 91% accuracy with 98% positive predictive value when turning events were not included. Furthermore, at velocities ranging from 0.1 to 4.8 m/s, three different commercial ACCs attached at the ankle, waist, and wrist, in addition to a custom-designed activity monitoring system (AMS) consisting of four ACCs positioned at the waist, right thigh, and bilateral ankles have demonstrated a diversity of median interquartile range (IQR) agreements with manual step counts (Fortune, Lugade, Morrow, et al., 2014). The authors conclude that the AMS algorithm could identify steps with a higher median agreement and/or smaller IQR (92% (8%)) than the commercial ACCs located at the ankle (92% (36%)), waist (93% (22%)), wrist (33% (35%)) in a laboratory-based setting, suggesting that their algorithm is suitable for detecting steps in a free-living environment (Fortune, Lugade, Morrow, et al., 2014).

Likewise, algorithms have been developed to discriminate falls among daily living activities of elderly people (Bourke et al., 2007). A recent experiment by Siregar et al. (2018) involved a tri-axial ACC and gyroscope, where the device was used to successfully detect the direction of falling and distinguished between intentional and accidental falling. Separate algorithms have been used to identify and measure jumps. Vertical jump height can be estimated via flight time (Linthorne, 2001) where flight time is the period that a body is not in direct contact with the ground. Although temporal bias has been found when estimating takeoff and touchdown when jumping (Casartelli et al., 2010; Choukou et al., 2014), Choukou et al.(2014) reported good reliability when assessing jump height during hops, countermovement jumps, and squat jumps (intraclass correlation coefficient (ICC) = 0.74 - 0.89, coefficient of variation (CV) = 4.25 - 6.42%) using a lower back mounted ACCs. Collectively this evidence seems to suggest that specific algorithms can be employed to identified various events using data from triaxial ACCs.

Sport Related Events

Movements specific to individual and team sports can also be identified using ACCs (Chambers et al., 2015). Events such as kicks (Ellens et al., 2017), throws (Koda et al., 2010), tennis strokes (Connaghan et al., 2011), baseball bat swings (Ghasemzadeh & Jafari, 2011) and golf swings (Lai et al., 2011) can be identified using specific algorithms. The quantity and intensity of kicks in Australian Football have been classified using ACCs placed above the approximate ankle joint (Ellens et al., 2017). Additionally, two IMU sensors were placed at a forearm and upper arm to analyze the upper limb's acceleration and angular velocity while pitching a baseball (Koda et al., 2010). The authors proposed an algorithm to estimate the trajectory of throws and were highly correlated to throws identified by the criterion method (Vicon 3D motion capture system). In tennis, an IMU system placed on a players' dominant forearm was used to classify strokes (serves, backhands, forehands) by measuring the spike in ACC data due to ball impact (Connaghan et al., 2011). Accelerometry data can also be used to discriminate between skilled golfers and non-golfers by assessing swing patterns via IMU sensors attached to the leading hand and upper arm, pelvis, and upper back (Lai et al., 2011). The authors stated that skilled golfers adequately perform high acceleration swings with lower pelvis movement than beginner golfers. Additionally, movement and event identification in water (Jensen et al., 2013), snow (Chardonnens et al., 2012), and combat (Shepherd et al., 2017) sports have also been reported. Taken together, these studies indicate that accelerometry can be used to analyze motion and detect events within a variety of sports.

Athlete Training Loads

ACCs are valid and reliable instruments to measure training load in the field and laboratory environments (Johnstone, Ford, Hughes, Watson, & Garrett, 2012a, 2012b; Johnstone, Ford, Hughes, Watson, Mitchell, et al., 2012). There is a growing body of literature that recognizes the ability of ACCs to quantify the external demand of team and individual sports. For instance, the within and between device reliability of ACCs has been established across a variety of movement demands in both laboratory and on-field conditions in Australian football

(Boyd et al., 2011). Gentles et al. (2018) found strong to nearly perfect correlations between accelerometry derived training load and session rating of perceived exertion (sRPE) ($r= 0.84$; $p < 0.001$) and total distance measured using GPS ($r = 0.95$; $p < 0.001$) among NCAA women's soccer players. ACCs have also been used to illustrate the differences in the activity profile between singles and doubles match play in tennis (J. A. Gentles et al., 2018). In rugby, ACCs outperformed GPS by recognizing the differences in training load between players based on their position on the field; additionally, the accelerometry derived training load clearly detected the decline in second half activity level compared to the first half (Howe et al., 2017). Moreover, accelerometry has also been shown to be a valid assessment of a test designed to simulate basketball play, suggesting that ACCs can be used to quantify the external demand of basketball (Staunton et al., 2017). Further, energy expenditure has been estimated based on linear regression equations derived from raw ACCs data (Freedson et al., 2005).

Many accelerometry derived metrics have been used to quantify training load, including Body Load (Aguiar et al., 2013), Player Load (Boyd et al., 2011), Force Load (Buchheit & Simpson, 2017), Dynamic Stress Load (Gaudino et al., 2015), and Impulse Load (J. Gentles et al., 2018). These metrics are modified vector magnitude based on the three planes' accelerations (x, y, and z), often detected by ACCs sampling at 100 Hz, and data are expressed in arbitrary units (AU). Body Load and Player Load are expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in each of the three planes and divided by the sampling frequency of the device (generally sampling at 100 Hz) (Aguiar et al., 2013; Boyd et al., 2011). As shown in the following formula (Table 2.1), all expressions are performed inside the square root in Player Load; however, in Body Load, the division of the 100 is processed outside the square root. Interestingly, different equations and descriptions for Player Load have also been reported in the literature (Boyd et al., 2011; Howe et al., 2017; Randers et al., 2014). Moreover, Howe et al. (2017) did not specify the scaling factor they used to divide the vector magnitude summation. Randers et al. (2014) did not include division in their formula. For instance, a recent study by Bredt et al. (2020) investigated different Player Load descriptions and equations reported in the literature by assessing training load during a team sport-related activity. Player Load equations across studies led to different training load values, making it difficult to compare athletes given that differences could be attributed to the calculation methods, not to athletes' mechanical effort (Bredt et al., 2020). Player Load has also been described as Acceleration Load (Schelling & Torres, 2016). Further, Dynamic-stress load is calculated as the total weighted impacts (collisions or steps impacts) identified as maximum ACC magnitude values above 2 g in 0.1 seconds over a defined period (Beato et al., 2019).

Although Player Load is the most commonly reported measure in the literature (Vanrenterghem et al., 2017), its potential to monitor training load has been questioned (Bredt et al., 2020). Compared to other metrics that include a variation of the sum of all accelerations, Player Load includes only the sum of the differences in acceleration and may not best represent training load (Bredt et al., 2020). Additionally, training load could be misrepresented due to the inclusion of non-locomotor activities in Player Load (Buchheit & Simpson, 2017). Force Load and Impulse Load are examples of metrics that aim to only include locomotor activities (e.g., walking, running, bounding, jumping) and impacts (Buchheit & Simpson, 2017; J. Gentles et al., 2018). Force Load is derived from the product of player body mass and magnitude vectors from a triaxial ACC, used to estimate ground-reaction forces during all foot impacts and collisions (Buchheit & Simpson, 2017). Impulse Load is derived from the square root of the sum of the magnitude vectors from a triaxial ACC divided by the force of gravity (g = 9,8067) (Table 2.1)

(J. Gentles et al., 2018). Training load may be better assessed using metrics that aim to include only locomotor activity, but future research is needed to investigate this possibility.

Table 2.1

Formula for Body Load, Player Load, and Impulse Load

Metric	Definition and formula*
Player Load	$PL = \sqrt{\frac{\left(a_{y1} - a_{y-1}\right)^2 + (a_{x1} - a_{x-1})^2 + (a_{x1} - a_{x-1})^2}{100}}$
Body Load	$BL = \frac{\sqrt{\left(a_{y1} - a_{y-1}\right)^2 + (a_{x1} - a_{x-1})^2 + (a_{x1} - a_{x-1})^2}}{100}$
Impulse Load**	$IL = \sum_{s=1}^{n} \frac{\sqrt{x_s^2 + y_s^2 + z_s^2}}{9.8067}$

*In the formulas above, x = forward and backward acceleration, y = lateral acceleration and z = vertical acceleration.

** IL is propriety by the manufacture and is only associated with locomotor events that are detected by Zephyr (e.g., walking, running, bounding, jumping).

Sensor Position

Accelerometry data can be collected using a single or multiple sensors (Fortune, Lugade, & Kaufman, 2014). Sensors can be placed at a variety of different anatomical locations including upper limb (shoulder, arm, elbow, forearm, or hands), lower limb (thigh, knee, leg, or foot), multiple limps (upper and/or lower limbs at the same time), or other body regions (head, trunk, back or hip) (López-Nava & Muñoz-Meléndez, 2016). Moreover, ACCs have been placed at specific anatomical locations to assess their accelerations, such as the wrist (Whiteside et al., 2017), head (Beanland et al., 2014), and tibia (Sinclair et al., 2016). ACCs have also been attached to sports equipment to assess their accelerations; this includes but is not limited to barbells (Balsalobre-Fernández et al., 2016), kayak cockpits (Janssen & Sachlikidis, 2010), and bikes (Macdermid et al., 2014). Furthermore, ACCs measure the body segment's acceleration attached to (Nedergaard et al., 2017); however, no consensus has been formulated regarding the best anatomical references to assess training load. The Center of Mass (COM) is a common location to assess whole-body movements (Barrett et al., 2014; Cleland et al., 2013), although COM is highly variable during movements that are not practical to track. Additionally, identifying sport-related events such as kicks, pitches, tennis strokes may not be optimized when a sensor is placed at COM.

It is common to fix ACCs between scapulae in team sports due to the inclusion of GNSS sensors given that GNSS sensors benefit from unobstructed signal orbiting satellites. Researchers have thus attempted to compare training load assessed using ACCs fixed at the COM and between scapulae (Barrett et al., 2014). Barrett et al. (2014) found moderate to high test-retest reliability at both the scapulae (ICC .80–.93, CV 5.3–14.8%) and the COM (ICC .87–.97, CV 4.2–11.5%) during a standardized bout of treadmill running. Nevertheless, the three planes' (*x*, *y*, *z*) relative contribution to loading was different as a result of unit position. The unit placed at scapulae underestimated training load by 15.7% ± 9.7%, mostly due to the lower contributions of the mediolateral-plane loading. Barrett et al. (2014) interpreted this as a weakness related to detecting hip rotation during running compared to the COM placement. Additionally, scapular units increased the vertical-plane percentage contribution to loading, which is likely caused by the greater vertical displacement associated with shoulder-girdle movements or trunk flexion during running. Furthermore, ACCs were observed to reliably measure training loads resulting from treadmill running and a Soccer-Specific Aerobic Field Test ($SAFT^{90}$) when placed at four locations: scapulae, lower back, knee, and ankle ($r^2 \geq 0.989$), in which scapular presented the least variable as a CV of 2.05% during the treadmill test, and a CV of 2.46% during the sport-specific test has been reported (Gómez-Carmona et al., 2019). The evidence reviewed here seems to suggest a pertinent relationship between sensor location and the object intended to be assessed, to which COM appears to be the most suitable location to assess the acceleration of whole-body during individual and team sports.

Global Navigation Satellite System

Global Navigation Satellite Systems (GNSS), of which there are several, are a constellation of satellites that provide location and time information for tracking objects. GNSS is an umbrella term that includes several different satellite networks such as Global Positioning System (GPS), Global Navigation Satellite System (GLONASS), Galileo, and BeiDou. GNSS was initially developed for military purposes, but has expanded to be used in many applications, including sports for athletes monitoring purposes. The first paper that investigated GPS applicability for sports purposes was published in 2001 (Larsson & Henriksson-Larsén, 2001). In recent years, researchers have shown an increased interest in the role of GNSS in load monitoring within sports.

GNSS in Sports

GNSS is primarily used to measure the horizontal displacement of the object the GNSS sensor is fixed. In sport, the GNSS sensor is most often secured to the athlete and provides information on player position, velocity, and on-field movement patterns. Total distance, speed, number of accelerations and decelerations ($m.s^{-2}$) are some variables that can be acquired by GNSS. Positional differentiation and Doppler shift are two different methods used to determine distance and velocity. Moreover, GNSS identifies the receiver location by continually calculating its distance to the satellites, from which GNSS receiver's latitude, longitude, and altitude acquired. Distance is calculated by measuring the change in location with each signal travels from satellites to the receiver (Positional differentiation) (Larsson, 2003). Velocity is calculated by measuring the change in location over time (Positional differentiation) or the change in frequency of satellite emitted periodic signal to the receiver, as the receiver's movement velocity influences the signaling rate (Doppler shift) (Larsson, 2003). While positional differentiation and doppler shift are both valid assessments of position and velocity, during linear running using a 1-Hz GPS device, the Doppler shift method was more precise and accurate (Townshend et al., 2008).

GNSS Validity and Reliability

Distance. An instrument is considered valid if it accurately assesses what it intends to assess (Hopkins, 2004), and an instrument is reliable if measurements are reproducible (Hopkins, 2000) Nonetheless, an instrument can be reliable but might consistently mismeasure what it intends to assess (Choukou et al., 2014). Moreover, an instrument's reliability is thought to be more valuable to practitioners as it helps identify meaningful changes in training load. The total distance covered by players during a playing period is perhaps the variable most routinely monitored using GNSS. GNSS networks such as GPS are valid indicators of distances of 40m completed during different movement patterns. However, GNSS may not accurately measure shorter distances (less than 20m) completed during high-speed running, sprinting, and changes of direction (Jennings et al., 2010). Higher sampling frequencies (5-10Hz) have been shown to improve the accuracy of GPS (Delaney et al., 2018; Jennings et al., 2010), although some evidence suggests that increasing sampling frequency to 15 Hz does not improve accuracy when assessing distance completed during unstructured movements (Vickery et al., 2014). Further, GPS sampling at 15Hz underestimated a longer distance (13,300m) completed during a rapid multidirectional movement (bias: -2.16%), and overestimated the same distance completed during a curvilinear trial (bias: 2.99%) compared to the criterion measure (surveyor's wheel) (Rawstorn et al., 2014) The authors attributed the miscalculation of distance by GPS during the shuttle trial to the interaction between GPS position sampling and movement demands. Moreover, the rapid multidirectional movements cause GPS to partition continuous movement paths into discrete linear segments, from which GPS calculates distance across individual sampling epochs. However, the source of the bias during the curvilinear trials is unclear (Rawstorn et al., 2014).

The inter-device and intra-device or test-retest reliability of GNSS sensors have also been assessed in numerous investigations (Akenhead & Nassis, 2016; Buchheit et al., 2014; Castellano et al., 2011; Johnston et al., 2014; Rawstorn et al., 2014; Vickery et al., 2014). Jennings et al. (2010) found moderate to poor test-retest reliability with 1Hz (CV= <7.0 - 77.2%) and 5Hz (CV= <6.6% - 39.5%) GPS devices when used to assess straight-line sprinting distance (10-40m, 20-40m interval). However, using a GPS unit sampling at 10Hz, Castellano et al. (2011) reported a good level of intra-unit (15m CV < 4%; 30m CV < 3%) and inter-unit (15m CV = 1.3%, ; 30m CV < 0.7%) reliability when measuring distance during a 15m and 30m straight-line sprint. Although a higher sampling frequency seems to improve reproducibility, GPS devices sampling at 15Hz did not improved test-retest reliability when assessing distance completed during a simulated team sports circuit compared to 10Hz units (Johnston et al., 2014).

Johnston et al. (2014) reported a typical error of measurement (TEM) of 1.9-12.1% for 15Hz units and a TEM of 1.3-11.5% for 10Hz devices. To be expected, the available evidence demonstrates that intra-unit reliability is better than inter-unit reliability; therefore, assigning a single unit for each individual is recommended (Buchheit et al., 2014; Castellano et al., 2011; Rawstorn et al., 2014; Scott et al., 2016). Considering the evidence, it seems that GNSS sensors sampling at 10Hz provide the highest accuracy and reproducibility. Additionally, assessing distance appears to be more precise over longer distances with few changes in velocity (Scott et al., 2016).

Speed. Measuring the instantaneous speed (Akenhead et al., 2014; Varley et al., 2012), peak speed (Johnston et al., 2014; Vickery et al., 2014), mean speed (MacLeod et al., 2009; Vickery et al., 2014) has been reported using GNSS. Instantaneous speed is defined as a player's speed at a given moment in time measured in meters per second (m/s), while mean speed is the average speed of a player during a certain playing period measured in meter per second (m/s) or kilometers per hour ($km.h^{-1}$). Peak speed is the maximum speed reached by a player for a one-second sample period. Acceleration and deceleration is the rate of change in velocity measured in meters per second squared (m/s^2). The number of accelerations and decelerations of a player, or the anatomical reference in which the unit is fixed, can also be reported using GNSS data (Hennessy & Jeffreys, 2018; Scott et al., 2016).

As with total distance, identifying speed measures using GNSS devices sampling at 10Hz seems to be more precise data than 1Hz, 5Hz, or 15Hz (Johnston et al., 2014; Scott et al., 2016; Varley et al., 2012; Vickery et al., 2014). It has been shown that GNSS is a useful tool to measure instantaneous speed (Akenhead et al., 2014; Varley et al., 2012; Vickery et al., 2014);

however, the accuracy and reproducibility might be compromised when a high rate of change in velocity occurred (Akenhead et al., 2014; Varley et al., 2012). Additionally, during repetitive and unstructured movements, Vickery et al. (2014) found that peak and mean speed were underestimated (14–29%, and 13–29%, respectively) compared to the criterion measure (VICON system); however, the differences were not statistically significant.

Speed can also be categorized into several zones, usually enumerated from one to six zones, ranging from 0 to 36 $km.h^{-1}$, where zone one represents low velocity while zone six represents high velocity (Cummins et al., 2013; Hennessy & Jeffreys, 2018). Distance covered and time spent in each zone can also be obtained by GNSS. Although the range of speed in each zone is diverse and not standardized across sports or brand of sensor, distance and time spent in each zone have been used to estimate an athlete's work rate during training or competition (Cummins et al., 2013; Hennessy & Jeffreys, 2018). Considering the evidence, it seems that GNSS could be utilized to assess the volume and intensity of training load; however, caution should be used in sports that feature high velocity and rapid directional change (e.g., soccer, football, rugby, tennis) as training load might be misrepresented by GNSS.

Metrics that integrate ACCs and GNSS data to monitor training load have also been developed; the so-called Dynamic stress load (Kampakis, 2016) or Fatigue index (Beato et al., 2019) are examples and are deemed as indicators of fatigue. Fatigue index is the ratio between instantaneous speed measured by GNSS and weighted impact values derived by ACC (Beato et al., 2019). Beato et al. (2019) found this metric to be sensitive to monitor fatigue during submaximal intermittent exercise. Additionally, Dynamic stress load has demonstrated the potential to predict injury among football players (Kampakis, 2016). However, further work is needed to confirm the validity and advantages of using such metrics in load monitoring.

Factors Influencing GNSS Precision

Assessing player position using GNSS networks may be influenced dramatically by the number and separation of satellites that are connected to the receiver. GNSS enables receivers to acquire signals from multiple satellite networks (e.g., GPS, GLONASS, Galileo, and BeiDou), increasing the number of available satellites. Combined satellite systems improve satellite geometry and resulting precision (Tahsin et al., 2015). Dilution of Precision (DOP) is a description of satellite geometry. DOP is composed of two elements: horizontal dilution of precision (HDOP) and vertical dilution of precision (VDOP) (for more detail about DOP, see Tahsin et al. (2015)). HDOP is one indicator of GNSS accuracy and is influenced by the separation of the satellites. HDOP values range from 0 to 50, with a value of less than 1 considered ideal distribution of satellites. HDOP is low and precision is excellent when substantial distance exists between satellites, while HDOP is high and precision is poor when satellites are in close proximity. Additionally, indoor fields, stadiums with high walls or roofs, and cloudy weather are factors that can reduce the quality of GNSS data (Cummins et al., 2013).

Relationship Between ACC and GNSS

Evaluating the precision of ACC and GNSS to assess sport-related events/locomotion or training load has been of interest to researchers and sports scientists (Boyd et al., 2011; Connaghan et al., 2011; Delaney et al., 2018; Ellens et al., 2017; J. Gentles et al., 2018; Howe et al., 2017; Jennings et al., 2010; Vickery et al., 2014). A systematic literature review by Chambers et al. (2015) concluded that an IMU has excellent potential to detect sports-related events and quantify external load. Additionally, a review by Scott et al. (2016) offers perhaps the most comprehensive review of the utility of GNSS in sport. The authors concluded that GNSS could assess external load in a variety of sport settings (Scott et al., 2016). However, little is known about the relationship between both technologies to assess the same event or training load.

To date, several investigations have assessed the relationship between accelerometry and GNSS derived measures. A study by Polglaze et al. (2015) found large to very large correlations between Player Load and total distance accumulated during men's hockey practice ($r = 0.742$; $p < 0.00001$) and competition ($r = 0.868$; $p < 0.00001$). Additionally, a strong correlation was found between Player Load and total distance completed in men's soccer training ($r = 0.70$; $p < 0.01$) (Casamichana et al., 2013), and a nearly perfect correlation ($r = 0.95$; $p < 0.001$) was found between Impulse Load and total distance in women's soccer matches (J. Gentles et al., 2018). However, no study has investigated the relationship between different accelerometry-based metrics and GNSS with a known distance to our knowledge.

Conclusion

The evidence reviewed here seems to suggest that monitoring training load during practices and competitions serves an essential role in optimizing sports performance. Various monitoring strategies are available to quantify athletes training load (external load) and assess responses to those training load (internal load). Due to the ease of use and capability to provide coaches with real-time data, ACC and GNSS sensors have been commonly utilized in various sports to monitor external load. ACCs and GNSS can be used separately or integrated to provide indicators of the external load. Despite this, the relationship between both technologies to assess the same task and the validity and reliability of these technologies to identify sport related events, has not been adequately investigated. Indeed, practitioners may be better able to manage training load if they better understand the capabilities and deficiencies of such technologies.

Chapter 3. STUDY I: Accelerometry Derived Training Loads Validity and Reliability

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Abstract

This study aimed to assess the validity and reliability of tri-axial accelerometers to identify steps and quantify external load during several locomotor conditions including walking, running, and sprinting. Thirty physically active college students (height = 176.8 ± 6.1cm, weight = 82.3 ± 12.8kg) participated. Acceleration data was collected via two tri-axial accelerometers (Device A and Device B) sampling at 100Hz, mounted closely together at the xiphoid process. Each participant completed two trials of straight-line walking, running, and sprinting on a 20m course. Device A was used to assess accelerometer validity to identify steps against steps counted manually from videography. Device A was also used to assess the test-retest reliability of the instrument to quantify the external load. Device A and Device B were used to assess inter-device reliability. The reliability of accelerometry derived metrics Impulse Load (IL) and Magnitude *g* (MAG) were assessed. The instrument demonstrated a positive predictive value (PPV) of 96.98-99.41% and an agreement of 93.08-96.29% for step detection during all conditions. Good test-retest reliability was found with a coefficient of variation (CV) < 5% for IL and MAG during all locomotor conditions. Good inter-device reliability was also found for all locomotor conditions (IL and MAG CV < 5%). These results indicated that tri-axial accelerometers are a valid and reliable tool used to identify steps and quantify external load when movement is completed at a range of speeds.

Key Words: wearable technologies, accelerometers, training load, external load, monitoring

Introduction

Wearable technologies have become common place in team and individual sports to assess internal and external loads of athletes. These technologies are used to measure various physiological-related variables including heart rate, oxidative muscle metabolism, breathing frequency, skin temperature (17,25,27,33), as well as activity-related variables such as total distance, acceleration, deceleration, and posture (7,25,27,34). The estimation of physical work performed by athletes is of particular importance to many practitioners and coaches. Therefore, devices used to evaluate the physical effort of athletes during practice and competition have become essential components of load monitoring (1). Accelerometers are one type of wearable technology used to indicate the quantity of mechanical work performed by athletes (10), that may improve the ability of practitioners to better manage fatigue and direct adaptation. The role of accelerometers in load monitoring has received increased attention across a number of sports in recent years (8,11). Despite this, the validity and reliability of accelerometers to detect events and quantify training load during sport-related activities is not well established.

Accelerometers are a responsive motion sensor that measure the magnitude of acceleration in one or more axes (x = *anterior-posterior*, y = *medial-lateral*, z = *vertical*). Accelerometers are often used to assess the intensity of human movement and identify specific types of motion or positions such as locomotor activities and posture (18,29). Events including steps, jumps, kicks and throws have been identified using accelerometers (9,16,28,32). However, most studies that have investigated the validity of this technology were conducted in a laboratory setting.

A variety of event-specific algorithms and acceleration thresholds are used in accelerometry based event identification and human movement assessment. For instance, steps are often counted based on toe-off, heel-strike, and/or mid-swing identification with established acceleration thresholds and time between sequential gait events (35). Algorithms using vertical acceleration (14) or anterior-posterior acceleration (31), have also been validated to identify steps. Pham et al. (32) provides an example of this, finding that in a home-like environment, accelerometry data could be used to detect steps that included turning events with an accuracy of 88% and positive predictive value of 94%, while steps without turning events were detected with 91% accuracy and 98% positive predictive value. Moreover, to validate steps identification using accelerometers, Fortune et al.(18) assessed a custom-designed activity monitoring system (AMS) that consisted of four accelerometers positioned at the waist, right thigh, and bilateral ankles. Three different commercial accelerometers were also attached at the ankle, waist, and wrist. The authors conclude that the AMS algorithm could identify steps at a higher median agreement and smaller interquartile range (92% and 8%) than the commercial accelerometers located at the ankle (92% and 36%), waist (93% and 22%), wrist (33% and 35%) when dynamic activities at velocities ranging from 0.1-4.8 m/s were performed. This suggests that the algorithms used by Fortune et al. (18) are suitable for detecting steps in a free-living environment. While multiple accelerometers may be difficult to use in sport, Armitage et al. (2) recently investigated the reliability of step counting using two accelerometers placed on the right shank. The authors reported excellent inter-unit reliability (intra-class coefficient (ICC) = 0.96) and (95% confidence interval (CI) = 0.90-0.99) during various running-based team sports (2). Additional sport related validation of step counting and identification via accelerometry remains necessary.

Accelerometry derived external loads have been assessed in field and laboratory environments (4,25–27). Johnstone et al. (27) validated accelerometry derived training load against oxygen (O_2) consumption in a field-based environment and reported a very strong relationship ($r > 0.90$; $p < 0.01$). Accelerometry derived training load has also been correlated to a heart rate-based training impulse during soccer training and showed a large relationship ($r > 0.80$; $p < 0.01$) (36). There is a growing body of literature that recognizes the ability of accelerometers to quantify the demands of team and individual sports. Gentles et al. (19) found strong to nearly perfect correlations between an accelerometry derived training load and session rating of perceived exertion (sRPE) ($r = 0.84$; $p < 0.001$) and total distance measured using GPS ($r = 0.95$; $p < 0.001$) among NCAA women's soccer players during an entire regular season. Accelerometers have also been used to illustrate the differences in the activity profile between single and double match play in tennis (20). In rugby, accelerometers outperformed GPS by recognizing the differences in players' movement demand based on their position on the field (backs vs. forwards) and period of match play (1st vs. 2nd) (24). Additionally, the within and between device reliability of accelerometers has been established across a variety of movement demands in a laboratory and on-field conditions (4,7,21). Two accelerometers aligned on players' upper back reliably quantified external load (CV 1.9%) during Australian football matches (7). Furthermore, Gomez et al. (21) assessed the within and between device reliability of eight devices mounted at four anatomical locations during a Sport-Specific Aerobic Field Test (SAFT[90]). The authors reported excellent between-device reliability (CV = 2.96%) and excellent values ($r = 0.86$-0.96; $p = 0.46$-0.98) for within-device reliability and no significant differences between trials. Current literature suggests that accelerometers may be used to assess external load, although additional research is needed to evaluate the use of accelerometry data to detect events (e.g., steps, jumps, impacts) and quantify training load during sport related movement.

Therefore, the purpose of this study was twofold. First, this study aimed to assess the validity of accelerometers to identify steps during several locomotor conditions including walking, running, and sprinting. Second, this study sought to assess the inter-device and test-retest reliability of accelerometers to quantify external load while walking, running, and sprinting.

Methods

Experimental Approach for the Problem

This investigation was conducted to assess the validity and reliability of a tri-axial accelerometer to identify steps and quantify external load while completing a twenty-meter straight-line course. Video recording was conducted and served as a reference instrument to evaluate step counts for construct validity.

Subjects

Thirty participants (height = 176.8 ± 6.1cm, weight = 82.3 ± 12.8kg) volunteered to participate in this study. Subjects were physically active and participated in some form of physical activity at least three times a week. This study was approved by the university's Institutional Review Board and participants provided written consent for their involvement and video recording.

Procedures

The twenty-meter straight-line course was designed on a grass field (Figure 3.1). Each participant completed six trials of the experiment. The six trials included two trials of each of the following locomotor conditions: walking, running, and sprinting. A research assistant served as a pacemaker in each locomotor condition. A metronome (Pro Metronome App, 2014 EUMLab, Xanin Tech) was used to gait the velocity of each condition (walking, running, sprinting) to limit the variation between subjects and trials. The research assistant was wearing headphones to listen to the metronome, and participants were directed to keep pace with the research assistant. The tempo was set at 45, 70 and 90 beats per minute for walking, running and sprinting, respectively. A full gait cycle (i.e., two steps) was complete for each beat and a single research assistant guided all trials. Before initiating each trial, participants were directed to remain still after positioning their feet precisely at the start position; they were also instructed to stop precisely at the end of the course. Additional signs were placed at 15m to alert subjects to decelerate in the sprinting course to allow for a precise stop at the finish line. Small stutter steps were sometimes used by subjects to break, particularly during the running and sprinting trials, as they approach the end of the course. To keep step counts consistent with the locomotor condition, stutter steps were removed from analysis. Each trial was preceded by a 5 second countdown followed by the command of "go" from the research assistant. Participants performed a familiarization trial for each condition. Following familiarization, each subject completed each condition twice on the 20m course.

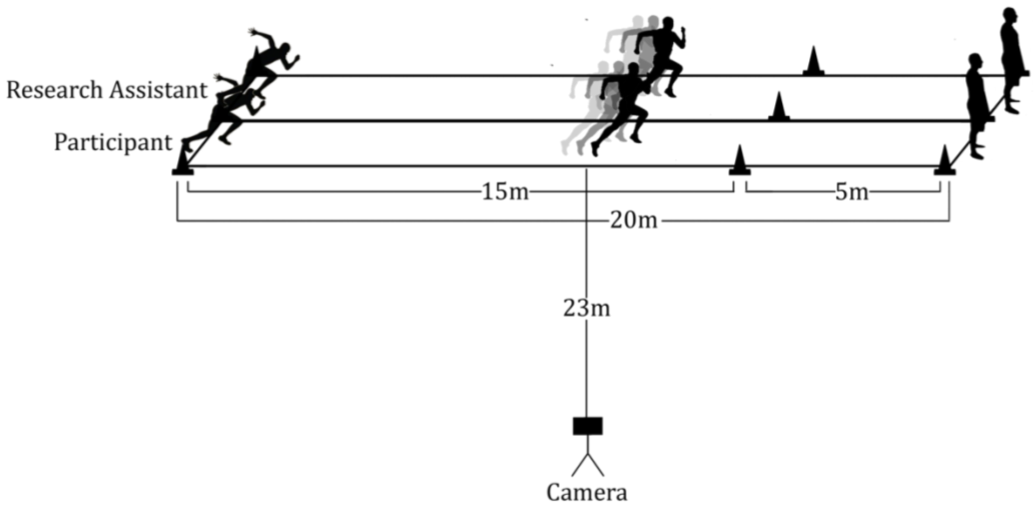

Figure 3.1 Illustration of The Course Design

*Each participant performed 2x 20m walking, running, and sprinting.

*5m is a deceleration zone for the sprinting course

Instrumentation

Acceleration data was collected during each 20m trial via two tri-axial accelerometers sampling at 100Hz (Zephyr^{TM} BioHarness v3, Zephyr Technology Corp., Annapolis, *MD, USA)*. Two accelerometry derived loads were assessed; 1) Impulse Load (IL) an accumulative measure of mechanical load defined in Table 3.1 and expressed in arbitrary units, and 2) the square root of the sum of squared accelerations (MAG) expressed as gravitational equivalents (1g = 9.81m/s^2). It should also be noted that IL aims to include only accelerations from locomotor events (e.g., walking, running, jumping) and impacts, but as a proprietary metric, the methods used to identify accelerations from these events are not public. Mean absolute IL and MAG were calculated for all conditions.

Each subject wore two Bioharness™ devices (A and B) located closely together at the xiphoid process level, along the midsternal line. Device A was used for the validity and test-retest reliability, while devices A and B were used to assess inter-device reliability. The beginning and end of each trial were marked by the subject tapping on the accelerometers four times; this served as identifier to expedite data analysis. Video of each trial was recorded for the purposes of step identification using a smartphone camera (iPhone 6; 1080p at 30 fps) and was placed 23m to the side of the 20m course (Figure 3.1).

Table 3.1 Formula for Each Accelerometry Based Metric

Metric	Definition and formula*
Impulse Load**	$IL = \sum_{s=1}^{n} \frac{\sqrt{x_s^2 + y_s^2 + z_s^2}}{9.8067}$
MAG	$MAG = \sum_{s=1}^{n} \sqrt{x_s^2 + y_s^2 + z_s^2}$

* In the formulas above, x = forward and backward acceleration, y = lateral acceleration and z = vertical acceleration.

** IL is propriety by the manufacture and is only associated with locomotor events that are detected by Zephyr (e.g., walking, running, bounding, jumping).

Event Detection Validity

Device A was used to assess the ability of the Bioharness™ to detect steps during each locomotion condition. The methods used by Zephyr™ to identify steps detected using the Bioharness™ are proprietary and therefore, we are not able to detail those methods here. Video recording and data from device A were uploaded to and synchronized using RaceRender software (version 3.7.3; 2019 HP Tuners LLC / RaceRender LLC, USA) to identify steps (Figure

3.2). Heel strike and toe-off were determined using video and associated acceleration data according to step classification recommended from a previous investigation (32).

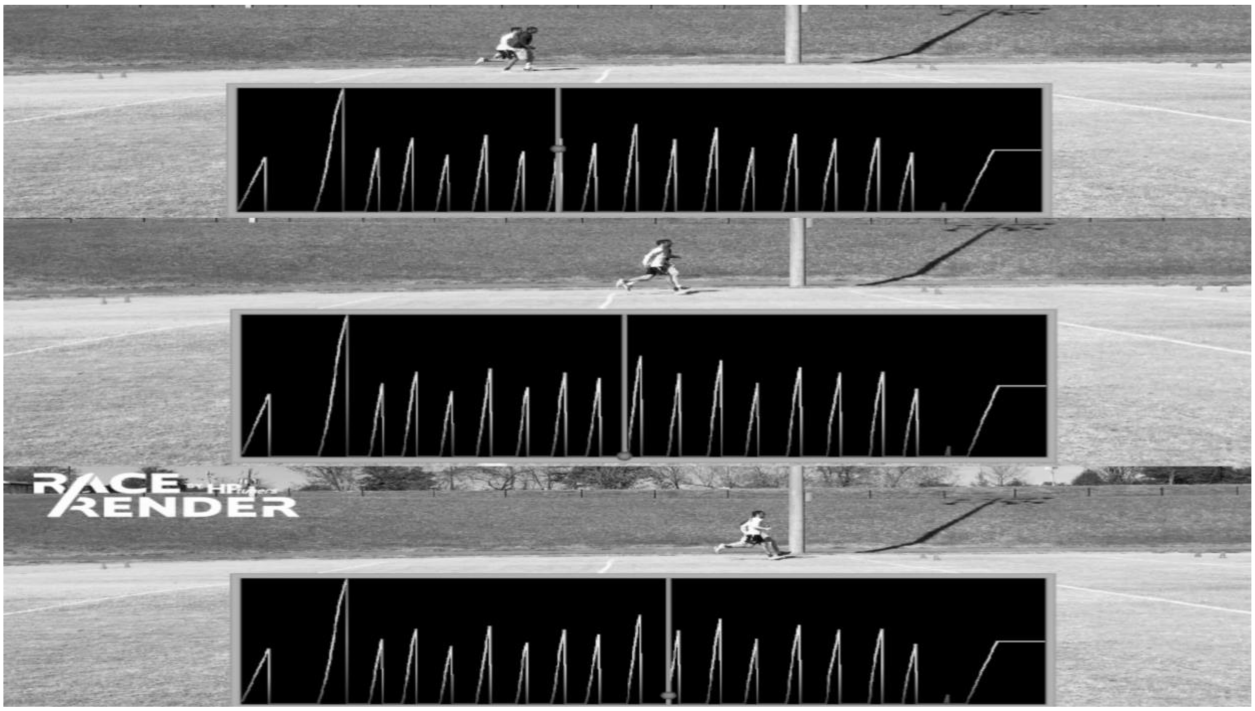

Figure 3.2 Video and Acceleration Data were Uploaded to and Synchronized Using RaceRender Software

*The research assistant (far side) and a participant (near side) performing a sprinting trial.

Test-Retest and Inter-Device Reliability

Device A was used to assess the test-retest reliability of the Bioharness^{TM} during each locomotor condition. IL and MAG from the first and second trials were assessed. Devices A and B were used to assess the inter-device reliability of the Bioharness^{TM} during each locomotor condition. IL and MAG from the first trial recorded by each device were used for analysis.

Statistical Analysis

Accelerometry data were downloaded to OmniSense^{TM} Analysis (version 4.1.4; Zephyr Technology Corporation, Annapolis, MD, USA), then exported to Microsoft Excel 2019 (Microsoft Corporation, Redmond, WA, USA) for analysis. Data were expressed as means and standard deviations for each locomotor condition.

Validity

Agreement and positive predictive value (PPV) were calculated for all trials to assess Bioharness^{TM}'s ability to detect steps. Agreement is the percentage of steps detected by device A relative to those counted manually from video. PPV is the ratio of true-positive steps to the sum of true- and false-positive steps. A true-positive step is defined as step identified on video, and identified by device A, while a false-positive step is defined as a step identified by device A, but not identified using video. Bland-Altman plots were also generated to identify systematic error and produce upper and lower limits of agreement between video and device derived methods of step detection (6).

Reliability

Using the first and second trials of each locomotor condition, test-retest reliability was assessed by calculating the CV and 90% CI for IL and MAG from device A. Additionally, using the first trial from each locomotor condition, inter-device reliability was assessed by calculating CV and 90% CI for IL and MAG from devices A and B. In sports literatures, CV has been categorized as good (< 5%), moderate (5-10%), or poor (> 10%) for reliability investigations (3,12,15,23,37).

Results

Thirty participants completed a total of 180 trials, 60 trials for each locomotor condition. Means and standard deviations for each metric and trial are detailed in Table 3.2

Table 3.2 Means and 90% CI for IL, MAG, and Step Counts for Each Trial from Device A, and IL and MAG of First Trials from Device B

	Device B Trial 1 Mean	(90% CI)	Device A Trial 1 Mean	(90% CI)	Device A Trial 2 Mean	(90% CI)
IL						
Walk	77.2 ± 12.1	73.5 - 80.9	77.0 ± 12.6	73.1 - 80.9	76.9 ± 11.8	73.2 - 80.5
Run	91.4 ± 9.6	88.5 - 94.4	91.1 ± 9.4	88.2 - 94.0	90.0 ± 10.7	86.7 - 93.3
Sprint	53.7 ± 4.9	52.2 - 55.3	53.9 ± 5.2	52.3 - 55.5	53.2 ± 3.6	52.1 - 54.3
MAG						
Walk	44.8 ± 3.1	43.9 - 45.8	44.4 ± 3.4	43.3 - 45.5	45.2 ± 2.3	44.5 - 45.9
Run	67.9 ± 9.3	65.1 - 70.8	67.2 ± 9.5	64.3 - 70.2	67.5 ± 11.4	64.0 - 71.1
Sprint	60.7 ± 8.5	58.0 - 63.3	60.4 ± 8.3	57.8 - 62.9	61.1 ± 10.4	57.9 - 64.3
Video steps						
Walk	-	-	31.5 ± 1.4	31.1 - 31.9	31.4 ± 1.3	31.0 - 31.8
Run	-	-	25.4 ± 2.5	24.6 - 26.1	25.2 ± 2.6	24.4 - 26.0
Sprint	-	-	16.8 ± 1.0	16.5 - 17.1	16.7 ± 1	16.4 - 17.0
Bioharness™ steps						
Walk	-	-	31.2 ± 2.5	30.5 - 32.0	31.1 ± 1.7	30.6 - 31.6
Run	-	-	26.0 ± 2.5	25.3 - 26.8	25.8 ± 2.7	25.0 - 26.7
Sprint	-	-	17.9 ± 1.3	16.5 - 18.3	17.4 ± 1.3	17.0 - 17.8

IL = Impulse Load; MAG = Magnitude g; CI = Confidence interval

Validity

Bioharness^{TM} demonstrated a PPV of 96.98-99.41 % and an agreement of 93.08-96.29 % in detecting steps during all conditions. The results of each locomotor are detailed in Table 3.3. Additionally, low systematic error was identifiable using the Bland-Altman plot of Bioharness^{TM} steps counts for all trials as illustrated in Figure 3.3.

Table 3.3 The Validity of Bioharness^{TM} in Detecting Steps

	Video	Device A	Percent	PPV	Agreement
Walk	1887	1870	-0.9%	96.98%	94.97%
Run	1516	1556	2.64%	99.41%	96.29%
Sprint	1006	1058	5.17%	98.91%	93.08%

PPV = positive predictive value

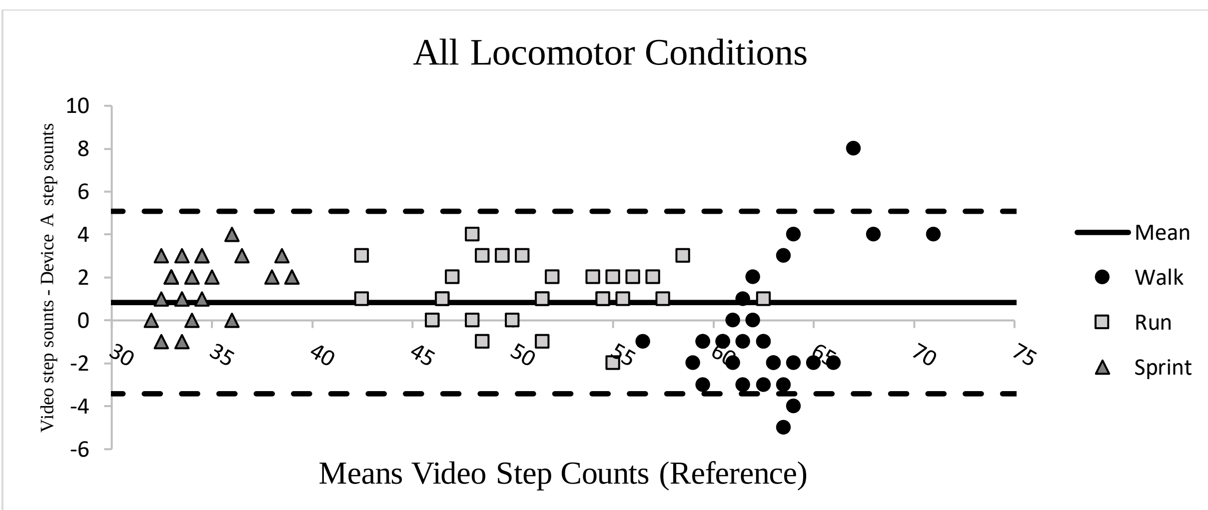

Figure 3.3 Bland-Altman Plot Demonstrating the Difference between the Bioharness^{TM} and Visual Step Counts

*The number of steps taken changes as a result of changes in each locomotor condition velocity.

*The solid line is the mean, while the dashed lines represent the repeatability coefficient (± 1.96 SD).

Reliability

Bioharness™ reliability quantified the external load during all courses. Both metrics (IL and MAG) demonstrated good reliability between repeated trials and between devices as the CV were below < 5% for all conditions. The results of both metrics during all courses are detailed in Table 3.4 (IL) and Table 3.5 (MAG).

Table 3.4 The Test-Retest and Inter-Device Reliability of the Accelerometry Derived Metrics IL

IL	Test-retest CV (%)	CV 90% CI	Inter-device CV (%)	CV 90% CI
Walk	4.99%	3.76 - 6.22%	2.67%	1.98 - 3.37%
Run	3.22%	2.45 - 3.99%	1.13%	0.81 - 1.43%
Sprint	4.54%	3.46 - 5.62%	1.82%	1.30 - 2.34%
All conditions	4.25%	3.65 - 4.85%	1.87%	1.55 - 2.19%

IL = Impulse Load; CV = Coefficient of variation; CI = Confidence interval

All conditions = all courses combined (walking, running, and sprinting).

Table 3.5 The Test-Retest and Inter-Device Reliability of the Accelerometry Derived Metric MAG

MAG	Test-retest CV (%)	CV 90% CI	Inter-device CV (%)	CV 90% CI
Walk	3.46%	2.59 - 4.33%	1.69%	1.09 - 2.28%
Run	3.12%	2.25 - 3.99%	1.61%	1.25 - 1.98%
Sprint	3.49%	2.54 - 4.44%	2.10%	1.61 - 2.59%
All conditions	3.36%	2.86 - 3.86%	1.80%	1.52 - 2.07%

MAG = Magnitude g; CV = Coefficient of variation; CI = Confidence interval

All conditions = all courses combined (walking, running, and sprinting).

Discussion

The purpose of this study was to assess the validity and reliability of accelerometers in identifying steps and quantify training load during different locomotor conditions. A primary finding is that the Bioharness^{TM} is a valid instrument used to detect steps when movement is completed at a range of speeds. Additionally, Bioharness^{TM} are highly reliable to assess external load when walking, running, and sprinting are performed. This may also suggest that accelerometry derived measures can quantify training loads associated with sport-related training and competition.

While Bioharness^{TM} precisely detected steps during all conditions, steps were best detected during running trials (PVV = 99.41%, agreement = 96.29%). It appears the Bioharness^{TM} may marginally underestimate total walking steps and slightly overestimate running and sprint steps (Table 3.3). During walking trials, the Bioharness^{TM} occasionally did not identify steps upon initiating and ending movement. Specifically for the walking condition, acceleration at the beginning and end of the trials may not be of sufficient magnitude to be identified as a step. In contrast, during high-velocity trials, particularly during sprinting, the Bioharness^{TM} recorded false positive steps, potentially due to trunk movement at the beginning and end of each trial. This appears consistent with previous investigations which found that inaccuracies when detecting steps occur most frequently at the beginning and end of locomotion (13,18). Nevertheless, Bland-Altman plots revealed low systematic error during all conditions evidenced by the similarity in number of steps detected by the Bioharness^{TM} and steps counted manually from video (Figure 3.3).

Despite the difficulties of repeating a locomotor effort accurately, this study used a metronome to gait the speed of participants to reduce intra- and inter-subject differences between trials. This investigation revealed promising test-retest (IL CV = 3.22-4.99 %; MAG CV = 3.12-3.49%) and inter-device (IL CV = 1.13-2.67 %; MAG CV = 1.61-2.10%) reliability during all conditions. There appears to be some agreement in the literature that step detection and activity classification accuracy using accelerometers improves with a prolonged activity (13,18,22). However, the Bioharness^{TM} was precise and reliable when detecting steps and quantifying external load from a short bout of exercise.

Several factors may confound accelerometry derived measures while quantifying external load, including movement artifact of the device, running economy, and stride properties (4,5,30). In the current study, the two Bioharness^{TM} devices were placed as close to the manufacture's recommended position, but using two devices simultaneously did not permit placement that followed manufacturer guidelines exactly. In addition to device placement, variation in participant anthropometrics and gait may also influence external load and steps detected during each trial. Despite potential confounding factors, test-retest and inter-device reliability for IL (test-retest CV = 3.22-4.99 %; inter-device CV = 1.13-2.67 %) and MAG (test-retest CV = 3.12-3.49%; inter-device CV = 1.61-2.10%) were good (< 5%).

Although this study has successfully demonstrated that the Bioharness^{TM} is a valid and reliable instrument for step detection and evaluation of external load, this study has several limitations. First, while the Bioharness^{TM} devices were placed closely together, they could not be placed in the same position. This may cause movement to be measured differently between devices, albeit the differences are likely trivial. Second, while walking, running and sprinting were performed, other actions such as change of direction, jumping and impacts, were not included. Therefore, caution should be used when applying the current results to individual and team sports. Third, while efforts were made to ensure that participants performed repeat trials in the same manner each time, locomotor variability in speed, stopping location, stride length and other variables are inevitable. While the Bioharness^{TM} demonstrated good reliability, these limitations make it difficult to isolate the source of variability. Future research should investigate whether accelerometry derived measures can accurately detect events (e.g., steps, jumps, kicks, and contact) and quantify external load during various sport-related movements including acceleration, deceleration, and directional change.

Practical Applications

The present research aimed to examine the validity and reliability of accelerometers when identifying events and assessing external load during sport-related movements. PVV and agreement analysis, as well Bland-Altman plots, revealed that steps could be accurately identified using accelerometers during walking, running, and sprinting. Additionally, good inter-device and test-retest reliability was found for accelerometry derived measures of external load when locomoting at a range of speeds. The findings of this study may suggest that accelerometry derived measures can quantify external loads associated with sports training and competition. However, additional research is needed to investigate the use of this technology to detect sporting events (e.g., contact, jumps, sprinting, kicks) and quantify external loads associated with various sports-related movements (e.g., directional change, shuffling, and backward running), which are considered essential characteristics of match play in many sports.

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Chapter 4. STUDY II: Accelerometry and Global Navigation Satellite System Derived Load

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Abstract

This study aimed to assess and compare accelerometry and Global Navigation Satellite System (GNSS) ability to predict known distance completed using different movement constraints. Thirty physically active college students (height: 176.8 ± 6.1cm, weight: 82.3 ± 12.8kg) participated. Acceleration data was collected via a tri-axial accelerometer sampling at 100Hz. Accelerometry derived metrics included the sum of the absolute values of acceleration (SUM), the square root of the sum of squared accelerations (MAG), Player Load (PL) and Impulse Load (IL). Distance (GNSSD) was measured from positional data collected using a triple GNSS unit sampling at 10Hz. Each subject walked two different known distances (DIST) around a 2m diameter circle (small circle), and a different distance around an 8m diameter circle (large circle). Each distance completed around the small circle by one subject, was completed around the large circle by a different subject. The same 30 distances were completed around each circle and ranged from 12.57 to 376.99m. Separate simple linear regression models were created to assess the ability of each independent variable to predict DIST. All regression models performed well (R^2 = 0.922-0.999; RMSE = 0.047-0.242). GNSSD (small circle, R^2 = 0.997, RMSE = 0.047; large circle, R^2 = 0.999, RMSE = 0.027), and the accelerometry derived metric MAG (small circle, R^2 = 0.983, RMSE = 0.112; large circle, R^2 = 0.995, RMSE = 0.064) performed best among all models. This research illustrates both GNSS and accelerometry may be used to indicate total distance completed while walking.

Key Words: wearable technologies, accelerometers, GNSS, GPS, monitoring, training load

Introduction

Wearable technologies have become popular tools used in team and individual sports. Tracking player activity using these microtechnologies is an essential component of load monitoring (2). Accelerometers and Global Navigation Satellite System (GNSS) devices have become some of the dominant wearable technologies used to monitor training load in sport (11). These technologies can be integrated or used separately to provide an indicator of the external work performed by athletes; consequently, practitioners may be better able to manage fatigue and direct adaptation. GNSS primarily measures horizontal displacement, while accelerometers primarily measure acceleration in single or multiple axes. The role of accelerometers and GNSS in load monitoring has received increased attention across a number of sports in recent years (10,12). Despite this, the relationship between both technologies to quantify the same load is not well established.

Accelerometers are a responsive motion sensor that measures the magnitude of acceleration in one or more axes. Accelerometers are valid and reliable instruments to measure training load in the field and laboratory environments (19–21). There is a growing body of literature that recognizes the ability of accelerometers to quantify the external demand of team and individual sports. For instance, the within and between device reliability of accelerometers has been established across a variety of movement demands in both laboratory and on-field conditions in Australian football (6). Gentles et al. (2018) found strong to nearly perfect correlations between accelerometry derived training load and session rating of perceived exertion (sRPE) (r= 0.84; $p < 0.001$) and total distance measured using GPS ($r = 0.95$; $p < 0.001$) among NCAA women's soccer players (15). Accelerometers have also been used to illustrate the differences in the activity profile between single and double match play in tennis (16). In rugby, accelerometers outperformed GPS in quantifying positional (backs vs. forward) and halves (1st vs. 2nd) differences in player maximum mean movement (17). Moreover, accelerometry has also been shown to be a valid assessment of a test designed to simulate basketball play, suggesting that accelerometers can be used to quantify the external demand of basketball (28).

Many accelerometry derived metrics have been used in the literature to quantify training load, including Body Load (1), Player Load (6), Force Load (8), Dynamic Stress Load (14), and Impulse Load (15). Although Player Load is the most commonly reported measure in the literature (30), its potential to monitor training load has been questioned (7). Player Load is the sum of the square root of the sum of absolute differences of acceleration divided by the device sampling frequency (7). Therefore, Player Load does not represent the sum of all accelerations, and of the available accelerometry derived measures, may not best represent training load (7). Additionally, training load could be misrepresented due to the inclusion of non-locomotor activities in Player Load (8). Interestingly, different equations and descriptions for Player Load have also been reported in the literature (6,17,24). Player Load has also been described as Body Load (1) and Acceleration Load (26). To our knowledge, no study has compared different accelerometry derived measures when assessing training load, indicating a need for further investigation of accelerometry based measures of training load.

GNSS is an umbrella term that includes several different satellite networks including Global Positioning System (GPS), Global Navigation Satellite System (GLONASS), Galileo, and BeiDou. In sport, GNSS networks are used to provide information about a player position, velocity, and movement patterns on the field. Total distance and distance in speed zones are common variables used to monitor training loads. GNSS networks such as GPS have been shown to be valid indicators of distances of 40m completed during different movement patterns, but may not be a valid measure of shorter distances (less than 20m) completed during high speed running, sprinting, and change of direction (18). Higher sampling frequencies (5-10Hz) have been shown to improve the accuracy of GPS (13,18), although some evidence suggests that increasing sampling frequency to 15 Hz does not improve accuracy when assessing distance completed during unstructured movements (31). Assessing player position using GNSS networks may be influenced dramatically by the number and separation of satellites that are connected to the receiver. GNSS enables receivers to acquire signals from multiple satellite networks (e.g., GPS, GLONASS, Galileo, and BeiDou), increasing the number of available satellites. Combined satellite systems improve satellite geometry and resulting precision (29). Dilution of Precision (DOP) is a description of satellite geometry. DOP is composed of two elements: horizontal dilution of precision (HDOP) and vertical dilution of precision (VDOP) (for more detail about DOP, see (29)). HDOP is one indicator of GNSS accuracy and is influenced by the separation of the satellites. HDOP values range from 0 to 50, with a value of less than 1 considered ideal distribution of satellites. HDOP is low and precision is excellent when substantial distance exists between satellites, while HDOP is high and precision is poor when satellites are in close proximity. Additionally, indoor fields, stadiums with high walls or roofs, and cloudy weather are factors that can reduce the quality of GNSS data (12).

Recently, receivers capable of acquiring signals from multiple GNSS networks simultaneously (e.g., GPS, GLONASS, Galileo, and BeiDou), have enhanced the availability and signal strength of surrounding satellites (22). Beato et al. (2018) suggested that using multiple GNSS networks could explain the smaller bias (2.3 ± 1.1%) when measuring total distance during a sport-specific movement protocol (5), compared to the author's previous research that used only GPS to detect total distance in a shuttle run over 5-20m (2.53 ± 6.03%) (4). Future research should compare the quality of data from single and multiple satellite systems in sport.

To date, several investigations have assessed the relationship between accelerometry and GNSS derived measures. A study by Polglaze et al. (2015) found large to very large correlations between Player Load and total distance accumulated during men's hockey practice ($r = 0.742$; $p < 0.00001$) and competition ($r = 0.868$; $p < 0.00001$) (23). Additionally, a strong correlation was found between Player Load and total distance completed in men's soccer training ($r = 0.70$; $p < 0.01$) (9) and a nearly perfect correlation ($r = 0.95$; $p < 0.001$) was found between Impulse Load and total distance in women's soccer matches (15). However, to our knowledge no study has investigated the relationship between different accelerometry based metrics and GNSS with a known distance. Therefore, this study aimed to assess and compare the ability of four different accelerometry derived metrics and a triple GNSS to predict known distance completed under different movement constraints.

Methods

Experimental Approach for the Problem

A correlational design was used to assess the relationship between known distance (DIST) and total distance measured via GNSS, and 4 accelerometry derived metrics. DIST was completed under two different movement constraints. Two courses, a small circle (SC) and a large circle (LC), were designed on a grass field. Table 4.1 details the dimensions of each circle, and Figure 4.1 Design of Small and Large Circles illustrates the course design. A measuring tape was used to measure the diameter of each circle, which was subsequently used to calculate circumference. Both circles were marked by flags to guide the walking path for subjects. Flags were approximately 5cm in height to minimize interference with walking. Circles were used to limit the influence of initiating movement and braking associated with changing direction. The total distance was the only variable evaluated through the investigation to assess training loads.

Table 4.1 Dimensions of Small and Large Circle.

	Small circle	**Large circle**
Diameter	2m	8m
Circumference	6.28m	25.13m
Distance	2x laps = 12.56m	Half-lap = 12.56m

Figure 4.1 Design of Small and Large Circles

Subjects

Thirty participants (height 176.8 ± 6.1 cm, weight 82.3 ± 12.8 kg) volunteered to participate in this study. Subjects participated in some form of physical activity at least three times a week. This study was approved by the university's Institutional Review Board, and participants provided written consent for their involvement and video recording.

Procedures

Prior to beginning each course, subjects were informed of the number of laps they were to complete around each course; participants also performed a familiarization trial prior to completing their trials. Following familiarization, each subject walked two different known distances (DIST), one distance around the SC and a different distance around the LC. Each distance completed around the SC by one subject was completed around the LC by a different participant. The same thirty distances were completed around each circle and ranged from 12.57 to 376.99 m. Table 4.2 details the number of laps and total distance each participant completed. Subjects were directed to walk at their normal speed and keep the flags between their feet during the walk to ensure each course was completed accurately. Laps were counted loudly by a research assistant during the trials. Each subject also wore a triaxial accelerometer and triple GNSS sensor.

Table 4.2 Number of Laps and Distance Traveled around Small and Large Circle.

Subjects	Large circle	Known Distance/m	Small circle	Known Distance/m
1	0.5	12.57	60	376.99
2	1	25.13	58	364.43
3	1.5	37.70	56	351.86
4	2	50.27	54	339.29
5	2.5	62.83	52	326.73
6	3	75.40	50	314.16
7	3.5	87.96	48	301.59
8	4	100.53	46	289.03
9	4.5	113.10	44	276.46
10	5	125.66	42	263.89
11	5.5	138.23	40	251.33
12	6	150.80	38	238.76
13	6.5	163.36	36	226.19
14	7	175.93	34	213.63
15	7.5	188.50	32	201.06
16	8	201.06	30	188.50
17	8.5	213.63	28	175.93
18	9	226.19	26	163.36
19	9.5	238.76	24	150.80
20	10	251.33	22	138.23
21	10.5	263.89	20	125.66
22	11	276.46	18	113.10
23	11.5	289.03	16	100.53
24	12	301.59	14	87.96
25	12.5	314.16	12	75.40
26	13	326.73	10	62.83
27	13.5	339.29	8	50.27
28	14	351.86	6	37.70
29	14.5	364.42	4	25.13
30	15	376.99	2	12.57

Instrumentation

Acceleration data was collected via a tri-axial accelerometer sampling at 100 Hz (Zephyr[TM] BioHarness v3, Zephyr Technology Corp., Annapolis, MD, USA*).* The accelerometer was placed at the level of the xiphoid process, along the midsternal line. Four accelerometry derived metrics were used in this study; the formula for each accelerometry based metric is described in Table 4.3. To expedite data analysis, the beginning and end of each trial were marked by the subject tapping on the accelerometer four times.

Table 4.3 Formula for Each Accelerometry Based Metric

Metric	Definition and formula*
SUM	$SUM = \sum_{s=1}^{n} \sqrt{x_s^2} + \sqrt{y_s^2} + \sqrt{z_s^2}$
MAG	$MAG = \sum_{s=1}^{n} \sqrt{x_s^2 + y_s^2 + z_s^2}$
Impulse Load**	$IL = \sum_{s=1}^{n} \frac{\sqrt{x_s^2 + y_s^2 + z_s^2}}{9.8067}$
Player Load	$PL = \sum_{s=1}^{n} \frac{\sqrt{(x_{s=i+1} - x_{s=i})^2 + (y_{s=i+1} - y_{s=i})^2 + (z_{s=i+1} - z_{s=i})^2}}{100}$

* In the formulas above, x = forward and backward acceleration, y = lateral acceleration and z = vertical acceleration.

** IL is propriety by the manufacture and is only associated with locomotor events that are detected by Zephyr (e.g., walking, running, bounding, jumping).

A triple GNSS sensor sampling at 10 Hz and acquiring signals from GPS, GLONASS and Galileo networks (Titan Sensors 2, Houston, TX, USA), was used to measure distance covered by each participant (GNSSD). All trials were performed on an outside field, clear of large buildings, and with a clear sky to enhance satellite acquisitions. The number of satellites connected to the receiver during the trials ranged between 19-26. A previous study that used GNSS reported the horizontal dilution of precision (HDOP) 0.4 ± 0 while the satellites connected held between 18-20 (5). The GNSS unit was activated 10-15 minutes prior to data collection and fixed to the back of the subjects at the base of the cervical spine between scapulae. Video was recorded (iPhone 6; 1080p at 30 fps, Cupertino, CA, USA) and synced with GNSS data to verify the beginning and end of each trial.

Statistical Analyses

GNSS data and recorded video were uploaded and analyzed using Titan Sensors software (Titan Sync 3.0.0, 2019 and Titan Video 3.7.0, 2019). Accelerometry data were downloaded to OmniSense™ Analysis (version 4.1.4; Zephyr Technology Corporation, Annapolis, MD, USA), then exported to Microsoft Excel 2019 (Microsoft Corporation, Redmond, WA, USA) for analysis. Data were log transformed using the natural logarithms (LN) of DIST, SUM, MAG, PL, IL, and GNSSD, to reduce the nonuniformity of error (27). Ten simple linear regression models were created to assess the ability of each independent variable (SUM, MAG, PL, IL, and GNSSD) to predict DIST completed during SC and LC. Residual and Q-Q plots were used to ensure the assumptions of homoscedasticity and normality were not violated. All data were analyzed using the statistical software JASP (JASP, Version 0.12.2, Amsterdam, Netherlands).

Results

All linear regression models performed well for both movement constraints (R^2 = 0.922-0.999; Root-mean-square error (RMSE) = 0.047-0.242, p<0.001). The results of all linear regression models are detailed in Table 4.4 and each model is illustrated in Figure 4.2 - Figure 4.6. GNSSD (SC, R^2 = 0.997, RMSE = 0.047, p<0.001; LC, R^2 = 0.999, RMSE = 0.027, p<0.001) and the accelerometry derived metric MAG (SC, R^2 = 0.983, RMSE = 0.112, p<0.001; LC, R^2 = 0.995, RMSE = 0.064, p<0.001) performed best among all models.

Table 4.4 Summary of Linear Regression Models

	Small Circle				**Large Circle**			
Independent Variable	***R***	***R²***	**RMSE**	***p***	***R***	***R²***	**RMSE**	***p***
GNSSD	0.999	0.997	0.047	<.001	1.000	0.999	0.027	<.001
Impulse Load	0.960	0.922	0.242	<.001	0.976	0.952	0.189	<.001
MAG	0.992	0.983	0.112	<.001	0.997	0.995	0.064	<.001
SUM	0.992	0.984	0.109	<.001	0.992	0.983	0.112	<.001
Player Load	0.994	0.987	0.098	<.001	0987	0.973	0.141	<.001

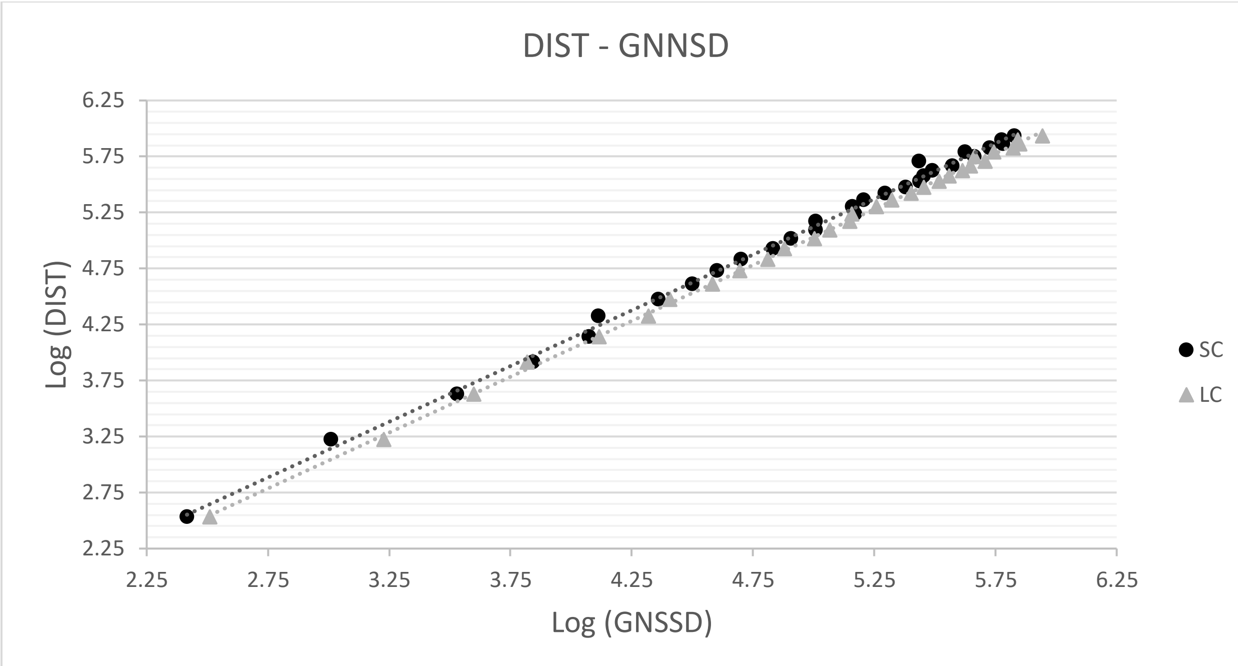

Figure 4.2 The Relationship between DIST and GNSSD around SC and LC

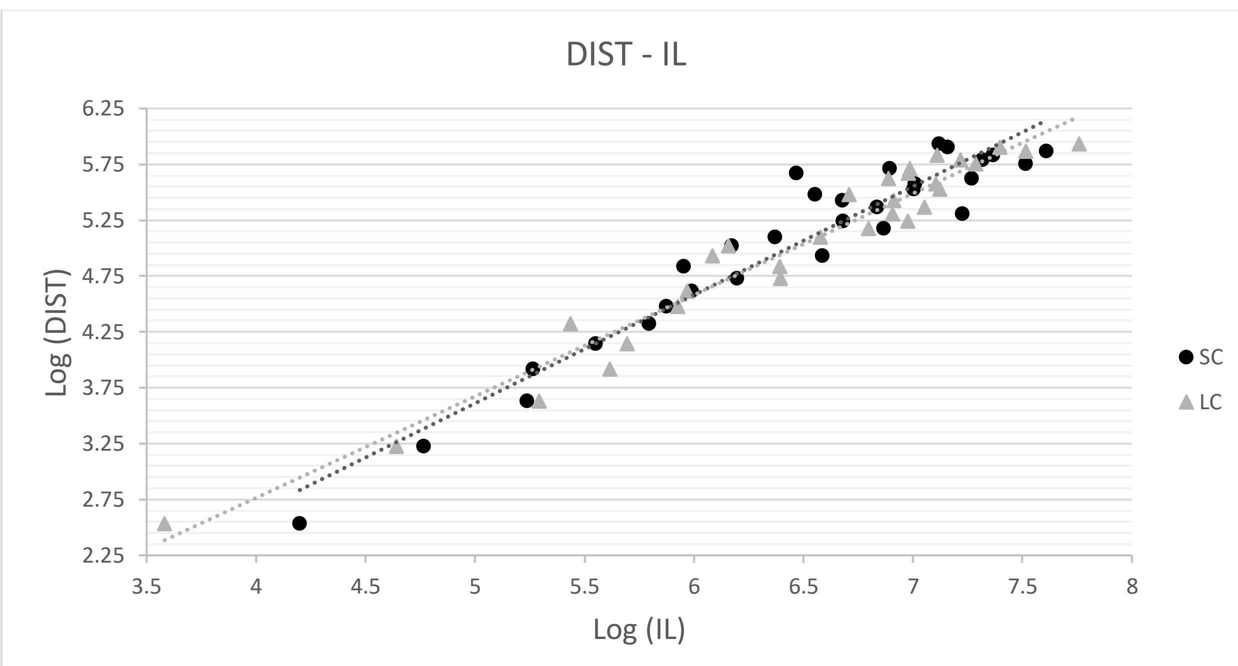

Figure 4.3 The Relationship between DIST and IL around SC and LC

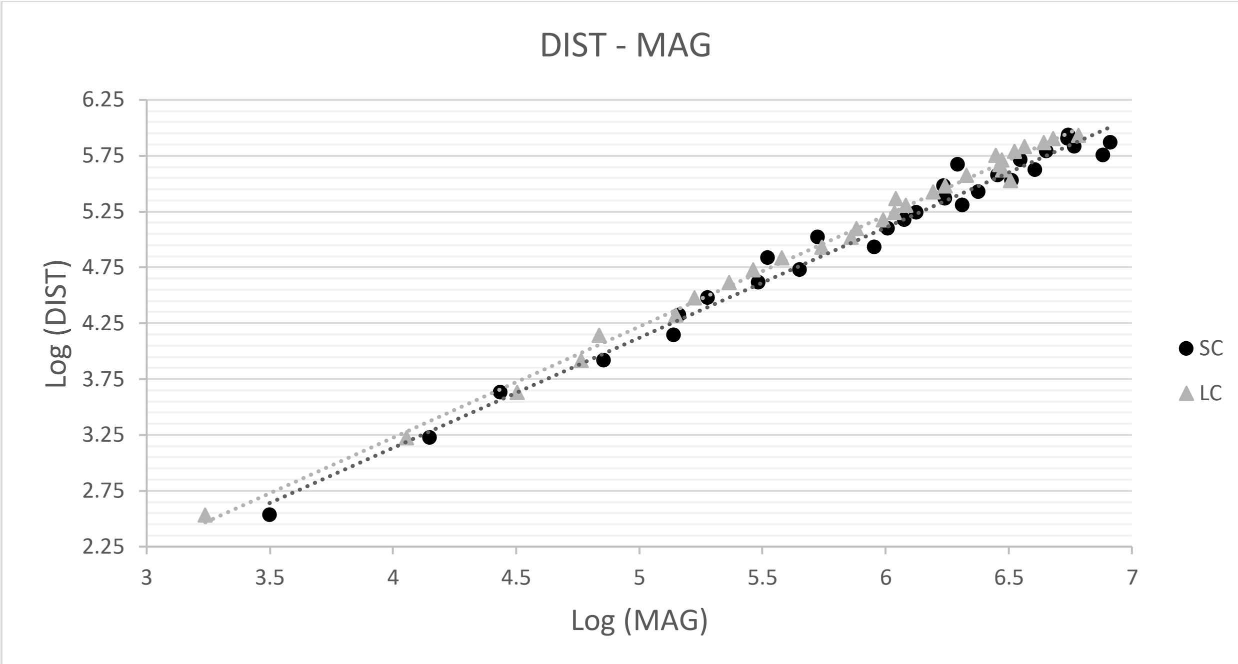

Figure 4.4 The Relationship between DIST and MAG around SC and LC

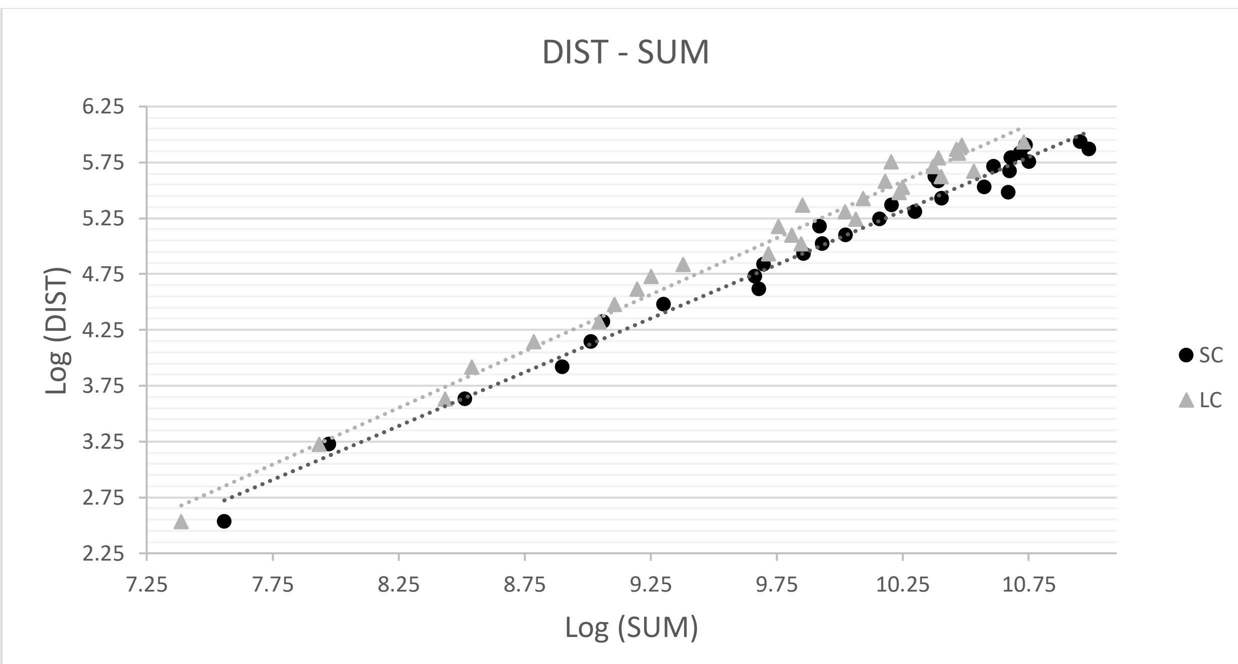

Figure 4.5 The Relationship between DIST and SUM around SC and LC

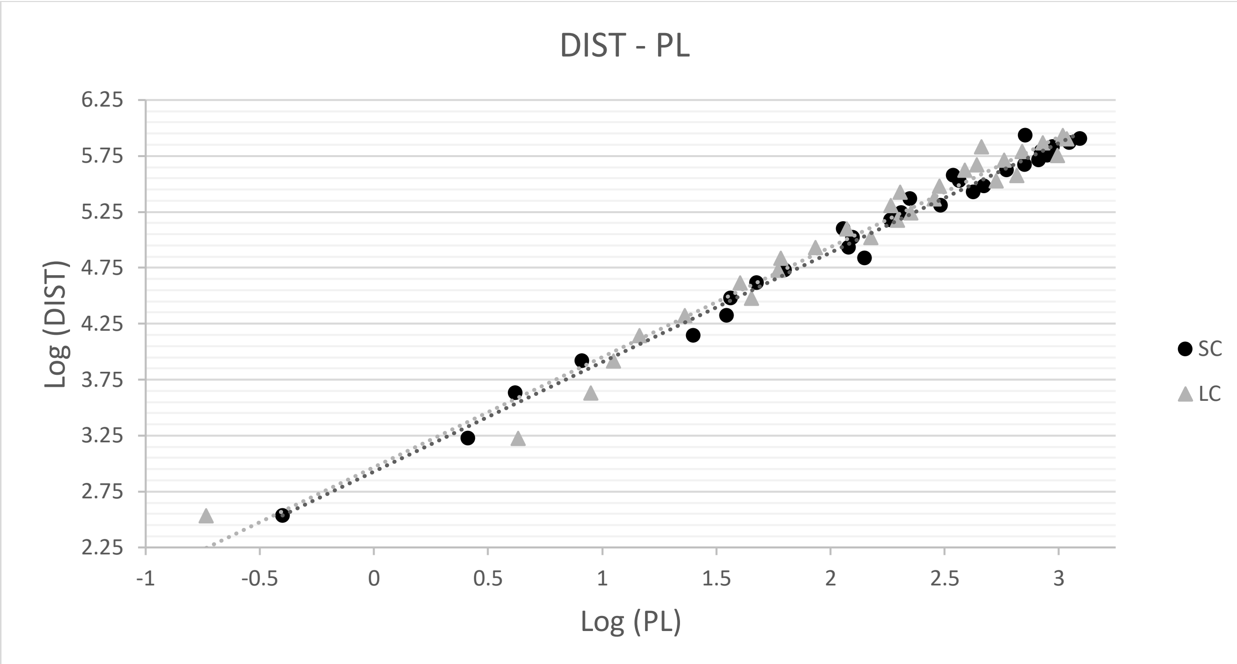

Figure 4.6 The Relationship between DIST and PL around SC and LC

Discussion

The purpose of this study was to assess and compare the ability of four different accelerometry derived metrics (IL, MAG, SUM, PL) and GNSS to predict a known distance completed using two movement constraints. A primary finding is that both GNSS and accelerometry derived measures are valid indicators of total distance when walking is performed around a SC and LC. This may also suggest that both GNSS and accelerometry are similarly capable of quantifying distance associated with sport-related training and competition under the current experimental conditions.

While all accelerometer derived measures performed well, MAG (SC, $R^2 = 0.983$, RMSE $= 0.112$, $p<0.001$; LC, $R^2 = 0.995$, RMSE $= 0.064$, $p<0.001$) and SUM (SC, $R^2 = 0.984$, RMSE $= 0.109$, $p<0.001$; LC, $R^2 = 0.983$, RMSE $= 0.112$, $p<0.001$) performed best among all accelerometry models. MAG and SUM include locomotor and non-locomotor activities. This outcome is contrary to Buchheit and Simpson (2017) who proposed that using accelerometer-derived measures that exclude non-locomotor activities may be more useful (8). However, this discrepancy could be attributed to the fact that little to no non-locomotor activity was included in this study, where sport includes a substantial quantity of both locomotive and non-locomotive activity. Our findings agree with previous suggestions that different accelerometry based metrics will not equally quantify training loads in sport-related events (7). Further research is needed to determine which accelerometry derived metrics best quantifies training load in sport. It is certainly possible that the simultaneous use of multiple accelerometry based load assessments is advantageous.

Unlike GNSS, accelerometers can be influenced by between-subjects' variability in loading patterns (e.g., stride characteristics) (3). However, in this study and others (9,15,23), strong relationships have been found between accelerometry derived loads and total distance, despite different subjects completing various distances. Much of the criticism that PL has attracted relates to calculating workloads by summing the rate of change in accelerations instead of the absolute value of accelerations (7). However, in this study, although PL did not perform best among the accelerometry derived measure, its potential to detect training load was encouraging (SC, $R^2= 0.987$, RMSE$= 0.098$, $p<0.001$; LC, $R^2= 0.973$, RMSE$= 0.141$, $p<0.001$).

Nonetheless, it may be important to address how PL would perform if repeat changes of direction were included, given that PL only increases with changes in acceleration. In accordance with the present results, a previous study demonstrated that the accelerometry derived metric average force (the product of the participant's body mass and MAG), was a better indicator of running demands compared to PL (28). Future studies should investigate what, if any, advantages MAG or other accelerometry based measures may provide compared to PL.

Previous research has indicated that, independent of movement velocity (i.e., walk, jog, run, sprint), rapid directional change degrades GNSS accuracy. For instance, GNSS may underestimate distance during shuttle trials (-2.16±3.84%) and overestimate distance during exercise completed on curvilinear tracks (2.99±2.96%) (25). However, the development of multiple GNSS technology may explain the high level of accuracy found in this study that included two different curvilinear conditions (SC, R^2= 0.997, RMSE= 0.047, p<0.001; LC, R^2= 0.999, RMSE= 0.027, p<0.001). Despite these promising results, questions remain about multiple GNSS system accuracy when measuring distance completed in sport-related movements, where many changes of direction are required, and movement velocity is often higher than that used in this study.

This investigation demonstrates that multiple GNSS systems and several accelerometry derived metrics can indicate total distance completed while walking. However, a host of questions remain regarding the potential advantages associated with these technologies to quantify training loads and detect events (e.g., contact, jumps, sprinting) in sport. In this study, total distance was the only load accounted for, and only locomotor movements were included. Of course, in sport different factors can influence training loads (e.g., acceleration, deceleration, jumping), and locomotor and non-locomotor movements will be performed. More broadly, further investigation is needed to assess the ability of GNSS and accelerometry derived metrics to measure training loads that include different movements and events such as running, sprinting, change of direction, jumping, collision, and kicking.

Although this study demonstrated that GNSS and accelerometry derived measures are valid indicators of total distance, three important limitations to this study should be considered. First, while walking was performed around circles to limit the influence of initiating movement and braking associated with changing direction and total distance was the only variable assessed, caution should be used when applying the current results to other activities. Second, subjects were asked to walk at their natural pace, and no method has been used to standardize the walking speed. In which differences in velocity rate between participants might induce some variation. Third, while investigators were precise during course set-up and participants followed instructions closely, actual distances completed by participants were likely different than planned; albeit these difference were probably very small. Future research should investigate whether training load quantification is enhanced using a combination of GNSS and accelerometry, or whether a single sensor, GNSS or accelerometer, is adequate to quantify training loads in sports that often include changes of direction, jumping, contact, and straight-line movement.

Practical Applications

This is the first study to investigate the ability of four different accelerometry derived metrics and a triple GNSS to predict known distance. Linear regression analysis revealed that GNSSD, IL, MAG, SUM, and PL could indicate total distance completed while walking. The findings will be of interest to researchers and sports scientists to investigate whether GNSS and accelerometry are equally capable of quantifying training loads associated with sport-related training and competition. More research using controlled trials are needed to compare these technologies to detect sports events (e.g., contact, jumps, sprinting) and quantify training loads associated with acceleration, deceleration, and directional change, which are considered crucial characteristics of match play in some sports. Another possible area of future research would be to investigate whether training load quantification is enhanced using a combination of GNSS and accelerometry, or whether a single sensor, GNSS or accelerometer is adequate to quantify training loads in sports, considering not all teams can afford the high-cost of both technologies.

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Chapter 5. Summary and Future Research

The primary objective of this dissertation was to investigate the validity and reliability of accelerometers (ACCs) to identify stepping events and quantify training load. The second aim was to assess the relationship between accelerometry and Global Navigation Satellite Systems (GNSS) derived measures in quantifying training load. Two studies were conducted to fulfill this purpose.

Based on our findings from Study I, steps were accurately identified using accelerometry data when straight-line walking, running, and sprinting were performed on an outside field. This research confirms previous findings and indicates ACC can be used to count steps during sport-related activities. Additionally, inter-device and test-retest reliability when quantifying training load during running-based activity was high. These findings add to a growing body of literature focused on the use of ACC in load monitoring. The results of Study I suggest that ACC may be a useful tool distinguish between sport-related events and quantify external load.

Study II assessed the ability of several accelerometry derived metrics and distance measured with a triple GNSS sensor, to predict a known distance. Separate simple linear regression analyses revealed that all accelerometry and GNSS derived measures were predictive of total distance completed while walking, indicating that both GNSS and accelerometry are similarly capable of quantifying distance completed while walking. Study II provides a much-needed analysis of accelerometry and GNSS to quantify the same external load.

Future research should include the following:

- The ability of ACC to detect steps during other sport-related activities, including accelerating, deceleration, and directional change.

- The ability of ACC to identify other events such as kicks, throws, collisions, and jumps while performing sport-related activities.
- The capability of ACC to quantify training loads associated with acceleration, deceleration, and directional change.
- Investigate whether a specific accelerometry derived metric possess advantages over others when quantifying training load in sport.
- The relationship between ACC and GNSS to quantify training loads associated with sports-related events (e.g., contact, jumps, sprinting) and acceleration, deceleration, and directional change.
- Examine whether training load quantification is adequately assessed using a single sensor or using a combination of GNSS and accelerometry enhances the assessment of training load in sports.

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