Benjamin Reksten Holme

Wearable microsensor technology to measure physical activity demands in handball

A reliability study of Inertial movement analysis and Player Load

Master thesis in Sport Sciences Department of Physical Performance Norwegian School of Sport Sciences, 2015

Abstract

Purpose: Wearable microsensor technology allows for measurements of physical activity in team sports. To use this technology with confidence, it is critical to determine its reliability. Therefore, the purpose of this study was to assess the reliability and sensitivity of a commercially available microsensor technology to measure physical activity demands in handball.

Methods: A total of twenty-two elite and sub-elite handball players (age, 22.6 ± 3.7 years; body mass, 84.0 ± 14.2 kg; height, 184.4 ± 12.0 cm; mean \pm SD) were included in the present study. The subjects were instrumented with two devices (Optimeye S5, Catapult Sports, Melbourne, Australia), and participated either in a laboratory assessment (n =10) or field assessment (n = 12). The laboratory assessment consisted of seven different handball specific movement tasks, whereas the field assessment was conducted in twelve handball-training sessions. Various variables were extracted from the manufacture's software (Catapult Sprint, Catapult Sports, Melbourne, Australia) including Inertial movement analysis (IMA) magnitude and counts, and tri-axial accelerometer data (Player Load). The reliability between devices and sensitivity was established using coefficient of variation (CV) and smallest worthwhile different (SWD).

Results: Laboratory assessment: IMA magnitude showed a good reliability (2.9%) in well-controlled movement tasks. The CV increased (4.4 to 8.2%) in more chaotic movement tasks. *Field assessment:* IMA counts showed a good reliability (CV 2.4%) when displayed as total counts. However, the CV increased when categorized in low (2.9%), medium (5.5%) and high (5.6%) intensity bands. Medium/high band (combined) showed a CV of 3.9%. The CV for low, medium/high and total counts was less than the SWD. Furthermore, it was observed a good reliability of Player Load (0.9%), which was less than the SWD.

Conclusion: The reliability of IMA counts was good, given that data were expressed as low, medium/high and total counts. It was observed a good reliability for Player Load. The CV of the aforementioned variables was well below the SWD, suggesting that Optimeye microsensors and its software are sensitive to detect "real and worthwhile" differences in handball activity.

Keywords: Team sport, accelerometer, gyroscope, measurement error

3

Contents

Ab	stra	ct	3
Co	nten	ts	4
Pre	eface	2	6
1.	Int	roduction	7
2.	The	eory	9
2.1	Ноч	w to measure physical activity in team sports?	
	2.1.1	Physical activity demands	
2	2.1.2	Methods to measure physical activity	9
2.2	Mic	crosensor technology	. 11
2	2.2.1	Accelerometers	
	2.2.2	Gyroscopes	
2	2.2.3	Magnetometers	. 12
23	The	e use of microsensor technology in team sports	12
	2.3.1	Workload variables	
	2.3.2	Event detection variables	
		iability of microsensor technology used in team sports	
	2.4.1	Design of reliability studies	
2	2.4.2	Review of the literature	. 10
2.5	Sun	nmary	. 17
		•	
3.	Me	thods	18
3.1	Stu	dy design	. 18
3.2	Mic	rosensor technology	. 18
	3.2.1	Optimeye S5	
	3.2.2	Inertial movement analysis	
3	3.2.3	Player Load	. 20
2 2	Lak	anatawy assassment	21
3.3	Lat 3.3.1	ooratory assessment Subjects	
-	3.3.2	Data collection	
	3.3.3	Data analysis	
		·	
3.4		d assessment	
	3.4.1 3.4.2	Subjects	
	8.4.2 8.4.3	Data collection	
5	л. . .	Dum unury 515	. 25
3.5	Sta	tistical analysis	. 24

4.	Results	25
4.1	Laboratory assessment	. 25
4.2	Field assessment	. 28
5.	Discussion	31
5.1	Reliability of IMA	. 31
-	.1.1 IMA magnitude and IMA direction	. 31
5	.1.2 IMA counts	. 32
5.2	Reliability of Player Load	. 33
	.2.1 Player Load	
5	.2.2 Formula variations	. 33
5.3	Usefulness of microsensors to measure activity in handball	21
-	.3.2 Generalization of the findings	
5.4	Limitations of the study	. 35
5.5	Future directions	. 35
5.6	Practical applications	. 35
6.	Conclusion	36
Ref	ferences	37
Lis	t of tables	45
Lis	t of figures	46
115	· · · · · · · · · · · · · · · · · · ·	10
Ab	breviations	47
Ap	pendix	48

Preface

I'm very grateful for the opportunity to complete my master thesis at the Norwegian School of Sport Sciences. It has been an exciting, but challenging year. I have received a lot of support and this has been of great value to me.

First of all, I would like to thank my main supervisor, Matt Spencer, for your outstanding support and confidence you have provided during this year. I would also like to thank my supervisor, Live Luteberget, for our useful discussions, and your good advices. You have both always been available for questions and the support from both of you have been highly appreciated.

I would like to thank my fellow students, Erik Wik and Bertine Fretheim Neverdal, for our useful discussions during this last year. To my good friend and fellow student, Even Bjoarvik, thank you for your support and friendship.

I would also like to thank the subjects in the study. Without you this master thesis's would not been possible.

To my girlfriend, Katharina Grindevoll Liljedahl, thank you all your care and support. I haven't always been there for you this year and I really appreciate all you have done.

Last but not least, I would like to thank my family for all your support this year and through my whole education. I really appreciate this.

Oslo, October 2015, Benjamin Reksten Holme

1. Introduction

Measuring the physical activity demands in training and games is today common practice in professional team sports (Aughey, 2011; Bradley et al., 2013; Povoas et al., 2012; Wisbey, Montgomery, Pyne, & Rattray, 2010). This can provide valuable information to coaches, sport scientists and medical staff. Game analysis can lead to a better understanding of the physical performance and game demands, which can help to improve the practice of training and the physical development of players (Cunniffe, Proctor, Baker, & Davies, 2009; Di Salvo et al., 2007; Michalsik, Madsen, & Aagaard, 2014). Furthermore, insight in the specific activity level can assist the weekly or day-by-day load management (Pyne, Spencer, & Mujika, 2014; Scott, Lockie, Knight, Clark, & Janse de Jonge, 2013). An improved periodization can optimize the performance in training and games, and may help the detection of injury, fatigue and overtraining (Cummins, Orr, O'Connor, & West, 2013).

In recent years, there has been an increased interest around the use of wearable microsensor technology, such as accelerometers, gyroscopes and magnetometers to measure the physical activity demands in team sports (Chambers, Gabbett, Cole, & Beard, 2015; Dellaserra, Gao, & Ransdell, 2014). This technology has been used by various team sports in training and games (Boyd, Ball, & Aughey, 2013; Cormack, Smith, Mooney, Young, & O'Brien, 2014; Montgomery, Pyne, & Minahan, 2010). By using specific software algorithms the technology can detect important activities and facets of the play (Gabbett, Jenkins, & Abernethy, 2010; Gastin, McLean, Spittle, & Breed, 2013; Polley, Cormack, Gabbett, & Polglaze, 2015). However, to confidently use this technology in the field is it critical to establish the reliability. Currently there is limited information about the reliability of such technology, as only a small quantity of research studies have been published to date.

The purpose of this study was therefore to assess the reliability of a commercial available microsensor technology to measure the physical activity demands in team sports such as handball. Furthermore, the sensitivity of such technology to detect "real and worthwhile" differences in handball activity was examined.

The present study has the following research question:

Is the Optimeye S5 (Catapult Sports, Melbourne, Australia) reliable and sensitive enough to measure the physical activity demands in elite handball based on Inertial movement analysis (IMA) and tri-axial accelerometer data (Player Load)?

2. Theory

2.1 How to measure physical activity in team sports?

The literature describes physical activity "as any bodily movement produced by skeletal muscles that results in energy expenditure" (Caspersen, Powell, & Christenson, 1985). This is a general definition that can be categorized in a variety of ways. In this context will physical activity be associated with the activity demands in team sports.

2.1.1 Physical activity demands

The activity (or movement) demands in team sports are highly complex (Gray & Jenkins, 2010; Karcher & Buchheit, 2014; Stolen, Chamari, Castagna, & Wisloff, 2005). Sports such as handball, basketball, football codes and rugby codes are very different in nature, however there is still a major resemblance in their general activity patterns. As such, the activity is intermittent and multidirectional (Ben Abdelkrim, El Fazaa, & El Ati, 2007; Faude, Koch, & Meyer, 2012; Michalsik, Aagaard, & Madsen, 2013). It consists of high-intensity running interspersed with periods of low intensity or recovery (Cunniffe et al., 2009; Di Salvo et al., 2007; Michalsik et al., 2014). In addition, the activity involves brief and explosive movement actions, as well as collisions between players, which are repeated frequently within confined spaces (Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004; Gabbett et al., 2010; Rampinini, Impellizzeri, Castagna, Coutts, & Wisloff, 2009). Therefore, is it very challenging to measure physical activity demands in team sports.

2.1.2 Methods to measure physical activity

In general, the physical activity demands in team sports can be measured externally or internally (Halson, 2014). As such, measures of external activity demands describe the physical stress ("stimuli") generated by the player (Impellizzeri, Rampinini, & Marcora, 2005). On the other hand, measures of internal activity demands describe the physiological and psychological stress ("response") experienced by the player based on a given external "stimuli" (Halson, 2014). These measures can compliment each other, as they measure different aspect of physical activity. Using a combination of such measures may therefore provide a better knowledge of the activity demands in team sports. With respect to the purpose, the study will focus only on methods that are used to measure external activity demands.

Traditionally, time-motion analysis has been a favoured method to measure the external activity demands in team sports. This method uses different systems (or technologies) such as notational video systems, semi-automatic camera systems, global positioning system (GPS) and local positioning system (LPS) to track player movements (Carling, Bloomfield, Nelsen, & Reilly, 2008). These systems have their well-described practical advantages and disadvantages as tools to measure activity in team sports (Barris & Button, 2008; Carling et al., 2008; Larsson, 2003).

Time-motion analysis are mostly known to measure displacement, or so-called "running based activities". As such, one of the most used activity measure has been distance or time spent within specific speed bands, with special attention on high-speed running (Bradley et al., 2009; Coutts, Quinn, Hocking, Castagna, & Rampinini, 2010; Mohr, Krustrup, & Bangsbo, 2003). In recent years, it has become more common to measure activities such as accelerations, decelerations and repeated sprint efforts (Varley & Aughey, 2013; Varley, Gabbett, & Aughey, 2014). Time-motion analysis systems have been established as reliable and valid to measure speed and distance in general (Coutts & Duffield, 2010; Di Salvo, Collins, McNeill, & Marco, 2006; Duffield, Reid, Baker, & Spratford, 2010; Frencken, Lemmink, & Delleman, 2010; Ogris et al., 2012). However, the aforementioned studies have reported that the reliability and validity for most of these systems decreases with faster and/or less linear activities, especially if performed within confined spaces. Moreover, time-motion analysis fails to measure important "non-running based activities" such as agility actions (e.g., changes of direction; CoD), jump efforts and player contact (e.g., collisions and tackles). These activities can be registered via notational frequency analysis (Mohr et al., 2003). However, this is timeconsuming, and more importantly, it cannot measure the magnitude and the direction of these activity events. The failure to precisely measure "non-running based activities" may result in an underestimation of the "true" physical activity demands in team sports, specifically in sports such as handball where these activities are performed frequently (Karcher & Buchheit, 2014). A wearable microsensor technology has therefore been introduced in team sports to measure the "non-running based activity". This technology can compliment existing time-motion analysis, and together they may better measure the overall external physical activity demands in team sports. The following sections will describe this microsensor technology in detail.

2.2 Microsensor technology

Microsensor (or inertial sensor) technology includes accelerometers, gyroscope and magnetometers. To understand how these microsensors measure physical activity in team sports, it is essential to understand their operation principles. The following is a general description, as the manufacturer did not reveal specifics about the microsensor technology that was used the present study.

2.2.1 Accelerometers

Accelerometers are motion sensors that can detect linear acceleration along one or several axes (Yang & Hsu, 2010). Aminian and Najafi (2004) explain that these sensors consist of a movable proof mass (or seismic mass) that is connected to a "frame" (accelerometer case) via a "beam", which can be associated with a spring structure. Due to external acceleration¹, the proof mass will cause a deformation of the "spring" with respect to the "frame" (Aminian & Najafi, 2004). The magnitude of this deformation is proportional to the external acceleration (Kavanagh & Menz, 2008), and can be measured via a specific "sensing scheme" within the sensor (Godfrey, Conway, Meagher, & OLaighin, 2008). The type of "sensing scheme" varies between different types of accelerometers, which have their well-described practical advantages and disadvantages (Godfrey et al., 2008; Kavanagh & Menz, 2008). For example, some accelerometers cannot detect gravity, whereas other accelerometers cannot separate between the applied acceleration in space and the gravitational acceleration (Kavanagh & Menz, 2008).

2.2.2 Gyroscopes

Gyroscopes are motion sensors that can detect angular velocity about one or several axes (Yang & Hsu, 2010). They use a vibrating mechanical element to detect angular velocity, via the "transfer of energy between two vibration modes ... caused by the Coriolis" acceleration (Aminian & Najafi, 2004). The "Coriolis effect is an apparent force that arises in a rotational reference frame and is proportional to the angular rate of rotation" (Aminian & Najafi, 2004). The angular velocity is measured with a specific "sensing scheme", which vary between different types of gyroscopes. Additionally, a gyroscope can estimate change in orientation (rotational angles) by integrating the angular velocity (Luinge & Veltink, 2005).

¹ External acceleration refers to the applied acceleration in space and/or gravitational acceleration

Accelerometers and gyroscope are often used together, as they have complimentary features (Luinge & Veltink, 2005). For example, together they can provide more precise acceleration data, as the inclination with respect to gravity is know.

2.2.3 Magnetometers

A magnetometer is a sensor that detects the earth's magnetic field; specifically "it can measure orientation relative to the magnetic north direction" (Aminian & Najafi, 2004). It is therefore often described as an electronic compass. A magnetometer is technical not a "true" microsensor, but is sometimes used together with an accelerometer and a gyroscope. For example, it can be used to correct the orientation to the gyroscope.

2.3 The use of microsensor technology in team sports

In team sports, microsensors are integrated within micro-electro-mechanical system (MEMS) devices that also include GPS sensors and heart rate compatibility (Chambers et al., 2015; Dellaserra et al., 2014). These devices are very practical to use in practice. As such, they contain a built-in microprocessor that offers automatic feedback in real time via telemetry. Moreover, the microsensor technology is available both outdoors and indoors, and does not require any stationary receivers or cameras to function (Chambers et al., 2015). The device is worn on the players' upper back in a custommade vest or within the jersey. These devices will herby be referred as wearable tracking devices.

To date, there are several different manufactures of wearable tracking devices for team sports. Some of the commercial available device models include MinimaxX and Optimeye (Catapult Sports, Melbourne, Australia), SPI-ProX and SPI-HPU (GPSports, Canberra, Australia), VX (VX Sport, Lower Hutt, New Zealand) and Viper pod (STATSports, UK, Ireland). In addition to their hardware technology, these manufactures have developed specific algorithms within the software to automatically convert the raw inertial data (input) into meaningful and standardized variables (output), which can be used to assess physical activity demands. In general, these variables can be categorized into so-called workload or event detection variables.

2.3.1 Workload variables

Workload variables have been used as a general measure of the physical activity (or exertion). These variables aims to measure both the "running based activity" and the "non-running based activity". Two commonly used variables are Player Load (Catapult Sports, Melbourne, Australia) and Body Load (GPSports, Canberra, Australia). The following will only contain a description of the Player Load variable.

Player Load can be described as a resultant vector magnitude derived from tri-axial accelerometer data. This variable has been used to measure physical activity demands in various team sports (Boyd et al., 2013; Cormack et al., 2014; Montgomery et al., 2010; Polley et al., 2015; Young, Hepner, & Robbins, 2012). For example, it has been reported to discriminate between training and game, playing positions and level of competition in Australian football (Boyd et al., 2013). In addition, Player Load has been observed to detect differences between periods in lacrosse games (Polley et al., 2015). Such findings may indicate that Player Load is a useful measure to assess differences in team sport activity profiles.

Previous research has documented a strong correlation between Player Load and total distance in Australian football (Gallo, Cormack, Gabbett, Williams, & Lorenzen, 2015) and field hockey (Polglaze, Dawson, Hiscock, & Peeling, 2015). This may indicate high sensitivity to "running based activity", possibly due to the vertical acceleration from heel strikes. In this respect, there are several formula variations of Player Load that can be used to assess different aspects of physical activity demands in team sports. A commonly used variable is Player Load 2D (Player Load^{2D}), which omits the vertical accelerometer axis to possibly better represent "non-running based activities". As such, this variable has been associated with agility demands in Australian football (Davies, Young, Farrow, & Bahnert, 2013) and collision demands in rugby league (Gabbett, 2015). Furthermore, previous research has separated the contributions of the individual axes to Player Load (Y, X and Z) for more detailed activity analysis (Cormack, Mooney, Morgan, & McGuigan, 2013; Cormack et al., 2014; Page, Marrin, Brogden, & Greig, 2015). For example, it has been reported an association between reduction in the vertical accelerometer data and jump performance in Australian football (Cormack et al., 2013), suggesting that the individual axes of Player Load may be used to detect neuromuscular fatigue. With respect to the aforementioned studies, the different formula variations of Player Load may be considered as valuable as measures of activity in team sports.

2.3.2 Event detection variables

Event detection variables are used to register the frequency and distinguish between different "non-running based activity" events. Such variables are often derived from accelerometer, gyroscope and magnetometer data. Although, it should be noted that magnetometer data are not actually used within the algorithms, but applied to correct the gyroscope's orientation.

A collision and/or tackle detection variable has been used in Australian football and rugby codes to detect events of physical contact during training and games (Gabbett et al., 2010; Gastin, McLean, Breed, & Spittle, 2014). Specifically, this variable has been used to detect and categorize between mild, moderate and heavy collision/tackle events (Gabbett et al., 2010). This can provide valuable insights in performance and load profile analysis in contact sports. However, this variable is to date only available for the aforementioned sports and will therefore not be discussed any further.

A new technological developed by Catapult Sports (Catapult Sports, Melbourne, VIC, Australia) offers specific variables that aim to describe a player's agility pattern. This technology is termed "Inertial movement analysis" (IMA). In addition to estimate the frequency, IMA may also calculate the magnitude and the direction of an agility action. It can potentially classify events within intensity, and distinguish between forward, backward, and left and right lateral events. IMA related variables could be useful to detect important facets of play and to distinguish between individual players' agility patterns. There are no published studies to date that have used this variable to analyse the activity patterns in team sports.

IMA may also detect jump efforts, which can be considered as relevant for handball analysis. However, this variable requires that the players land on their feet. As handball players often land on their back, this variable will not be discussed further.

2.4 Reliability of microsensor technology used in team sports

The usefulness of microsensors can be determined by its precision. The precision of the observed value of a measure can be associated with the degree of measurement error (or variation), which "makes the observed value … differ from the true value" (Hopkins, 2000). Measurement error is typically categorized between random error and systematic bias. Systematic bias can refers to the general trend of variation (positive or negative), whereas random error is a randomized selected variation (positive and negative) (Hopkins, 2000). Random error can further be classified between technical error and biological error. In this context, random error refers to the inhered variation in the device, while biological variation may be caused by variation in the device-setup.

Reliability and validity are described as important aspect of precision. Reliability is defined as the consistency of a measure (Atkinson & Nevill, 1998). A good reliability is critical to evaluate the value of a single measure and to detect "real" differences in a measure (Atkinson & Nevill, 1998; Hopkins, 2000). Validity is defined as the "agreement between the observed value and the true or criteria value of a measure" (Hopkins, 2000). Reliability and validity are both related, but usually studied separately. With respect to the present purpose, the focus of this study is the assessment of reliability.

2.4.1 Design of reliability studies

The reliability of microsensors can either be assessed within devices (i.e., test and retest trials) or between devices. Research has often examined the reliability via a calibration device (e.g., mechanical apparatus) (Esliger & Tremblay, 2006; Krasnoff et al., 2008). This type of procedure provides a highly controlled assessment and is considered to be a "gold standard" to assess the technical error in the device. However, such procedures lacks of specificity to applied situations. Research has therefore investigated reliability also via human trials. Human trials are typically categorized in assessments consisting of laboratory-based activities (Powell & Rowlands, 2004) or more practical field based activities (Fulton, Pyne, & Burkett, 2009). Although human trials are conducted in more practical settings, they are vulnerable to biological variation. It is therefore critical to be precise to determine the source of error.

2.4.2 Review of the literature

The following sections will summarise the available research that has examined the reliability of commercially available microsensor technology used to measure the physical activity demands in team sports. This refers to both the hardware and its software algorithms (or variables).

Boyd, Ball, and Aughey (2011) were the first to assess the reliability of MinimaxX microsensors and its Player Load calculations. The assessment consisted of static tests and dynamic tests (0.5 and 3.0 g) via a calibration device. In was observed a coefficient of variation (CV) of 1.01% within devices and 1.10% between devices in static tests. The CV in dynamic tests was reported as 0.91% to 1.05% (0.5 and 3.0 g) within devices, and 1.04 to 1.02% (0.5 and 3.0 g) between devices. Additionally, the reliability between devices (CV 1.94%) was also established in Australian football games. As such, MinimaxX microsensors were suggested to be a reliable tool to measure physical activity demands in Australian football based on Player Load.

Johnston et al. (2012) examined the reliability between MinimaxX microsensors for calculating Player Load in a team sport running circuit. The circuit consisted of standing, walking, jogging, fast running and sprinting, along with some agility demands. It was reported a CV of 4.9%. Player Load was therefore recommended to be a reliable measure of activity in team sports.

The reliability of Player Load has also been investigated during incremental treadmill running (7-16 km/t) (Barrett, Midgley, & Lovell, 2014). It was observed a CV of 5.9% within MinimaxX microsensors. Furthermore, the reliability of the individual axes to Player Load showed 9.1% antero-posterior axis, 12.0% medio-lateral axis and 6.3% vertical axis. Based on the findings, it was concluded that caution should been taken for comparing Player Load data between devices.

Recently, the reliability of SPI-Pro microsensors was evaluated via a calibration device for measuring raw resultant tri-axial accelerometer data (Kelly, Murphy, Watsford, Austin, & Rennie, 2015). It was reported a CV of 1.87 to 2.21% within four devices. Additionally, it was observed excellent reliability between devices, based on no significant difference between raw peak gravitational acceleration (p < 0.5). The SPI-Pro microsensors was therefore suggested to be a reliable tool for use in the field.

2.5 Summary

Measuring the physical activity demands is today common practice in professional team sports. However, based on a complex activity profile, it is difficult to measure the external physical activity demands. Microsensor technology such as accelerometer, gyroscope and magnetometer has therefore in recent years been introduced to compliment traditional time-motion analysis to measure "non-running based activity". These microsensors are integrated within wearable tracking devices that contain additionally sensor technology (e.g., GPS). These microsensors have several practical benefits, such as that the devices are transportable and are easy to use. They can offer automatic feedback in real time, and are available indoors and outdoors. This technology uses advanced mathematical algorithms with their software to convert raw data into meaningful activity variables, which is typically categorized in so-called workload and event detection variables. Among these, Player Load and IMA may provide valuable insights in physical activity demands in team sports such as handball.

The reliability of this microsensor technology is critical to determined and interprets the data correctly. To the authors' knowledge, there are to date only four published research studies on its reliability. The reliability has been studied via calibration devices and human trials, in both a laboratory and field setting. Among the available research, three studies have assessed the reliability of MinimaxX devices and its Player Load variable (and individual axes). One study has examined the reliability of SPI-Pro microsensors for measuring raw accelerometer data. To date, there are no studies that have assessed the reliability of Optimeye microsensors and IMA variables. It is therefore warrant for more research of this commercially available microsensor technology.

3. Methods

3.1 Study design

The present study assessed the between-device reliability of a microsensor technology integrated within a commercial available wearable tracking device (Optimeye S5, version 6.109, Catapult Sports, Melbourne, Australia). This was established via two different assessments. The laboratory assessment examined the reliability in handball specific movement tasks. The field assessment determined the reliability in handball-training sessions that included typical team training drills. The research was completed accordance to the Helsinki declaration. All subjects were verbally informed about the purpose and procedures of the study, and signed consent forms prior to participation (see appendix II and III). Data storage was granted by the Norwegian Social Science Data Service (see appendix IV).

3.2 Microsensor technology²

3.2.1 Optimeye S5

The Optimeye S5 contains a built-in \pm 2-16 g tri-axial accelerometer, 200-2000 deg·s⁻¹ tri-axial gyroscope and tri-axial magnetometer, which samples at a frequency of 100 Hz. The microsensors were calibrated by the manufacture prior to and after completion of the study. No meaningful drift was reported in any of the devices. The Optimeye device is also featured with a fifth-generation microprocessor with 1 GB flash memory to record and store data, and a USB interface to upload data. The device weighs 66.8 g and is 96 x 52 x 13 mm in dimension, and is powered by an internal battery with five hours of life (charged via USB interface).

All subjects were instrumented with two devices, as illustrated in figure 3.1. Both devices were worn in a custom-made vest (Catapult Sports, Melbourne, Australia), placed in a pouch on the posterior side of the upper trunk. The two devices were taped together with sports tape to align the accelerometer, gyroscope and magnetometer axes. The devices switched position between the sessions, so each device produced data in both sites. A total of seven pars of devices were randomly assigned to the subjects. The same subject used the same two devices during all testing.

² Information is based on the guidelines defined in manuals from the manufacture (Catapult-Sports, 2013a, 2013b).



Figure 3.1 The OptimEye S5 device (left). Two devices were taped together (middle), and fitted in a custom-made vest (right) during data collection in a laboratory and field assessment.

3.2.2 Inertial movement analysis

IMA uses raw accelerometer and gyroscope data to create a non-gravitational acceleration vector (or data) based on advance Kalman filtering algorithms. Further, IMA aims to detect certain acceleration event and calculate its magnitude and direction. Specifically, such acceleration event will be referred as an IMA event, and defined as an instant one-step movement effort (e.g., sudden CoD). Based on specific algorithms, the start and end point of such an event is identified in the acceleration curve. The magnitude of an event (IMA magnitude) is calculated as the area under the curve, based on the sum of antero-posterior and medio-lateral accelerations. This value is measured in terms of delta velocity (m·s⁻¹), which is a measure of impulse. Furthermore, the direction of an event (IMA direction) is calculated based on the angle of the applied acceleration, and is measured in degrees ($\pm 180^\circ$). This value is calculated relative to the device's orientation at the time of the step.

Based on IMA magnitude, the manufacture's software (version 5.14, Catapult Sprint, Catapult Sports, Melbourne, Australia) can count the number of IMA events that occurs during activity (IMA counts). To exclude running based activity from the estimate, only IMA events $\geq 1.5 \text{ m} \cdot \text{s}^{-1}$ were included. Further, these IMA counts can be categorized into narrow intensity bands such as low 1.5 to 2.5 m·s⁻¹, medium 2.5 to 3.5 m·s⁻¹ and high > 3.5 m·s⁻¹ (default bands). IMA counts can also be categorized within specific directional bands, based on IMA direction. These include forward (-45 to 45°), backward (-135 to 135°), left lateral (-135 to -45°) and right lateral (45 to 135°) counts. Figure 3.2 gives an overview of the specific IMA variables used in the present study.

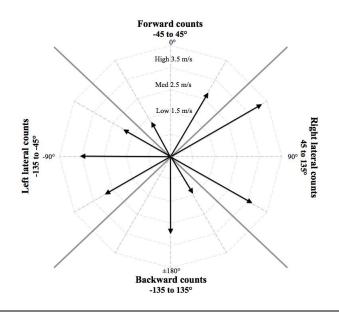


Figure 3.2 IMA counts can be divided into low, medium and high intensity based on IMA magnitude, or divided into forward, backward, left lateral and right lateral direction based on IMA direction. The figure is modified from Catapult Sports (2013a)

3.2.3 Player Load

Player Load is a resultant vector magnitude derived from tri-axial accelerometer data. It is "expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in each of the three vectors (X, Y and Z axis) and divided by 100" (Boyd et al., 2011). The calculation utilize a scaling factor of "100" to make the output data more practical applicable to use. It is reported in arbitrary units (au). See following equation.

$$Player \ Load = \sqrt{\frac{(a_{Y1} - a_{Y-1})^2 + (a_{X1} - a_{X-1})^2 + (a_{Z1} - a_{Z-1})^2}{100}}$$

Note: a_{Y} = antero-posterior acceleration; a_{X} = medio-lateral acceleration; a_{Z} = vertical acceleration.

Formula variations of Player Load included Player Load^{2D} and individual axes: anteroposterior (Player Load^Y), medio-lateral (Player Load^X) and vertical (Player Load^Z).

3.3 Laboratory assessment

3.3.1 Subjects

Five male and five female handball players (age, 21.2 ± 1.3 years; body mass, 73.9 ± 12.3 kg; height, 175.1 ± 7.4 cm; mean \pm SD) participated in this assessment. All subjects competed in the elite (n = 5) or first division (n = 5) in Norway. Only outfield players were included.

3.3.2 Data collection

The assessment was performed on an indoor court. Subjects were tested separately on two different days (1-10 days between tests), where the same protocol was completed in both sessions. The subjects underwent a warm-up of 10 minutes, consisting of dynamic stretching and sport specific running exercises (i.e., jogging, changes of direction and accelerations). The intensity was regulated individually. Furthermore, familiarisation trials were undertaken prior to each movement task until the subject was confident in executing the tasks, typically 2 to 5 trials.

The subjects completed a total of seven different movement tasks (Figure 3.3). Four of the tasks consisted of an explosive, single one-step movement action (one-step action) that was performed in different force directions. These efforts can be described as a start action (T1), stop action (T2), left CoD (T3) and right CoD (T4). Furthermore, three movement tasks consisted of repeated lateral CoD (T5), start and stop actions (T6), and multidirectional CoD (T7). The subjects were instrumented to complete the movement tasks with a clear and explosive foot-strike of maximal intensity. Facing direction is illustrated in Figure 3.3. Each task was repeated four times, and the subjects were given two minute of recovery between trials.

3.3.3 Data analysis

The manufacture's software was used to control the devices via telemetry during testing. Each trial was marked as a distinct period in the software. Raw inertial data was uploaded to computer via a USB interface, and processed in the manufacturer's software. IMA data were expressed as IMA magnitude and IMA direction, and the values were viewed graphically in the software and registered manually. Only IMA magnitude values $\geq 1,5 \text{ m}\cdot\text{s}^{-1}$ evident in one of the two devices were included. IMA direction data were changed to be only positive values.

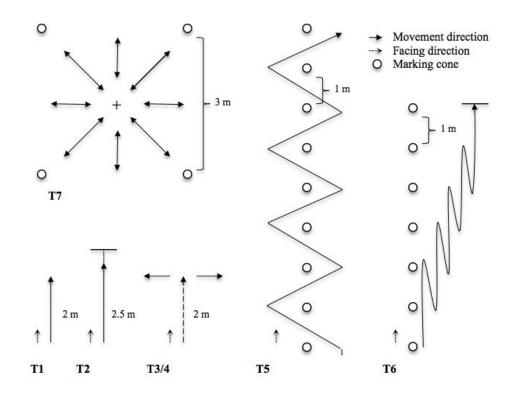


Figure 3.3 Illustration of the movement tasks. Well-controlled one-step actions: start action (T1), stop action (T2), left CoD (T3) and right CoD (T4). Chaotic movement patterns: lateral CoD (T5), start-stop action (T6) and multidirectional CoD (T7).

3.4 Field assessment

3.4.1 Subjects

Twelve male handball players (age, 23.8 ± 4.6 years; body mass, 92.4 ± 9.7 kg; height, 192.3 ± 9.1 cm) from an elite handball team in Norway participated in this assessment. All playing positions were included. The subjects had a minimum of three organized training sessions and one match per week during the experimental period.

3.4.2 Data collection

A total of twelve handball-training sessions were included. Data were collected throughout the first half of the in-season period (October to December, 2014). Three different indoor courts were used. All sessions were performed as planned by the coach, without any intervention from the analyst. The analyst tracked the device signal from a courtside position via telemetry. The training drills, intensity and volume of each session were adjusted to the game schedule. The training drills were classified as following:

- *Warm-ups:* General and handball specific running exercises, and soccer play.
- *Technical drills:* Individual skills development (i.e., passing, shooting, marking), with or without external pressure. Plus goalkeeper specific drills.
- *Tactical drills:* Situations to simulate technical decision making via a reduction of court size, using one goal (i.e., 5 vs. 3, 6 vs. 4, 6 vs. 6 etc.). Both defensive and offensive focus.
- *Transition games:* High intensity work on a full-court sized court with two goals (i.e., 1 vs. 1, 2 vs. 1, 4 vs. 2 etc.).
- *Match practice:* Match simulation, 7 vs. 7 full-court size with two goals.

3.4.3 Data analysis

A separate period was created for each drill in the manufacture's software. Rest periods and interchanges were excluded. The analyses consisted therefore of only active periods, which accounted for 63.8 ± 7.2 min. Start and end time point of each period was aligned to 0.01 s to minimise bias. Raw inertial data was uploaded to a computer via a USB interface, and processed in the software. IMA and Player Load data were downloaded via a custom designed report. IMA data was expressed as IMA counts and categorized into intensity and direction bands. Player Load was expressed in original formula, in addition to its associated variables.

3.5 Statistical analysis

IMA and Player Load data were analysed using a customized spreadsheet (Hopkins, 2011). Descriptive data were presented as mean \pm SD. The reliability between devices was established using the typical error of measurement (TE), expressed in absolute terms and as a percentage (CV). The uncertainty was expressed as 90% confidence interval (CI). The CV was rated as good (CV < 5%), moderate (CV 5 to 10%) or poor (CV > 10%), based on previous recommendations (Duthie, Pyne, & Hooper, 2003; Jennings, Cormack, Coutts, Boyd, & Aughey, 2010). Data presented as CV were log-transformed to reduce bias from potentially non-uniformity error (Hopkins, Marshall, Batterham, & Hanin, 2009). Measures of angles have an absolute reference point, and are not appropriate to log-transformation (Hopkins, 2011). IMA direction values were therefore not presented as CV.

Intraclass correlation coefficient (ICC) was calculated to evaluate the relationship between devices from the field assessment. The correlations were interpreted as following: < 0.1 trivial, 0.10-0.29 small, 0.30-0.49 moderate, 0.50-0.69 large, 0.70-0.89 very large, and > 0.90 nearly perfect (Hopkins, 2002).

The smallest worthwhile difference (SWD) was calculated as the 0.2 x between-subject SD, and was used as a measure to identify "real" differences (Pyne, 2003). As such, Optimeye microsensors were considered capable to detect "real and worthwhile" differences if the CV was less than the SWD, and thus rated as a "useful" tool to measure physical activity demands in handball.

4. Results

4.1 Laboratory assessment

The reliability statistics for IMA magnitude and IMA direction are presented in Table 4.1. The CV for IMA magnitude was good (CV < 5%) in well-controlled movement tasks (T1-4), which was less then the SWD. The CV increased in more chaotic movement tasks (T5-7). In the multidirectional CoD task, it was observed a CV that was less than the SWD. The CV from lateral CoD and start-stop actions was greater than the SWD. IMA direction calculations are not presented in CV, due to its impracticability (see Section 3.5). An illustration of between-device variation for IMA magnitude and IMA direction calculations are presented in Figure 4.1.

Movement tasks	IMA event	Device 1 Mean ± SD	Device 2 Mean ± SD	TE (Abs)	CV (%)	90% CI (%)	SWD (%)	Trials (n)	IMA events (n)
T1-4: One-step action	Magnitude (m·s ⁻¹)	3.2 ± 1.0	3.3 ± 1.0	0.1	2.9	2.7 - 3.1	6.0		
	Direction (deg)	100.9 ± 50.6	100.4 ± 50.1	2.6				616	519
T5: Lateral CoD	Magnitude (m·s ⁻¹)	3.0 ± 0.7	3.1 ± 0.7	0.1	4.4	4.3 - 4.6	4.3	0	
	Direction (deg)	94.6 ± 19.0	94.4 ± 19.0	2.5	·		·	00	1130
T6: Start-stop action	Magnitude (m·s ⁻¹)	2.9 ± 0.9	2.9 ± 0.9	0.2	8.2	7.9 - 8.6	6.3	00	050
	Direction (deg)	86.0 ± 69.9	85.2 ± 68.9	3.6				00	وره
T7: Multidirectional CoD	Magnitude (m·s ⁻¹)	3.4 ± 1.4	3.4 ± 1.4	0.2	6.0	5.8 - 6.2	8.2	0	1200
	Direction (deg)	97.6 ± 33.5	97.5 ± 33.5	2.8	ı	I	·	00	1290

Table 4.1 Reliability between microsensors for IMA magnitude and IMA direction values from handball-specific movement tasks.

Note: CoD, changes of direction; deg, degrees; TE, typical error of measurement (abs; absolute); CV, coefficient of variation; CI, confidence interval; SWD, smallest worthwhile difference.

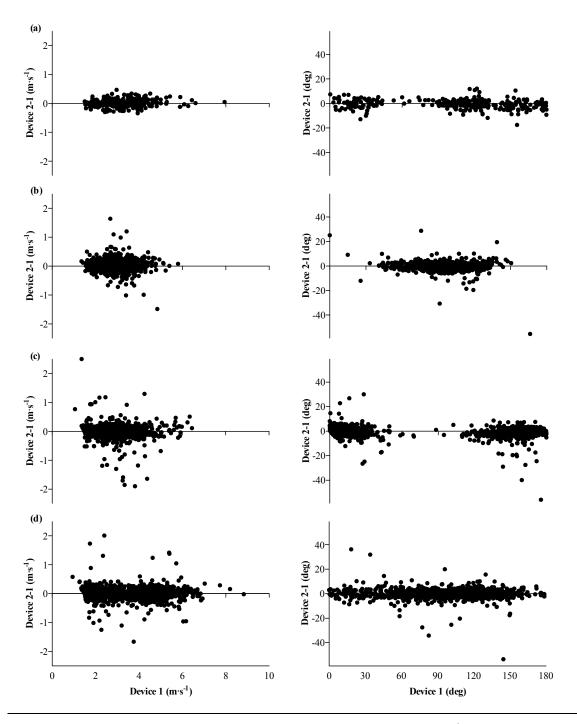


Figure 4.1 The variation between two microsensors for IMA magnitude $(m \cdot s^{-1})$ and IMA direction (degrees; deg) values from handball-specific movement tasks: one-step action (a; n = 319 IMA events), lateral CoD (b; n = 1136 IMA events), start-stop action (c; 859 IMA events) and multidirectional CoD (d; n = 1296 IMA events).

4.2 Field assessment

The reliability statistics for IMA count variables are displayed in Table 4.2 and 4.3. The CV for total IMA counts was good (CV < 5%), which was less then the SWD (Table 4.2). The CV increased slightly when IMA counts were categorized into intensity bands. The CV for low, high and medium/high (combined) intensity counts was less then the SWD. IMA counts of medium intensity showed a CV greater than the SWD.

IMA counts categorized within direction bands showed a moderate reliability (CV 5 to 10%; Table 4.3). The CV for forward, backward and left lateral counts were greater than the SWD. Right lateral counts showed a CV slightly less than the SWD. The CV increased substantial when forward, backward, left lateral and right lateral counts were categorised further into intensity bands, with a CV ranging from 5.3 to 22.6%. The CV for these variables was greater than the SWD, except for the right CoD events of low and medium/high intensity.

The reliability statistics for Player Load and its associated variables are displayed in Table 4.4. All variables showed good reliability (CV < 5%), with the CV being less then the SWD. Furthermore, it was demonstrated a nearly perfect (ICC = 0.99) and perfect (ICC = 1.00) relationship between devices for total IMA counts and Player Load, respectively (Figure 4.2). These data shows a range of low, medium and high intensity training sessions in handball.

	Device 1	Device 2	ТЕ	CV	90% CI	SWD
Intensity bands (n)	Mean ± SD	Mean ± SD	(Abs)	(%)	(%)	(%)
Low	406.2 ± 96.1	427.5 ± 97.6	11.8	2.9	2.6 - 3.3	4.6
Medium	117.4 ± 31.0	123.3 ± 32.1	6.4	5.5	4.9 - 6.4	5.2
High	65.7 ± 25.9	72.6 ± 28.8	4.2	5.6	5.0 - 6.5	7.9
Medium/High	183.1 ± 53.7	195.8 ± 57.7	7.3	3.9	3.5 - 4.5	5.9
Total	589.3 ± 141.6	623.4 ± 145.8	13.9	2.4	2.1 - 2.8	4.7

Table 4.2 Reliability between microsensors for accumulated IMA counts in handball training.

Note: TE, typical error of measurement (*abs*; absolute); *CV*, coefficient of variation; *CI*, confidence interval; *SWD*, smallest worthwhile difference. n = 83.

	Device 1	Device 2	ТЕ	CV	90% CI	SWD
Direction bands*	Mean ± SD	Mean ± SD	(Abs)	(%)	(%)	(%)
Forward (n)						
Low	46.8 ± 14.8	50.9 ± 15.3	5.3	11.6	10.2 - 13.4	6.2
Medium	16.7 ± 7.3	19.4 ± 8.2	3.1	22.4	19.6 - 26.1	8.6
High	15.1 ± 9.6	19.8 ± 12.5	3.1	22.6	19.8 - 26.4	12.8
Medium/High	31.8 ± 15.7	39.1 ± 18.9	4.1	13.4	11.8 - 15.5	9.8
Total	78.6 ± 26.4	90.0 ± 30.0	6.9	8.8	7.8 - 10.2	6.7
Backward (n)						
Low	60.3 ± 21.7	58.2 ± 21.0	5.6	10.6	9.3 - 12.3	7.2
Medium	23.0 ± 7.2	22.3 ± 7.6	2.6	13.0	11.5 - 15.1	6.5
High	14.2 ± 6.2	13.7 ± 5.6	1.9	14.8	13.0 - 17.2	8.4
Medium/High	37.3 ± 11.4	36.0 ± 11.1	3.5	9.4	8.3 - 10.9	6.1
Total	97.6 ± 29.7	94.2 ± 28.9	7.8	8.5	7.5 - 9.9	6.1
Left lateral (n)						
Low	151.3 ± 49.9	153.9 ± 51.1	10.1	7.5	6.6 - 8.7	6.6
Medium	40.4 ± 15.5	40.9 ± 15.6	3.9	10.7	9.4 - 12.4	7.7
High	18.7 ± 9.4	19.5 ± 10.3	1.9	13.3	11.7 - 15.4	10.3
Medium/High	59.1 ± 23.4	60.4 ± 24.6	4.6	8.7	7.7 - 10.1	8.0
Total	210.4 ± 68.8	214.3 ± 70.9	13.1	7.0	6.2 - 8.1	6.6
Right lateral (n)						
Low	147.8 ± 45.0	164.5 ± 48.6	9.1	5.8	5.2 - 6.7	6.0
Medium	37.3 ± 13.4	40.7 ± 13.9	3.3	10.5	9.2 - 12.1	7.0
High	17.7 ± 10.0	19.6 ± 11.0	2.0	16.6	14.6 - 19.2	11.3
Medium/High	55.0 ± 21.6	60.4 ± 23.2	3.7	7.3	6.4 - 8.4	7.8
Total	202.8 ± 61.8	224.9 ± 66.1	10.5	5.3	4.7 - 6.1	6.0

Table 4.3 Reliability between microsensors for accumulated IMA counts in handball training.

Note: TE, typical error of measurement (*abs*; absolute); *CV*, coefficient of variation; *CI*, confidence interval; *SWD*, smallest worthwhile difference. n = 83.

*IMA counts were categorized within direction bands and divided further into intensity bands.

	Device 1	Device 2	TE	CV	90% CI	SWD
Variables [*] (au)	Mean ± SD	Mean ± SD	(Abs)	(%)	(%)	(%)
Player Load	410.6 ± 79.0	426.6 ± 81.2	4.1	0.9	0.8 - 1.0	3.8
Player Load ^{2D}	258.7 ± 48.0	262.1 ± 48.3	2.7	1.0	0.9 - 1.1	3.7
Player Load $^{\rm Y}$	154.4 ± 27.9	154.1 ± 27.7	0.7	0.4	0.4 - 0.5	3.6
Player Load ^X	173.6 ± 35.1	178.5 ± 35.6	3.1	1.6	1.4 - 1.9	4.0
Player Load ^Z	272.8 ± 56.5	289.7 ± 59.2	3.8	1.1	1.0 - 1.3	4.1

 Table 4.4 Reliability between microsensors for accumulated Player Load and associated variables in handball training.

Note: TE, typical error of measurement (*abs*; absolute); *CV*, coefficient of variation; *CI*, confidence interval; *SWD*, smallest worthwhile difference. n = 83.

*2D, antero-posterior and medio-lateral axes; Y, antero-posterior axis; X, medio-lateral axis; Z, vertical axis.

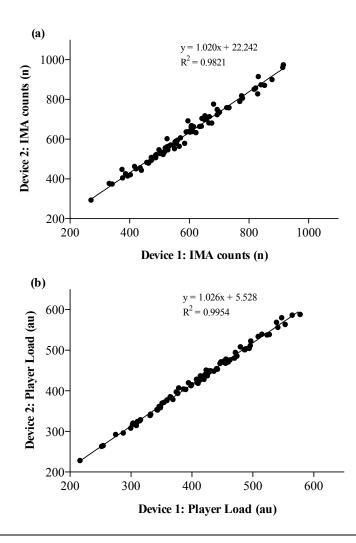


Figure 4.2 The relationship between two microsensors for accumulated IMA counts (a) and Player Load (b) in handball training. n = 83.

5. Discussion

The aims of this investigation were to evaluate the between-device reliability and sensitivity of Optimeye microsensors to measure physical activity demands in handball based on IMA and Player Load. To the authors' knowledge, this is the first study to establish the reliability of IMA. The main findings showed that IMA count were a reliable variable, given that data were expressed as total counts or within low and medium/high (combined) intensity bands. Furthermore, it was demonstrated a good level of reliability for Player Load and its associated variables. The CV of the aforementioned variables was well below the SWD, suggesting that Optimeye microsensors and its software are capable to detect "real and worthwhile" differences in handball activity.

5.1 Reliability of IMA

5.1.1 IMA magnitude and IMA direction

The laboratory assessment showed a good to moderate reliability for IMA magnitude values. The literature has listed intensity and type of activity (or movement) as potential factors to affect the reliability of raw inertial signals (Welk, 2005). This may partially account for the variation that was observed between devices. However, the CV appeared to increase in more chaotic movement tasks (T5-7), possibly due to certain "outliers" in the data set (Figure 4.1). These "outliers" (or large variations) were a result of inconsistency in data filtering between devices. As such, a device could detect one large IMA event, whereas the other device could detect two small consecutive IMA events. This may appear in situations where events of foot-strike impacts within the same movement pattern (e.g., instant left to right CoD) occur close together. This finding represents a critical shortcoming for IMA event detection algorisms, as team sports are highly chaotic in nature. Such variations in IMA magnitude (and IMA direction) values will logically affect the precision of IMA counts. As mention previously, no CV data were presented for IMA direction and will therefore not be discussed.

5.1.2 IMA counts

It was established a good reliability of total IMA counts in the field assessment. Furthermore, nearly perfect relationships between devices suggest that IMA counts are consistent regardless of the device used. However, it was observed a decreased reliability when IMA counts were categorized in more narrow intensity bands such as low, medium and high. Such a challenge is also reported in GPS analysis, when categorizing running activity within multiple speed bands (Scott, Scott, & Kelly, 2015). To ensure a more precise assessment, some research studies have therefore classified running activity into broader speed bands that only include low and high speed (Coutts et al., 2010; Jennings, Cormack, Coutts, & Aughey, 2012). Similarly, based on the present data the author recommends that IMA counts should be categorized in low and high (combined medium and high) intensity bands, to reduced variation between devices. However, the threshold of these bands may need to be adjusted to the individual sport, level of competition and sex. To minimise the influence of running activity, it is critical that these thresholds are appropriate. Therefore, there is a need for further research to determine appropriate band settings.

A categorization of IMA counts within direction bands could provide detailed insights in the players' agility patterns. However, this is a very challenging task given the chaotic nature of team sports and the individual variation of player movement characteristics. The present data showed only a moderate reliability of forward, backward, and left and right lateral counts. The reliability decreased further when these were separated into intensity bands. Caution should therefore be taken when interpreting IMA counts with respect to direction bands. Improvements are required for this IMA variable to be applicable in elite sports.

5.2 Reliability of Player Load

5.2.1 Player Load

Similar to the present study, previous research has observed good between-device reliability of Player Load when MinimaxX microsensors were tested via a calibration device and in Australian football games (Boyd et al., 2011). However, the present study showed a slightly lower CV, about 1%, compared to the aforementioned study when devices were tested in a field setting. As both studies used a similar device set-up, it can be speculated that the lasted version of the Optimeye device contains superior microsensors. The Optimeye microsensors showed far greater reliability compared to Johnston et al. (2012) and Barrett et al. (2014) that used MinimaxX microsensors to calculate Player Load during treadmill running (CV 5.9%) and in team sport movements (CV 4.9%), respectively. However, it should be acknowledged that Johnston et al. (2012) used a different device set-up than the present study, as two devices were fitted in separate vests. This may possibly explain some of the variation that was observed between devices. Barrett et al. (2014) assessed the reliability within devices, and some of the difference may therefore be due to biological variation between the test and retest trials.

Boyd et al. (2011) showed a nearly perfect relationship between devices for the Player Load calculation, using the Pearson correlation coefficient (r = 0.99). This is comparable to the results of the present study. Previous research has also observed a nearly perfect relationship (ICC = 0.93) within devices in a laboratory setting (Barrett et al., 2014). These findings indicate that Player Load can be used with confidence in the field regardless of what devices that are being used.

5.2.2 Formula variations

This study is the first to assess the between-device reliability of Player Load^{2D} and the individual axes (Y, X and Z) of Player Load. The present findings suggest that these variables can be confidently used in the field. In this respect, previous research has only demonstrated poor to moderate level of within-device reliability for the individual Player Load axes (Barrett et al., 2014). Once again, this may be explained by a variation between test and retest trials. Although the aforementioned study investigated the reliability within devices, it was reported that the highest CV was in the medio-lateral

axis similar to the present study. The observed variation between the axes can possibly be explained by the device-set up used in the present study (Section 5.4).

5.3 Usefulness of microsensors to measure activity in handball

5.3.1 SWD

The CV of total IMA counts was well below the SWD. This was also apparent for IMA counts within low and medium/high (combined) intensity bands. These findings support the use of IMA as a useful measure of activity in handball. For example, if a difference of eight medium/high counts were evident between two training sessions, this would be considered as "real and worthwhile" as the difference is greater than both the CV and the SWD. However, the CV of IMA counts within direction bands was slightly below or greater then the SWD, and greater when divided further into intensity bands. These data may therefore be considered as less useful, due to the fact that interpretation of a "real and worthwhile" difference can only be made when the difference is more than the CV (Pyne, 2003).

In agreement with previous research of Australian football (Boyd et al., 2011), the CV of Player Load was well below the SWD. This was also evident for Player Load^{2D} and the individual axes. Player Load and associated variables may therefore be considered as sensitive to measure physical activity demands in team sports.

Previous research of time-motion analysis in team sports has reported a CV greater than the SWD, specifically for high-intensity activities in confined spaces (Jennings et al., 2010). With respect to the explosive and multidirectional nature of handball (Karcher & Buchheit, 2014), it may therefore be challenging to detect meaningful outcomes using time-motion analysis. This provides further support for the application of microsensors in professional handball.

5.3.2 Generalization of the findings

The cohort of this study is representative for elite handball. However, the literature specifies that microsensors should be tested in activities that represent the type and the intensity of those executed in the target population (Welk, 2005). The best practise would therefore involve an assessment in real game situations, similar to the study of Boyd et al. (2011). However, handball players land or fall frequently on their back, and

using two devices would possibly affect their focus in games. The study therefore aimed to assess the reliability in training sessions, which were considered as best available alternative for the Optimeye devices to be tested in conditions representative for elite handball demands.

5.4 Limitations of the study

In addition to assess reliability between Optimeye microsensors, it would also be of interest to examine the reliability within devices in handball activity. However, it is challenging to assess the inherent (or technical) error in the device, as repeated trials are difficult to complete (Hopkins, 2000). Using a calibration device is probably the only acceptable alternative. However, this option is less specific to team sport activity.

The devices were taped together during data collection and their positions were switched between sessions. This was considered as the best alternative to minimise variations between devices. Descriptive data showed that the device placed distally to the body recorded slightly higher values for most IMA and Player Load variables. A similar observation has also been reported by previous research (Boyd et al., 2011). Therefore, the device placement could account for some of the observed variation (systematic bias) in this study.

5.5 Future directions

To use IMA variables with full confidence it is critical to also investigate its validity. Although there are some available validity studies of IMA, these have only assessed the raw acceleration signals (Wundersitz, Gastin, Richter, Robertson, & Netto, 2014; Wundersitz, Gastin, Robertson, Davey, & Netto, 2015). Therefore, there is a need for more studies to assess the validity of the IMA event detection algorithms.

5.6 Practical applications

The Optimeye microsensors can be confidently used to assess differences in players' activity profiles based on IMA counts and Player Load variables. However, IMA should only be expressed as total counts, or within broad intensity bands (i.e., low and high). Although low variation between devices, this should be taken into account when interpreting data.

6. Conclusion

The present study showed that Optimeye microsensors and its software are reliable to register IMA counts, given that data were expressed as total counts or within low and medium/high (combined) intensity bands. This technology was also reliable to measure Player Load and its associated variables. The CV of these variables was well below the SWD, suggesting that Optimeye microsensors are sensitive to detect "real and worthwhile" differences in handball activity. These findings may also be extended to other team sports where the SWD is greater than 3.9 and 1.6% for IMA and Player Load variables, respectively. Although good reliability was determined between devices, the data should be interpreted with caution since the validity of these variables is currently unclear, especially for IMA variables.

References

- Aminian, K., & Najafi, B. (2004). Capturing human motion using body-fixed sensors: outdoor measurement and clinical applications. *Computer Animation and Virtual Worlds*, 15(2), 79-94.
- Atkinson, G., & Nevill, A. M. (1998). Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports Med*, 26(4), 217-238.
- Aughey, R. J. (2011). Applications of GPS technologies to field sports. Int J Sports Physiol Perform, 6(3), 295-310.
- Barrett, S., Midgley, A., & Lovell, R. (2014). PlayerLoad: Reliability, Convergent Validity, and Influence of Unit Position During Treadmill Running. Int J Sports Physiol Perform, 9(6), 945-952. doi: 10.1123/ijspp.2013-0418
- Barris, S., & Button, C. (2008). A review of vision-based motion analysis in sport. Sports Med, 38(12), 1025-1043. doi: 10.2165/00007256-200838120-00006
- Ben Abdelkrim, N., El Fazaa, S., & El Ati, J. (2007). Time-motion analysis and physiological data of elite under-19-year-old basketball players during competition. Br J Sports Med, 41(2), 69-75; discussion 75. doi: 10.1136/bjsm.2006.032318
- Boyd, L. J., Ball, K., & Aughey, R. J. (2011). The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *Int J Sports Physiol Perform, 6*(3), 311-321.
- Boyd, L. J., Ball, K., & Aughey, R. J. (2013). Quantifying external load in Australian football matches and training using accelerometers. *Int J Sports Physiol Perform*, 8(1), 44-51.
- Bradley, P. S., Carling, C., Gomez Diaz, A., Hood, P., Barnes, C., Ade, J., ... Mohr, M. (2013). Match performance and physical capacity of players in the top three competitive standards of English professional soccer. *Hum Mov Sci*, 32(4), 808-821. doi: 10.1016/j.humov.2013.06.002
- Bradley, P. S., Sheldon, W., Wooster, B., Olsen, P., Boanas, P., & Krustrup, P. (2009). High-intensity running in English FA Premier League soccer matches. J Sports Sci, 27(2), 159-168. doi: 10.1080/02640410802512775

- Carling, C., Bloomfield, J., Nelsen, L., & Reilly, T. (2008). The role of motion analysis in elite soccer: contemporary performance measurement techniques and work rate data. *Sports Med*, *38*(10), 839-862.
- Caspersen, C. J., Powell, K. E., & Christenson, G. M. (1985). Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research. *Public Health Rep, 100*(2), 126-131.
- Catapult-Sports. (2013a). Sprint Help Inertial Movement Analysis (IMA): For Sprint 5.8 and subsequent releases.

Catapult-Sports. (2013b). Sprint Help: For Sprint 5.1 and subsequent releases.

- Chambers, R., Gabbett, T. J., Cole, M. H., & Beard, A. (2015). The Use of Wearable Microsensors to Quantify Sport-Specific Movements. *Sports Med*, 45(7), 1065-1081. doi: 10.1007/s40279-015-0332-9
- Cormack, S. J., Mooney, M. G., Morgan, W., & McGuigan, M. R. (2013). Influence of neuromuscular fatigue on accelerometer load in elite Australian football players. *Int J Sports Physiol Perform*, 8(4), 373-378.
- Cormack, S. J., Smith, R. L., Mooney, M. M., Young, W. B., & O'Brien, B. J. (2014). Accelerometer load as a measure of activity profile in different standards of netball match play. *Int J Sports Physiol Perform*, 9(2), 283-291. doi: 10.1123/ijspp.2012-0216
- Coutts, A. J., & Duffield, R. (2010). Validity and reliability of GPS devices for measuring movement demands of team sports. J Sci Med Sport, 13(1), 133-135. doi: 10.1016/j.jsams.2008.09.015
- Coutts, A. J., Quinn, J., Hocking, J., Castagna, C., & Rampinini, E. (2010). Match running performance in elite Australian Rules Football. *J Sci Med Sport*, 13(5), 543-548. doi: 10.1016/j.jsams.2009.09.004
- Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Med*, 43(10), 1025-1042. doi: 10.1007/s40279-013-0069-2
- Cunniffe, B., Proctor, W., Baker, J. S., & Davies, B. (2009). An evaluation of the physiological demands of elite rugby union using Global Positioning System tracking software. J Strength Cond Res, 23(4), 1195-1203. doi: 10.1519/JSC.0b013e3181a3928b

- Davies, M. J., Young, W., Farrow, D., & Bahnert, A. (2013). Comparison of agility demands of small-sided games in elite Australian football. *Int J Sports Physiol Perform*, 8(2), 139-147.
- Dawson, B., Hopkinson, R., Appleby, B., Stewart, G., & Roberts, C. (2004). Player movement patterns and game activities in the Australian Football League. J Sci Med Sport, 7(3), 278-291.
- Dellaserra, C. L., Gao, Y., & Ransdell, L. (2014). Use of integrated technology in team sports: a review of opportunities, challenges, and future directions for athletes. *J Strength Cond Res, 28*(2), 556-573. doi: 10.1519/JSC.0b013e3182a952fb
- Di Salvo, V., Baron, R., Tschan, H., Calderon Montero, F. J., Bachl, N., & Pigozzi, F. (2007). Performance characteristics according to playing position in elite soccer. *Int J Sports Med*, *28*(3), 222-227. doi: 10.1055/s-2006-924294
- Di Salvo, V., Collins, A., McNeill, B., & Marco, C. (2006). Validation of Prozone ®: a new video-based performance analysis system. *Int J Perform Anal Sport, 6*, 108-119.
- Duffield, R., Reid, M., Baker, J., & Spratford, W. (2010). Accuracy and reliability of GPS devices for measurement of movement patterns in confined spaces for court-based sports. J Sci Med Sport, 13(5), 523-525. doi: 10.1016/j.jsams.2009.07.003
- Duthie, G., Pyne, D., & Hooper, S. (2003). The reliability of video based time motion analysis. *J Hum Mov Stud.*, 44, 259-272.
- Esliger, D. W., & Tremblay, M. S. (2006). Technical reliability assessment of three accelerometer models in a mechanical setup. *Med Sci Sports Exerc*, 38(12), 2173-2181. doi: 10.1249/01.mss.0000239394.55461.08
- Faude, O., Koch, T., & Meyer, T. (2012). Straight sprinting is the most frequent action in goal situations in professional football. J Sports Sci, 30(7), 625-631. doi: 10.1080/02640414.2012.665940
- Frencken, W. G., Lemmink, K. A., & Delleman, N. J. (2010). Soccer-specific accuracy and validity of the local position measurement (LPM) system. J Sci Med Sport, 13(6), 641-645. doi: 10.1016/j.jsams.2010.04.003
- Fulton, S. K., Pyne, D. B., & Burkett, B. (2009). Validity and reliability of kick count and rate in freestyle using inertial sensor technology. J Sports Sci, 27(10), 1051-1058. doi: 10.1080/02640410902998247

- Gabbett, T. (2015). Relationship between Accelerometer Load, Collisions, and Repeated High-Intensity Effort Activity in Rugby League Players. *J Strength Cond Res.* doi: 10.1519/JSC.000000000001017
- Gabbett, T., Jenkins, D., & Abernethy, B. (2010). Physical collisions and injury during professional rugby league skills training. J Sci Med Sport, 13(6), 578-583. doi: 10.1016/j.jsams.2010.03.007
- Gallo, T., Cormack, S., Gabbett, T., Williams, M., & Lorenzen, C. (2015). Characteristics impacting on session rating of perceived exertion training load in Australian footballers. J Sports Sci, 33(5), 467-475. doi: 10.1080/02640414.2014.947311
- Gastin, P. B., McLean, O., Spittle, M., & Breed, R. V. (2013). Quantification of tackling demands in professional Australian football using integrated wearable athlete tracking technology. J Sci Med Sport, 16(6), 589-593. doi: 10.1016/j.jsams.2013.01.007
- Gastin, P. B., McLean, O. C., Breed, R. V., & Spittle, M. (2014). Tackle and impact detection in elite Australian football using wearable microsensor technology. J Sports Sci, 32(10), 947-953. doi: 10.1080/02640414.2013.868920
- Godfrey, A., Conway, R., Meagher, D., & OLaighin, G. (2008). Direct measurement of human movement by accelerometry. *Med Eng Phys*, 30(10), 1364-1386. doi: 10.1016/j.medengphy.2008.09.005
- Halson, S. L. (2014). Monitoring training load to understand fatigue in athletes. *Sports Med, 44 Suppl 2*, S139-147. doi: 10.1007/s40279-014-0253-z
- Hopkins, W. G. (2000). Measures of reliability in sports medicine and science. *Sports Med*, *30*(1), 1-15.
- Hopkins, W. G. (2002). A Scale of Magnitudes for Effect Statistics. In: *A New View of Statistics*. (http://www.sportsci.org/resource/stats)
- Hopkins, W. G. (2011). Precision of measurement In: A New View of Statistics. (newstats.org/precision.html)

- Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Med Sci Sports Exerc*, *41*(1), 3-13. doi: 10.1249/MSS.0b013e31818cb278
- Impellizzeri, F. M., Rampinini, E., & Marcora, S. M. (2005). Physiological assessment of aerobic training in soccer. J Sports Sci, 23(6), 583-592. doi: 10.1080/02640410400021278
- Jennings, D., Cormack, S., Coutts, A. J., Boyd, L., & Aughey, R. J. (2010). The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *Int J Sports Physiol Perform*, 5(3), 328-341.
- Jennings, D., Cormack, S. J., Coutts, A. J., & Aughey, R. J. (2012). GPS analysis of an international field hockey tournament. *Int J Sports Physiol Perform*, 7(3), 224-231.
- Johnston, R. J., Watsford, M. L., Pine, M. J., Spurrs, R. W., Murphy, A. J., & Pruyn, E. C. (2012). The validity and reliability of 5-Hz global positioning system units to measure team sport movement demands. *J Strength Cond Res*, 26(3), 758-765. doi: 10.1519/JSC.0b013e318225f161
- Karcher, C., & Buchheit, M. (2014). On-court demands of elite handball, with special reference to playing positions. *Sports Med*, 44(6), 797-814. doi: 10.1007/s40279-014-0164-z
- Kavanagh, J. J., & Menz, H. B. (2008). Accelerometry: a technique for quantifying movement patterns during walking. *Gait Posture*, 28(1), 1-15. doi: 10.1016/j.gaitpost.2007.10.010
- Kelly, S. J., Murphy, A. J., Watsford, M. L., Austin, D., & Rennie, M. (2015). Reliability and validity of sports accelerometers during static and dynamic testing. *Int J Sports Physiol Perform*, 10(1), 106-111. doi: 10.1123/ijspp.2013-0408
- Krasnoff, J. B., Kohn, M. A., Choy, F. K., Doyle, J., Johansen, K., & Painter, P. L. (2008). Interunit and intraunit reliability of the RT3 triaxial accelerometer. J Phys Act Health, 5(4), 527-538.
- Larsson, P. (2003). Global positioning system and sport-specific testing. *Sports Med*, 33(15), 1093-1101.

- Luinge, H. J., & Veltink, P. H. (2005). Measuring orientation of human body segments using miniature gyroscopes and accelerometers. *Med Biol Eng Comput, 43*(2), 273-282.
- Michalsik, L. B., Madsen, K., & Aagaard, P. (2014). Match performance and physiological capacity of female elite team handball players. *Int J Sports Med*, 35(7), 595-607. doi: 10.1055/s-0033-1358713
- Michalsik, L. B., Aagaard, P., & Madsen, K. (2013). Locomotion characteristics and match-induced impairments in physical performance in male elite team handball players. *Int J Sports Med*, *34*(7), 590-599. doi: 10.1055/s-0032-1329989
- Mohr, M., Krustrup, P., & Bangsbo, J. (2003). Match performance of high-standard soccer players with special reference to development of fatigue. J Sports Sci, 21(7), 519-528. doi: 10.1080/0264041031000071182
- Montgomery, P. G., Pyne, D. B., & Minahan, C. L. (2010). The physical and physiological demands of basketball training and competition. *Int J Sports Physiol Perform*, 5(1), 75-86.
- Ogris, G., Leser, R., Horsak, B., Kornfeind, P., Heller, M., & Baca, A. (2012). Accuracy of the LPM tracking system considering dynamic position changes. J Sports Sci, 30(14), 1503-1511. doi: 10.1080/02640414.2012.712712
- Page, R. M., Marrin, K., Brogden, C. M., & Greig, M. (2015). Biomechanical and Physiological Response to a Contemporary Soccer Match-Play Simulation. J Strength Cond Res, 29(10), 2860-2866. doi: 10.1519/JSC.00000000000949
- Polglaze, T., Dawson, B., Hiscock, D. J., & Peeling, P. (2015). A comparative analysis of accelerometer and time-motion data in elite men's hockey training and competition. *Int J Sports Physiol Perform*, 10(4), 446-451. doi: 10.1123/ijspp.2014-0233
- Polley, C. S., Cormack, S. J., Gabbett, T. J., & Polglaze, T. (2015). Activity profile of high-level Australian lacrosse players. J Strength Cond Res, 29(1), 126-136. doi: 10.1519/JSC.00000000000599
- Povoas, S. C., Seabra, A. F., Ascensao, A. A., Magalhaes, J., Soares, J. M., & Rebelo, A. N. (2012). Physical and physiological demands of elite team handball. J Strength Cond Res, 26(12), 3365-3375. doi: 10.1519/JSC.0b013e318248aeee

- Powell, S. M., & Rowlands, A. V. (2004). Intermonitor variability of the RT3 accelerometer during typical physical activities. *Med Sci Sports Exerc*, *36*(2), 324-330. doi: 10.1249/01.MSS.0000113743.68789.36
- Pyne, D. (2003). Interpreting the results of fitness testing In: *International Science and Football Symposium*.
- Pyne, D. B., Spencer, M., & Mujika, I. (2014). Improving the value of fitness testing for football. Int J Sports Physiol Perform, 9(3), 511-514. doi: 10.1123/ijspp.2013-0453
- Rampinini, E., Impellizzeri, F. M., Castagna, C., Coutts, A. J., & Wisloff, U. (2009). Technical performance during soccer matches of the Italian Serie A league: effect of fatigue and competitive level. J Sci Med Sport, 12(1), 227-233. doi: 10.1016/j.jsams.2007.10.002
- Scott, B. R., Lockie, R. G., Knight, T. J., Clark, A. C., & Janse de Jonge, X. A. (2013). A comparison of methods to quantify the in-season training load of professional soccer players. *Int J Sports Physiol Perform*, 8(2), 195-202.
- Scott, M. T., Scott, T. J., & Kelly, V. G. (2015). The validity and Reliability of Global Positioning Systems In Team Sport: A Brief Review. J Strength Cond Res. doi: 10.1519/JSC.000000000001221
- Stolen, T., Chamari, K., Castagna, C., & Wisloff, U. (2005). Physiology of soccer: an update. Sports Med, 35(6), 501-536.
- Varley, M. C., & Aughey, R. J. (2013). Acceleration profiles in elite Australian soccer. *Int J Sports Med*, 34(1), 34-39. doi: 10.1055/s-0032-1316315
- Varley, M. C., Gabbett, T., & Aughey, R. J. (2014). Activity profiles of professional soccer, rugby league and Australian football match play. J Sports Sci, 32(20), 1858-1866. doi: 10.1080/02640414.2013.823227
- Welk, G. J. (2005). Principles of design and analyses for the calibration of accelerometry-based activity monitors. *Med Sci Sports Exerc*, 37(11 Suppl), S501-511.
- Wisbey, B., Montgomery, P. G., Pyne, D. B., & Rattray, B. (2010). Quantifying movement demands of AFL football using GPS tracking. J Sci Med Sport, 13(5), 531-536. doi: 10.1016/j.jsams.2009.09.002

- Wundersitz, D. W., Gastin, P. B., Richter, C., Robertson, S. J., & Netto, K. J. (2014). Validity of a trunk-mounted accelerometer to assess peak accelerations during walking, jogging and running. *Eur J Sport Sci*, 1-9. doi: 10.1080/17461391.2014.955131
- Wundersitz, D. W., Gastin, P. B., Robertson, S., Davey, P. C., & Netto, K. J. (2015). Validation of a Trunk-mounted Accelerometer to Measure Peak Impacts during Team Sport Movements. *Int J Sports Med*, 36(9), 742-746. doi: 10.1055/s-0035-1547265
- Yang, C. C., & Hsu, Y. L. (2010). A review of accelerometry-based wearable motion detectors for physical activity monitoring. *Sensors (Basel)*, 10(8), 7772-7788. doi: 10.3390/s100807772
- Young, W. B., Hepner, J., & Robbins, D. W. (2012). Movement demands in Australian rules football as indicators of muscle damage. J Strength Cond Res, 26(2), 492-496. doi: 10.1519/JSC.0b013e318225a1c4

List of tables

Table 4.1 Reliability between microsensors for IMA magnitude and IMA direction values from handball-specific movement tasks.	26
Table 4.2 Reliability between microsensors for accumulated IMA counts in handball training.	
Table 4.3 Reliability between microsensors for accumulated IMA counts in handball training.	
Table 4.4 Reliability between microsensors for accumulated Player Load and associativariables in handball training.	

List of figures

Figure 3.1 The OptimEye S5 device (left). Two devices were taped together (middle), and fitted in a custom-made vest (right) during data collection in a laboratory and field assessment. 19
Figure 3.2 IMA counts can be divided into low, medium and high intensity based on IMA magnitude, or divided into forward, backward, left lateral and right lateral direction based on IMA direction. The figure is modified from Catapult Sports (2013a)
Figure 3.3 Illustration of the movement tasks. Well-controlled one-step actions: start action (T1), stop action (T2), left CoD (T3) and right CoD (T4). Chaotic movement patterns: lateral CoD (T5), start-stop action (T6) and multidirectional CoD (T7) 22
Figure 4.1 The variation between two microsensors for IMA magnitude $(m \cdot s^{-1})$ and IMA direction (degrees; deg) values from handball-specific movement tasks: one-step action (a; n = 319 IMA events), lateral CoD (b; n = 1136 IMA events), start-stop action (c; 859 IMA events) and multidirectional CoD (d; n = 1296 IMA events)
Figure 4.2 The relationship between two microsensors for accumulated IMA counts (a) and Player Load (b) in handball training. $n = 83$

Abbreviations

CI	Confidence interval
CoD	Change of direction
CV	Coefficient of variation
GPS	Global positioning system
ICC	Intraclass correlation coefficient
IMA	Inertial movement analysis
LPS	Local positioning system
MEMS	Micro-electro-mechanical systems
SD	Standard deviation
SWD	Smallest worthwhile difference
TE	Typical error of measurement

Appendix

- I Reliability statistics from field assessment
- II Information to subjects laboratory assessment (Norwegian)
- III Information to subjects field assessment (Norwegian)
- IV Approval of data storage Norwegian Social Science Data Service (Norwegian)

	Absolute			
Variables*	ТЕ	90% CI	SWD	ICC
Player Load	4.14	3.68 - 4.76	16.02	1.00
Player Load min ⁻¹	0.06	0.05 - 0.07	0.20	1.00
Player Load ^{2D}	2.65	2.35 - 3.05	9.63	1.00
Player Load ^Y	0.72	0.64 - 0.83	5.56	1.00
Player Load ^X	3.05	2.71 - 3.50	7.08	0.99
Player Load ^Z	3.80	3.37 - 4.37	11.57	1.00

Table x Reliability between microsensors for accumulated Player Load and associated variables in handball training.

Note: TE, typical error of measurement (*abs*; absolute); *CV*, coefficient of variation; *CI*, confidence interval; *SWD*, smallest worthwhile difference. n = 83.

*2D, antero-posterior and medio-lateral axes; Y, antero-posterior axis; X, medio-lateral axis; Z, vertical axis.

	Absolute			
Intensity bands	TE	90% CI	SWD	ICC
Low	11.76	10.43 - 13.51	19.37	0.99
Medium	6.41	5.69 - 7.36	6.31	0.96
High	4.17	3.70 - 4.79	5.47	0.98
Medium/High	7.30	6.48 - 8.39	11.15	0.98
Total	13.93	12.36 - 16.00	28.74	0.99

Table x Reliability between microsensors for accumulated IMA counts in handball training.

Note: TE, typical error of measurement (*abs*; absolute); *CV*, coefficient of variation; *CI*, confidence interval; *SWD*, smallest worthwhile difference. n = 83.

		Absolute		
Direction bands [*]	TE	90% CI	SWD	ICC
Forward (n)				
Low	5.27	4.67 - 6.05	3.01	0.88
Medium	3.14	2.79 - 3.61	1.55	0.84
High	3.11	2.76 - 3.57	2.24	0.92
Medium/High	4.05	3.59 - 4.65	3.48	0.95
Total	6.92	6.14 - 7.95	5.65	0.94
Backward (n)				
Low	5.63	5.00 - 6.47	4.28	0.93
Medium	2.63	2.34 - 3.03	1.48	0.88
High	1.85	1.64 - 2.13	1.18	0.90
Medium/High	3.49	3.10 - 4.01	2.25	0.91
Total	7.78	6.90 - 8.94	5.86	0.93
Left lateral (n)				
Low	10.06	8.93 - 11.56	10.11	0.96
Medium	3.86	3.43 - 4.44	3.11	0.94
High	1.93	1.72 - 2.22	1.97	0.96
Medium/High	4.58	4.07 - 5.27	4.80	0.96
Total	13.13	11.65 - 15.08	13.98	0.97
Right lateral (n)				
Low	9.10	8.08 - 10.46	9.37	0.96
Medium	3.31	2.94 - 3.80	2.73	0.94
High	2.01	1.78 - 2.31	2.10	0.96
Medium/High	3.72	3.30 - 4.27	4.49	0.97
Total	10.52	9.34 - 12.09	12.80	0.97

Table x Reliability between microsensors for accumulated IMA counts in handball training.

Note: TE, typical error of measurement (*abs*; absolute); *CV*, coefficient of variation; *CI*, confidence interval; *SWD*, smallest worthwhile difference. n = 83.

*IMA counts were categorized within direction bands and divided further into intensity bands.

Forespørsel om deltakelse i forskningsprosjektet: *"Wearable microsensor technology to measure the physical activity demands in handball"*

Bakgrunn og hensikt

Dette er en forespørsel til deg om å delta i en forskningsstudie for å undersøke reliabiliteten av et akselerometer basert trackingsystem, designet for lagidrett. Studien er en del av et forskningsprosjekt ved Norges idrettshøgskole, hvor hensikten er å kartlegge bevegelseskarakteristikk og fysiologisk belastning under trening og kamp i norsk håndball. Prosjektet gjennomføres i samarbeid med Norges Håndballforbund og informasjonen vil kunne brukes til å forbedre planlegging av trening og belastningsstyring. Systemets nøyaktighet er imidlertid vesentlig for hvordan data kan tolkes. Vi ønsker derfor å undersøke inter-enhet reliabiliteten av systemet, i forhold til håndballspesifikke bevegelser. For å delta som forsøksperson må du være regelmessig fysisk aktiv og ha erfaring fra lagidrett.

Hva innebærer studien?

Deltagelse i prosjektet vil kreve at du møter opp og deltar på to separate testdager ved Norges idrettshøgskole. Varighet av forsøket er beregnet til omtrent 60 min, og består av ulike eksplosive agility bevegelser, hvor deltagere bruker en spesiallaget vest, integrert med to elektroniske transmittere. Tidspunkt avtales individuelt.

Mulige ulemper og risiko

Testene utføres ved maksimal intensitet, noe som vil oppleves anstrengende. Dette kan forårsake noe ubehag, men ikke mer enn hva du er kjent med fra å ha drevet med lagidrett. Studien innebære dermed få ulemper for deg.

Hva skjer med prøvene og informasjonen om deg?

Prøvene tatt av deg og informasjonen som registreres om deg skal kun brukes slik som beskrevet i hensikten med studien. Alle opplysninger vil bli behandlet uten navn og fødselsnummer, eller andre direkte gjenkjennende opplysninger. En tallkode knytter deg til dine data gjennom en navneliste, som kun autorisert personell har tilgang til. Det betyr at alle data vil bli behandlet anonymt. Data vil presenteres eller publiseres på gruppenivå, slik at det ikke vil være mulig å identifisere deg i resultatene.

Frivillig deltagelse

Dersom du ønsker å delta, undertegner du samtykkeerklæringen. Du kan senere når som helst og uten å oppgi noen grunn trekke ditt samtykke til å delta i studien. Dersom du ønsker å trekke deg eller har spørsmål til studien, kan du kontakte masterstudent Benjamin R. Holme (tlf. 41283881) eller veileder Matthew Spencer (tlf. 98404378).

Samtykke til deltagelse i studien

Jeg er villig til å delta i studien

(signert av prosjektdeltaker, dato)

Jeg bekrefter å ha gitt informasjon om studien

(signert, rolle i studien, dato)

Forespørsel om deltakelse i forskningsprosjektet: *"Wearable microsensor technology to measure the physical activity demands in handball"*

Bakgrunn og hensikt

Dette er en forespørsel til deg om å delta i en forskningsstudie for å undersøke reliabiliteten av et akselerometer basert trackingsystem, designet for lagidrett. Studien er en del av et større forskningsprosjekt ved Norges idrettshøgskole, hvor hensikten er å kartlegge bevegelseskarakteristikk og fysiologisk belastning under trening og kamp i norsk håndball. Prosjektet gjennomføres i samarbeid med Norges Håndballforbund og informasjonen vil kunne brukes til å forbedre planlegging av trening og belastningsstyring. Systemets nøyaktighet er vesentlig for hvordan data kan tolkes. Vi ønsker derfor også å undersøke inter-enhet reliabiliteten av systemet, i forhold til håndballspesifikke bevegelsesmønstre. For å delta som forsøksperson må du spille håndball aktivt ved norsk elite nivå.

Hva innebærer studien?

Deltagelse i prosjektet vil kreve at du bruker en spesiallaget vest under drakten, integrert med en eller to elektroniske transmittere under henholdsvis kamp og trening. Du vil bli overvåket i et minimum av åtte treninger og fire kamper. Treningshverdagen vil foregå som normalt, studien ønsker ikke å påvirke rammene rundt trening og kamp. Tidspunkt for overvåking avtales med lagets hovedtrener, slik det passer inn.

Mulige ulemper og risiko

Det er få ulemper assosiert ved å delta i studien. Vesten som benyttes er tettsittende og designet som en sports bh, transmitter lokalisert øverst på ryggen. Det er risiko for å oppleve noe ubehag av transmitteren(e) ved dueller og fall, men dette er noe vi ikke har hatt problem med tidligere.

Som deltagere i studien vil du kunne få innblikk i din eksterne belastning under trening og kamp. Dette vil gi deg god kontroll over totalbelastning og legge til rette for fornuftig belastningsstyring.

Hva skjer med prøvene og informasjonen om deg?

Prøvene tatt av deg og informasjonen som registreres om deg skal kun brukes slik som beskrevet i hensikten med studien. Alle opplysninger vil bli behandlet uten navn og fødselsnummer, eller andre direkte gjenkjennende opplysninger. En tallkode knytter deg til dine data gjennom en navneliste, som kun autorisert personell har tilgang til. Det betyr at alle data vil bli behandlet anonymt. Data vil presenteres eller publiseres på gruppenivå, slik at det ikke vil være mulig å identifisere deg i resultatene.

Frivillig deltagelse

Dersom du ønsker å delta, undertegner du samtykkeerklæringen. Du kan senere når som helst og uten å oppgi noen grunn trekke ditt samtykke til å delta i studien. Dersom du ønsker å trekke deg eller har spørsmål til studien, kan du kontakte masterstudent Benjamin R. Holme (tlf. 41283881) eller veileder Matthew Spencer (tlf. 98404378).

Samtykke til deltagelse i studien

Jeg er villig til å delta i studien

(signert av prosjektdeltaker, dato)

Jeg bekrefter å ha gitt informasjon om studien

(signert, rolle i studien, dato)

IV*Approval of data storage – Norwegian Social Science Data Service (Norwegian)*

Norsk samfunnsvitenskapelig datatjeneste AS NORWEGIAN SOCIAL SCIENCE DATA SERVICES

Vår dato: 02.09.2014

Matthew Spencer Seksjon for fysisk prestasjonsevne Norges idrettshøgskole Postboks 4014 0806 OSLO

Vår ref: 39602 / 3 / LT



TILBAKEMELDING PÅ MELDING OM BEHANDLING AV PERSONOPPLYSNINGER

Vi viser til melding om behandling av personopplysninger, mottatt 28.08.2014. Meldingen gjelder prosjektet:

Deres dato:

Deres ref:

39602	Arbeidskravsanalyse av håndballspillere på nasjonalt/internasjonalt nivå - fysiske krav og taktiske profiler
Behandlingsansvarlig	Norges idrettshøgskole, ved institusjonens øverste leder Matthew Spencer
Daglig ansvarlig	Matthew Spencer

Personvernombudet har vurdert prosjektet og finner at behandlingen av personopplysninger er meldepliktig i henhold til personopplysningsloven § 31. Behandlingen tilfredsstiller kravene i personopplysningsloven.

Personvernombudets vurdering forutsetter at prosjektet gjennomføres i tråd med opplysningene gitt i meldeskjemaet, korrespondanse med ombudet, ombudets kommentarer samt personopplysningsloven og helseregisterloven med forskrifter. Behandlingen av personopplysninger kan settes i gang.

Det gjøres oppmerksom på at det skal gis ny melding dersom behandlingen endres i forhold til de opplysninger som ligger til grunn for personvernombudets vurdering. Endringsmeldinger gis via et eget skjema, http://www.nsd.uib.no/personvern/meldeplikt/skjema.html. Det skal også gis melding etter tre år dersom prosjektet fortsatt pågår. Meldinger skal skje skriftlig til ombudet.

Personvernombudet har lagt ut opplysninger om prosjektet i en offentlig database, http://pvo.nsd.no/prosjekt.

Personvernombudet vil ved prosjektets avslutning, 31.12.2018, rette en henvendelse angående status for behandlingen av personopplysninger.

Vennlig hilsen

Katrine Utaaker Segadal

Lis Tenold

Kontaktperson: Lis Tenold tlf: 55 58 33 77 Vedlegg: Prosjektvurdering

Dokumentet er elektronisk produsert og godkjent ved NSDs rutiner for elektronisk godkjenning.

Audelingskantorer / Eistner Offices OSEO: NSD: Universitetet i Oski, PostDicks 1955: Bindem, 0.116: Osko: Tel: +47-22: B5-52: 11. end@hao.no TRONDFIEM: NSD: Norges teitrak-naturitenkagelege universitet, 7491: Bondhem: Tel: +47-37: 59: 19: 07: kyme-siania@hvt.ntmi.no TRONASIT: NSD: SVF, Universitetet i Bromise, 9017: Bromae: Tel: +47-77: 64:43: 36: midmaa@hscut.no