The validity, reliability and sensitivity of utilising a wearable GPS based IMU to determine goalkeeper specific training demands.

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Abstract

Despite the plethora of football focused literature, there is still very little known about the training practices of the goalkeeper (GK). The development of portable Global Positioning System (GPS) and Inertial Measurement Unit (IMU) devices ensured physical activities can be accurately measured within the training environment. The integration of inertial sensor fusion algorithms has allowed the IMU the ability to also detect non-locomotive activities that are specific to a sport. This technology is shown to be a valid method of analysis for the demands of an outfield football player, however, similar research into the GK position is required. Thus, the aim of this study was to investigate the validity, reliability and sensitivity of utilizing a wearable GPS based IMU to determine goalkeeper specific training demands.

A total of 123 event variables were recorded via OptimEye G5 GPS units over 14 sessions from 6 professional GKs during the 2017-2018 Scottish Premiership season. GPS data was collected as part of normal daily monitoring and compared against corresponding computerized notational analysis of the same training sessions. Event variables were split into specific IMU events by a GK specific algorithm: Total Dives (TD), Dives Right (DvR), Dives Left (DvL), Dive Returns (DR) and Jumps. The intra-unit variation was derived from reproducibility of trends within the difference between GPS and corresponding Video Analysis (VA) counts. Unit sensitivity was investigated according to the relationship between average DR times and countermovement jump (CMJ) and ballistic press-up (BP) results which corresponded to lower and upper body velocity at peak power (m/s) respectively.

There was no significant difference ($p<0.05$) between TD (91% false positive), DvL (89% false positive), DvR (87% false positive) and DR (78% false positive) but this was not the case for Jumps (18% false positive; $p>0.05$). Bland Altman 95% Limits of Agreement (LOA) show minimal variation for TD (-3.6 to 5.6), DvL (-1.75 to 4.04) and DvR (-3.38 to 3.13). However, DR (-13 to 12.6) and Jumps (-8.8 to 15.7) showed much wider LOA and variation from VA counts. Intra-unit variability was significantly different across all metrics with GPS units, over-estimating movement event counts compared to VA counts. Inter-unit sensitivity suggested that CMJ and lower body velocity at peak power (m/s) performance had the greatest correlation ($r=0.992$) with average DR times compared to BP and upper body velocity at peak power ($r=0.684$) and CMJ + BP combined ($r=0.603$).

Based on these findings, the sensitivity of the OptimEye G5 GPS to count GK specific events was almost perfect (r = 903), however, the specificity of the IMU algorithm to distinguish the different movements was questionable. Jumps were significantly over-estimated, and in the meantime, we would suggest using video footage to compliment GPS data for accurate longitudinal analysis. This study provided novel information regarding the DR action, of which the lower body muscular profile plays the dominant part in. Although there are limitations within this study, these investigations should only act as the first step in understanding if the GPS coupled IMU has a place in accurately determining the training demands of a goalkeeper.

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Declaration of Originality

I declare, except where explicit reference is made to the contributions of others, that this dissertation is the result of my own work and has not been submitted for any other degree here at the University of Glasgow or at any other institution.

Signature:……………………………………………………………………………

Date:……………………………………………………………………………..

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Abbreviations List

ANOVA	One Way Analysis of Variance
BP	Ballistic Press-up
CV%	Coefficient of Variation
CMJ	Countermovement Jump
DR	Dive Return
DvL	Dive Left
DvR	Dive Right
GK	Goalkeeper
GPS	Global Positioning System
HSD	Honestly Significant Sifference
IMU	Inertial Measurement Sensor
LOA	Limits of Agreement
MD	Match Day
MEMS	Microelectronic Mechanical Systems
SD	Standard Deviation
SSG	Small Sided Game
TD	Total Dives
TEE	Typical Error of Estimate
VA	Video Analysis
$\dot{V}O_{2max}$	Maximal Oxygen Uptake

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1. Literature Review

1.1 Introduction & Overview

Football is an internationally recognised sport, played in every country across the world from developmental to professional level in both the men's and women's game (Mujika et al., 2009). Due to its increasing popularity, the commercialization process has intensified as well as the financial rewards and losses of playing at a top tier level. While the duration of each match has remained relatively constant, match schedules have become increasingly congested. In the Scottish Premiership alone, teams play up to 50 games between August and May, including domestic league and cup games. The top teams in the Scottish Premiership are also entered into Champions League or Europa League Qualification rounds adding mid-week match fixtures. On top of this, players selected to represent their home nations must also play international fixtures and tournaments. This progressive increase in the volume of competitive fixtures being observed in the elite level of football produces a greater physiological demand on players, leaving fewer days between match fixtures to recover and optimise training.

This increase in match load means that in-season training programs are becoming more maintenance and recovery based rather than developmental to prevent fatigue accumulation. It is also important for coaching staff to monitor the content of training sessions to optimise the limited contact time available. As a result, there has been an extensive increase in football based research, particularly around the applications of accurate activity monitoring technology and the physical demands of match play and training. These monitoring techniques allow practitioners to record match content and thus manipulate training sessions to produce an appropriate physiological stimulus. Surprisingly, the goalkeeper position is often excluded from this literature, despite their importance to the team's success. Their unique purpose within the game requires specialised training and so the physiological characteristics and physical demands of the GK position are much different to that of their outfield counterparts. As a result, researchers often exclude the potentially outlaying data and focus on the dominant position within the game. Unfortunately, this has limited the volume of available research into the match and training demands of the GK and practitioners tend to use outfield based monitoring technology to monitor match and training demands, if any at all.

Manual and computerised notational analysis methods have proven to be valid and reliable means of monitoring in team sports (Reilly & Thomas, 1976; De Baranda et al., 2002; Bradley et al., 2009). However, they can be labour intensive, require extensive installation processes and may lack the accuracy required to measure the demands of non-locomotive activities such as that of a goalkeeper (Padulo et al., 2015). The commercialisation of portable Global Positioning System (GPS) and Inertial Measurement Unit (IMU) devices ensured physical activities could be accurately measured within the training environment and real time analysis could be conducted as an alternative to the labour intensive motion analysis (Dwyer & Gabbet, 2012; Malone et al, 2017b). The integration of inertial sensor fusion algorithms has allowed the IMU the ability to detect non-locomotive activities that are specific to a sport such as collisions in rugby league (Reardon et al. 2017), jumping in volleyball (Gageler, Wearing & James 2017) and aerial acrobatics in skiing/snowboarding (Lee et al. 2015). This technology is shown to be a valid method of analysis for the demands of an outfield football player, however, similar research into the GK is needed. Such information of the physiological load imposed during training would offer practitioners a greater understanding into the physical demands within training.

The following review will explore the physiological differences between outfield positions and goalkeepers in football. Various methods of external training analysis will be discussed. I will provide a historical overview and critique of past and current methods of performance analysis in field sports, in particular repeated sprint ability sports such as football and rugby. A rational for a more detailed analysis of the physical demands in dynamic movement sports and the proposal for the use of sophisticated IMU based GPS for physical performance analysis will then be provided. A valid method would allow practitioners to accurately monitor GK specific training load and also provide information to deliver more specific and therefore more optimal physical conditioning programs which would ultimately enhance GK performance.

1.2 Physiological Demands of Football

1.2.1 Outfield Players

Elite football is described as a high intensity intermittent team sport (Bangsbo et al., 2006). Outfield football players must display high levels of endurance, strength, speed and agility, taxing multiple metabolic energy systems and causing significant mechanical loading of the musculoskeletal system (Stolen et al., 2005).

For outfield players, the match day is the greatest physiological load of the training week (Malone et al., 2015). Over a 90-minute game, players can cover a distance of 10-12km, most of which by walking and low intensity running (Bangsbo, Mohr & Krustrup, 2006). Match intensity has been shown to reach approximately 85% of maximum heart rate and an expenditure of 75% of maximal oxygen consumption thus taxing primarily the aerobic metabolic system (Stolen et al., 2006; Bangsbo, Mohr & Krustrup, 2006). Players must also possess a well-developed anaerobic system as high intensity running accounts for 10% of total distance, while sprint bouts occur every 90 seconds lasting ~2-4s, interspersed with recovery periods (Stolen et al, 2005). Several studies have found that high intensity activity separates the top class players from that of a lower standard (Stolen et al., 2005). Mohr et al., (2003) found international players performed 28% more ($p<0.05$) high intensity running (2.43 vs 1.90km) and 58% more sprinting (650 vs 410m) than professional players of a lower standard. Additional anaerobic efforts of discrete activities such as jumps, kicks, tackles and changes of direction, with and without the ball, at varying frequencies and intensities, are also performed throughout the game (Stolen et al, 2005, Buchheit et al, 2010; Akenhead et al., 2014). Match demands have also been shown to differ positionally; mid-fielders usually cover the most over-all distance while fullbacks and attackers tend to cover a greater distance at high speed than central-backs and midfielders (Bangsbo et al, 2006). It is the accumulation of these individual player demands that can lead to significant mechanical loading of the musculoskeletal system and metabolic system during a match.

Training content and goals must be focused on match requirements, thus inflicting an appropriate training stimulus (Barry, 2009). During the days prior to the match, training load has been shown to fluctuate. Coaches commonly inflict a similar over all training load on the majority of training days then de-loading on the day before the match in order to limit fatigue (Malone et al., 2015). However, if there are two matches per week, this narrows the training window and the primary objective becomes implementing recovery strategies and effective training load monitoring in order to maintain optimum athlete health. Due to the physical and technical elements of outfield player demands discussed previously, the external loading points of interest are highly locomotion based; total distance (Casamichana et al., 2013), high speed running (>14.4km.hr), number of impacts and number of accelerations >3m.s^{-2} (Gaudino et al., 2015). Technology used to measure these points of interest during matches and training sessions should therefore compliment this.

1.2.2 Goalkeepers

Goalkeepers have a highly specific position within a football team. A goalkeeper's ability to protect the goal can win or lose a game (Matsukura, Asai & Sakamoto, 2014). They are required to perform various short but strenuous defensive and offensive aspects which are integral to match play. These include defensive acts such as diving or jumping to catch a shot, deflecting and saving a shot in one-on-one situations as well as offensive acts such as distribution and kicking of the ball to offensive players (Ziv & Lidor, 2011).

During a competitive game, the GK requires relatively low aerobic energy demands. The locomotive movements of elite GKs consist of walking (4,025m) and jogging (1,233±256m) with significantly less distance covered running (221±90m), at high speed running (56±34m) and sprinting (11±12m) (Di Salvo et al., 2008). When we compare the average locomotive data of GKs to outfield players, GKs cover approximately 50% less distance (5,611m vs 10,714m) and approximately 90% less sprint distance (61m vs 905m) during a game. Considering GKs spend around 44.4% of their game time within the penalty area (16x40 meters) (De Baranda et al., 2002), this suggests that the lack of high speed running is due to the restriction in space compared to outfield players. This also explains the large difference in $\dot{V}O_{2max}$ between male GKs (50-55mL/kg/min) and out-field football players (50-

75mL/kg/min). The locomotive demands and aerobic capacity of GKs compared to their outfield counterparts are much less and physiological demands lie elsewhere.

The physical actions required of a goalkeeper during a match are determined pre-dominantly by the anaerobic energy system with the majority of activity comprised of dives (6.2±2.7), jumps (3.8 ± 2.3) and displacements (18.7±6) (De Baranda et al., 2002). These are short, accelerated and technically demanding actions requiring high levels of strength, power and agility (Ziv & Lidor, 2011). GKs are shown to have the best average results for vertical jump power compared to outfield players as shown by squat jump (46.8 ± 1.4cm vs 44.1 ± 1.3cm respectively) and CMJ (48.5 ± 1.5cm vs 45.1 ± 1.7cm respectively) results (Sporis et al., 2009). However, GKs were found to be the slowest players in the team over 10m (2.35 ± 0.8s) and 20m (3.51 ± 0.9s) but not over 5m (1.45 ± 0.7s), indicating their power and acceleration abilities over shorter distances but reduced maximal velocity capacities. For example, the goalkeeper must have the ability to react quickly to save the ball. During a penalty kick, it takes 400-600ms for the ball to reach the goal from the penalty spot (Kuhn, 1988). The goals are 7.32 x 2.44m in size so huge amounts of power, force and skill are needed to cover this area and prevent a possible goal. Goalkeepers are, on average, the tallest players in the team (185 ± 3.1cm) and also the heaviest (81 ± 2.3kg) with the highest body fat percentage (14.2 ± 1.9%) compared with other positions (Sporis et al., 2009). This has been attributed to the lower aerobic metabolic demands and distance covered and may also be part related to the slower sprinting performance. Clearly the match physical requirements of goalkeepers are significantly different to those of outfield players.

Due to their specialized role, very little outfield player focused literature has included the GK position, especially with regards to training content. In comparison with the training periodisation across in-season training micro-cycles, professional outfield players were found have greater mean total distance values (4000-6000m) compared to that of GKs (2553-3742m) (Malone et al., 2015; Owen et al., 2016; Malone et al., 2017). Malone et al., (2017) found that GKs only cover ~17% of high-speed distance running compared to that of outfield players. Goalkeeper specific training drills are conducted in restricted spaces, limiting the ability to reach higher speed thresholds. However, when comparing periodisation patterns, to that of outfield players, findings are fairly similar (Malone et al., 2015; Malone et al., 2017). Training load was generally reduced on match day (MD) -1 but remained similar on MD-4 to MD -2. However, this study did not include GK actions, such as diving and jumping. Total distance, high deceleration efforts and player load only showed a small to moderate correlation with wellness scores. Monitoring the biomechanical loading of the non-locomotive GK specific actions may be more relevant than the locomotor variables used to monitor outfield positions. This was the first study to investigate the in-season training demands of the GK position. As there is currently no published literature of GK specific training load monitoring, this made it difficult to confirm if the results produced are typical for GKs. In order for practitioners to accurately monitor training content and its longitudinal physiological impact, it is important that the appropriate technology can be used and in a valid and reliable way. The following subsections will outline methods which are currently implemented within competitive and training environments.

1.3 Methods of Sports Performance Analysis

Evaluating physical training load is particularly important in team sports, such as football, due to demanding match schedules and sometimes limited time for effective training periodization. This can create implications for injuries depending on individual tolerances to accumulated training and competition load, therefore, it is vital to accurately monitor internal and external responses to these demands. This would allow practitioners to design specific programs knowing exactly what physiological response they would like to elicit, making coach-athlete contact time more productive. The development in technology has produced several methods of match and training analysis for outfield players that include the use of video or notational analysis – manual notational analysis, multi-camera computerised notational analysis and GPS. However, as the demands of the GK are significantly different to other positions on the field, the application of outfield technology being directly applied to GKs requires investigation.

1.3.1 Manual Notational Analysis

Motion capture technology has been extensively used in sports performance analysis to monitor the physical content in a wide variety of repeated sprint ability sports: football (Barris & Button, 2008), basketball (Remmert, 2003) and rugby union (Gabbett, Jenkins & Abernethy, 2010). The monitoring of football players during match play was originally achieved using manual video-based notational analysis techniques such as that developed by Reilly & Thomas (1976). These traditional methods involved the positioning of video cameras near the side of the pitch, usually at the level of the midfield line giving the best picture of the field without zooming in or out (Carling et al., 2008). Afterwards, matches would then be played back and subjectively analysed by an investigator and coded for various physical (high speed running, jumps), technical (passes, kicks, tackles) and tactical (set plays, corners) actions through frequency of occurrences, total occurrences and direction of movement (Spalding, 2017; Castellano et al., 2014). However, this type of motion classification system was extremely time consuming and only provided crude measurements of physical exertion for one player at a time. For example, early studies by Erdmann in 1991 and 1992 developed a method of monitoring every moving object on the pitch (players, ball, referee) using a television camera with a wide angle lens (130") placed above the stadium. Due to the cameras half-fish lens, a white tape was laid out to create longitudinal 1m intervals across the pitch to control for any radial distortion. This was then transferred from the tv monitor on to the transparent foil to create a reference grid. By matching the two foils, player displacements could be calculated followed by their velocity and acceleration.

Technological advancements have permitted the development of better quality cameras and computer software for more sophisticated manual coding methods which have been shown to demonstrate a high level of reliability, objectivity and validity (Carling et al., 2005; Carling et al., 2008). For example, Bloomfield, Polman & O'Donoghue, (2004) used video footage (Sky Sports Interactive Service, British Sky Broadcasting Group, UK) of FA Premier League football matches to focus on individual player movements and actions. The footage was analysed according to movement categories (e.g. walk, sprint, shuffle), directions (e.g. forwards diagonally right, forwards diagonally left) and intensities (e.g. low, medium, high) of outfield players, on and off the ball. By creating a more comprehensive profile, a more detailed account of the physical performance demands of different positions on the pitch was obtained.

Similarly, Mohr, Krustrup & Bangsbo (2003) used computerised time-motion analysis on 18 top-class and 24 moderate professional soccer players. A VHS-format camera was positioned at the midfield line and 30-40m from the touchline in order to achieve a good view of the pitch. The players were individually recorded in up to seven different matches across two seasons. A single experienced observer studied each player’s unique style of locomotion. Afterwards, the video footage was coded for activity patterns: standing (0km.h$_{-1}$), walking (6km.h$_{-1}$), jogging (8km.h$_{-1}$), low-speed running (12km.h$_{-1}$), moderate-speed running (15km.h$_{-1}$), high-speed running (18km.h$_{-1}$), sprinting (30km.h$_{-1}$) and backward running (10km.h$_{-1}$). The locomotor categories were chosen in accordance with Bangsbo et al., (1991). Following detailed analysis of the video footage, the mean speed of each activity was calculated by the time for the player to pass specific points on the pitch, for example, the centre circle or other known distances. The results of the study found that top class players performed more high intensity running during a game compared to players of a less elite standard.

One of the few GK orientated studies was conducted by De Baranda et al., (2008), who analysed the defensive interventions of GKs during the 2002 football World Cup by systematic observation. Four experienced observers used the methodology applied by Remmert, (2003), to examine the GK defensive characteristics surrounding various opposition attacks, movements in front of the goal as well as the most common defensive technical actions carried out within the game. The selected variables were determined using field zones; the area of last pass of attack, the area used for shooting as well as the shooting angle and distance, shots into areas of the goal. Providing such information informs coaches on match behaviours which may influence the planning and content of training sessions. Although this is an indirect means to quantifying goalkeeper characteristics, the study provided valuable information, highlighting areas of GK performance which may need more technical focus. However, applying this method directly to goalkeepers removes the additional detail of measures such as directional changes, jumps and accelerations which are key external loading variables (Castellano et al., 2014; Malone et al., 2017a).

Manual notational analysis has been found to be a useful, non-invasive and relatively inexpensive method of providing information into the physiological demands of sports and characteristics of individual positions within such sports (Carling et al., 2008). However, this method does not allow for real time analysis and human error can still occur in entering data incorrectly due to the subjective nature of player movement recognition, the potential for variable observer reaction to events being performed by the player and different interpretations of performance indicators (Carling et al., 2008). For example, the reliability of video-based time-motion analysis was examined during the 2001-2002 Super 12 rugby union competitions in New Zealand (Duthie, Pyne & Hooper, 2003). Footage was analysed twice by a single investigator one month apart. It was concluded to be only moderately reliable for examining movement demands during competitive rugby. The frequency of individual movements showed good to poor reliability (4.3-13.6% typical error of measurement) while the duration of each movement category had moderate to poor reliability (5.8-11.1% typical error of measurement).

Due to the laborious process involved in manually tracking multiple players in a team, research has tended to focus only on small numbers of players in possession of the ball or on certain positions. Some studies have been left incomplete due to difficulties trying to identify multiple players from the video footage as well as the time required to complete the project (Hughes et al., 1989). This method is also extremely labour-intensive in terms of the capture and analysis of data, which is not ideal as the intense competitive schedules of elite football clubs require data to be available usually within 24-36 hours' post-match (Gabbett, 2013).

1.3.2 Computerized Notational Analysis

Due to the numerous limitations associated with manual video analysis, elite football clubs now opt to use expensive and increasingly advanced computerized video tracking systems. Unlike manual video analysis, multiple player and ball movements can be tracked simultaneously (sampling between 10-25Hz dependent on the system) by automatic tracking processes to produce collective physical, technical and tactical real time match feedback. These systems require the installation of several cameras fixed in optimal positions around the roof of the stadium overlooking the whole pitch. All cameras are in perfect synchronisation with each other and at least two cameras cover each area of the pitch at all times for greater accuracy (Di Salvo et al., 2006). During match situations, such as free-kicks or corners, additional information such as shirt colour, optical character recognition of shirt numbers and prediction of running patterns helps to maintain accurate player identification and tracking (Carling et al., 2008). Researchers have used this automated technology to determine outfield player's activity profiles in relation to a variety of match-related physical performance tests (Rampinini et al., 2007a), comparison of player positions (Carling et al., 2008; Castellano et al., 2014), match half variations and the effect of the quality of the opposition on performance (Rampinini et al., 2007b).

The AMISCO Pro and Prozone systems are currently the most popular and comprehensive computerised motion analysis systems used in professional European football (Carling et al., 2008). Bradley et al., (2009) investigated the high intensity running profile of 370 players across 28 English FA Premier League games using the Vicon colour cameras and the Prozone computerised tracking system. Their results highlighted the differences in high intensity running and total distance between various outfield positions with wide (3138 and 11,535 m) and central midfielders (2825 and 11,450 m) covering greater distances than full-backs (2605 and 10,710 m), attackers (2341 and 10,314 m) and central defenders (1834 and 9885 m). Such findings should be considered within fitness and technical specific training drills in order to make them match specific.

Large scale studies have also shown the longitudinal physical and technical development of the game. Barnes et al., (2014) conducted a study examining the evolution of physical and technical outfield performance across 7 seasons in the English Premier League. The data was again derived from Prozone's multiple camera computerised tracking system. Across the 7-year period, 1036 individual players and 22846 player observations were coded into locomotive speed thresholds, with and without the ball as well as when the ball was out of play. This study also coded matches for technical events based detailing the number of passes (successful and received), number of touches per possession, dribbles, shots, tackle events, corners, possessions won and lost. Analysis indicated high intensity running distance and sprinting distance increased 30-35% between the seven-year period and players performed 40% more passes, with an 8% increase in success rate. There was also an increase in the number of short and medium passes, indicating an increase in match tempo.

The Prozone system has been shown to be a valid tracking method from the studies mentioned previous, especially over long distances. However, this validity decreases with high accelerations and speeds over multi-directions. Di Salvo et al., (2006) compared various displacement and velocity tests, captured by Prozone analysis system within an open roofed stadium, with timing gate data collected for the same runs. They found excellent correlations between 60m running (r = 0.999), 50m curving (r = 0.999) and 15m sprint (r = 0.999) but a slightly less correlation with 20m sprint and turn (r = 0.950) suggesting a possible discrepancy for sprints and changes of direction on the football pitch.

Buchheit et al., (2014) also compared the Prozone system (10 Hz, Leeds, UK) with timing gates within an open roof stadium. Testing protocols included running at varies speeds around a 200m oval track, 40m maximal sprints, L-shaped sprints (10m + 10m, 90º change of direction) and zigzag-shaped sprints (four 5m 90º changes of direction). The Prozone system's accuracy to measure acceleration (over 10m) was poor-moderate with a typical error of estimate (TEE) of 3.6% as was the accuracy to measure change of direction speed based on L-shaped (TEE: 2.7%) and zigzag shaped drills (2.8%). Therefore, highly accelerated and multi-directional movements may be underestimated by this system and require further investigation.

A finite number of studies have analysed the GK position, who are usually only involved in small areas requiring highly accelerated and reactive movements. Di Salvo et al., (2008) used the Prozone System (sample rate 3Hz) to monitor the locomotive activity profile of 62 elite goalkeepers across 109 matches over three seasons of the English Premier League. They found that GKs covered 5611 ± 613m during a 90-minute game, 73% of which by walking and only 2% dedicated to high intensity running. Unlike outfield players, goalkeepers rarely cover high intensity distances greater than 10 meters and activities are highly accelerated such as dives and jumps (De Baranda et al, 2002; Di Salvo et al, 2008). This system had been previously validated for angular displacements of 10+10 meters and showed excellent correlation with the average velocity measured by speed gates over 40-60m but poor correlation with accelerations and displacements of 5-10 meters (Di Salvo et al, 2006; Buchheit et al., 2014). The Prozone system requires an acceleration to be occur for a minimum of 0.5 seconds in order to be classified (Di Salvo et al, 2008) but given their limited space, it may be difficult for a GK to reach this acceleration threshold.

For this reason, Padulo et al., (2015) used two high speed digital cameras (sample rate 210-Hz) to assess the match performance of 10 goalkeepers from the Italian third/forth divisions. One camera was positioned behind the goal and the second was positioned at the side of the pitch, 5m from the touchline. The video footage was analysed afterwards using Dartfish 5.5 Pro motion software for frontal-lateral (left and right) actions, the total number of changes of direction and the total distance covered. From their analysis, the authors found GKs conducted 92 high intensity actions during a game (52 forward and 40 lateral actions), one every ~60 seconds. On average, the GKs covered distances of ~4m, which is in agreement with previous studies (Di Salvo et al., 2008; Ziv & Lidor, 2011). The high speed digital cameras were able to detect novel information regarding the speed of the first meter of forward (1.34 ± 0.08 $m.s^{-1}$) and lateral actions (1.32 ± 0.22 $m.s^{-1}$) and the last meter of forward (4.18 ± 2.34 $m.s^{-1}$) and lateral actions (3.48 ± 0.88 $m.s^{-1}$). Accumulating all high intensity accelerations and actions, this equated to to 270 ± 162.6m of total distance. These results support the suggestion that the Prozone system may not be accurate enough to highlight the highly accelerated and multidirectional demands of the GK performance. Systems with a higher frequency acquisition may be more suitable to investigate the kinematic variables and neuromuscular demands of this unique position.

Unfortunately, multi-camera systems carry a large installation and upkeep expense as well as extensive operator intervention to process the data after capture. However, their ability to provide detailed physical, technical and tactical information to practitioners within 24-48 hours following a match has greatly enhanced research in match analysis. They do not require the players to wear additional technology which could potentially inhibit or restrict natural performance, but their lack of portability means they cannot be used during training sessions. Most training facilities do not have the infrastructure for the multi-camera systems, limiting their use to match analysis. As a result, all of the studies mentioned previously are aimed at match content only. Additionally, these systems do not consider acceleration and abrupt change of direction movements. For the GK position, this may mean important key performance events and neuromuscular loading information are absent from match analysis. Whilst computerised systems have been shown to measure distance and speed to an acceptable standard, a more comprehensive analysis of GK specific match induced stimuli is warranted. A wearable micro sensor technology has been introduced which can complement the existing time motion analysis technology to measure non-locomotive activities. This could lead to a better understanding of the external physical demands of goalkeeping.

1.4 Microsensor Technology

The time intensive method of video analysis must now compete with the ever-developing GPS satellite technology in the sporting and football world. Whilst GPS devices can only be worn during training and friendly matches, the magnitude of data output on player movements has made this technology so desirable to elite football clubs (Gaudino et al., 2015; Malone et al., 2017b). This technology has the ability to collect and process large volumes of data very quickly and provide detailed information on player positions, displacement, velocity and accelerations that video analysis methods could not yet obtain (Dwyer & Gabbet, 2012). Portable GPS devices are worn by each player which draws signal from at least four satellites orbiting the earth to determine player movement. Commercial GPS technology continues to develop and has led to the integration of other inertial measurement units (IMU) such as accelerometers, gyroscopes and magnetometers – collectively known as microelectronic mechanical systems (MEMS). To understand how these inertial sensors measure physical activity, we must first understand their operational principles. The following is a general description, as the manufacturer of the microsensor technology used within the present study did not reveal which specific IMU models were used.

1.4.1 Accelerometer

Accelerometers are motion sensors that can measuring impact, reaction times and body loading from accelerations along one or several axes (Yang & Hsu, 2010): x-axis (front to back), y-axis (left to right), z-axis (up and down). The typical structure of an MEMS accelerometer sensor involves a silicon mass, suspended by springs within the accelerometer frame (Fig. 1). Any displacement of the mass within the case due to external acceleration and movement is measured by the capacitance change between the mass and electrodes and is proportional to the external acceleration (Maenaka, 2008).

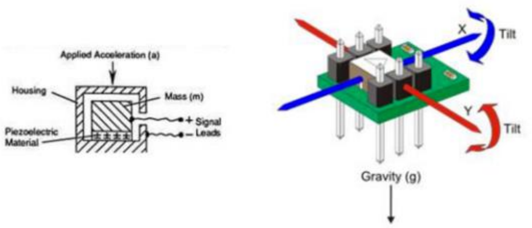


***Figure 1**: Schematic diagram of a triaxial accelerometer (Guard, 2017)*

1.4.2 Gyroscope

A MEMS gyroscope analyses biomechanics and angular velocity (roll, pitch, yaw, turn rate). The structure of the gyroscope is similar to that of the accelerometer. A proof mass, suspended by flexible mechanical springs, is continuously vibrated within the device and the Coriolis force generated by the applied angular velocity affects the movement of the mass (Fig. 2). 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 motion is measured with differential capacitance techniques by use of interdigitated comb electrodes (Patal & McCluskey, 2019).

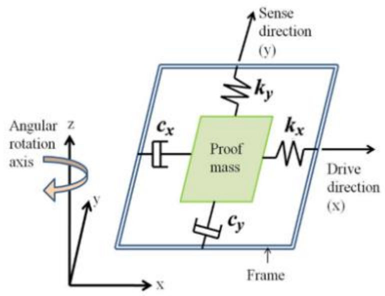


***Figure 2**: Schematic diagram of a triaxial gyroscope (Patel & McCluskey, 2019)*

1.4.3 Magnetometer

The tri-axial magnetometer measures magnetic fields and works in tandem with the accelerometer, gyroscope and GPS to decipher which direction the unit is pointing much like a digital compass (Aminian & Najafi, 2004).

The inertial sensors within commercial GPS units often work in combination to complement each other. For example, gyroscope angular velocities produce additional noise causing orientation drift. The accelerometer and magnetometer can be applied to compensate this drift error and correct the orientation of the gyroscope as the vertical (the gravity) and horizontal (the Earth's Magnetic force) references respectively (Zihajehzadeh et al., 2014).

1.5 The Use of Microsensor Technology in Sport

There are several commercial wearable inertial sensor manufacturers available for team and individual sports. For example; Optimeye and MinimaxX (Catapult Sports, Melbourne, Australia) and Viper pod (STATSports, UK, Ireland). Figure 3 shows the integration of the MEMS inertial sensors with a Catapult GPS unit. As mentioned, GPS is very popular within distance orientated sports and research. On the other hand, it may underestimate the true physical demands of sports involving few locomotor demands (e.g. volleyball jumping, rugby tackling and football goalkeeping). However, these commercial GPS manufacturers often include specific algorithms to help automatically smooth software derived data into relevant and standardised outputs such as event detection variables. This gives the IMU the capacity to register the frequency and distinguish between non-locomotive activities of individual and team sports, both indoors and outdoors, allowing the detection of movements that even video analysis could not easily recognise (Chambers et al., 2015).

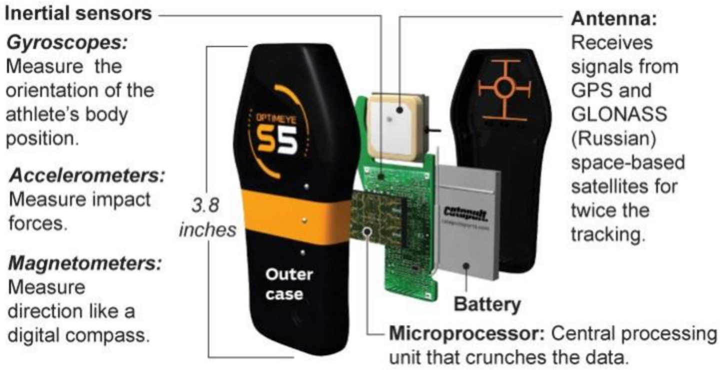


Figure 3*: Integration of inertial sensors of a popular commercial GPS unit (Catapult Innovations, Australia).*

Harding, Small & James, (2007) was one of the first studies to investigate the use of an IMU as an alternative to video analysis for providing specific feedback to coaches and athletes on key performance variables within snowboarding. They used a basic signal processing technique to demonstrate its ability to measure "air-time" and “average degree of rotation" for 4 athletes during an elite level half-pipe snowboarding competition. The technique involved a two-pass filter method which could detect the rapid increase and decrease in acceleration (up/down and forward/backwards) when the snowboarder performs aerial acrobatic skills, accelerating up and out of the half pipe before re-entering. The second pass technique removes unimportant movements whilst performing manoeuvres during a period where the trace is expected to remain at a certain level by focusing on durations of acrobatic air-times that meet the threshold (0.8 – 2.2 seconds). This filtering algorithm technique produced a 100% identification of aerial manoeuvres and presented a strong correlation with the video derived air-time calculation ($r = 0.78 \pm 0.08$).

A study by Gageler, Wearing & James, (2017) validated the ability of a GPS based IMU to detect the jumps count as well as the flight time of each jump of elite volleyball players using a specific algorithm. Data was collected by a 100Hz tri-axial IMU (GPSports Systems, Pty Ltd, Fyshwick, Austrialia) for each athlete during training (~ 1 hour 30 mins). Accompanying video footage was also collected using three 25fps cameras and synchronised with the inertial sensor data. Jumps were defined as "an intentional movement to leave the ground or period of flight not associated with movements around the court such as running," (Gageler, Wearing & James, 2017). The video data was than manually coded for jumps for each athlete by a single observer. The detection method involved a low-pass filter to calculate the magnitude of the anterior-posterior and vertical axes. Further, a conditional filter was then applied to find the key IMU events of the jump which could help recognise the movement from its acceleration trace (take-off and landing). All movements which met these criteria were recognised as jumps. Flight time was estimated by calculating the start and end of flight during the jump. This system performed to a satisfactory level with 95% of jumps detected, 5% being missed and 4% counted as false positives. Jump height was also calculated to within 0.015 ± 0.06m of force plates, similar to that of Nielsen et al., (2018). By using this technology, practitioners processed 17 hours of data within 3 minutes thus the appeal of using GPS based IMU's within the fast paced environment of elite sport.

On the other hand, Reardon et al., (2017) investigated the use of micro technology as an alternative to time-motion analysis for the quantification of collision events in professional rugby union players. Data was collected by a 100Hz IMU (OptimEye S5, Catapult Innovations, Scoresby, VIC Austrialia) across 13 competitive Pro12 rugby matches for 36 different athletes, each within one of the 9 positional sub-categories. For a collision to be registered by the Optimeye S5, it had to reach a collision threshold of between 2 and 5.5g in increments of 0.5g with the maximum impact force threshold set at 15g. Two highly experienced video analysts also gathered collision data from corresponding video footage for each match. While the IMU was found to be an inaccurate method of quantifying rugby union tackles for any playing position, it was able to differentiate between forward and backs and their appropriate g force threshold for detecting collisions (2.5 and 3.5 g respectively).

This is most likely due to the fact that forwards are usually involved in more collisions that backs. However, this study did not separate collision types (e.g. tackles, carries, mauls, rucks) or consider that the IMU used (OptimEye S5) may be better at recognising certain types of collisions more than others. They speculated that further research and work into more specific coding for individual collision types, may gain a better outcome

Chambers, Gabbett & Cole, (2018) validated a microsensor-based scrum algorithm for the automatic detection of scrum events during training and match-play of rugby union. The authors developed an algorithm, based on movement characteristics of the scrum instances identified via video footage and orientation measures of the scrum technique. In order for a scrum to be counted all of these criteria had to be met. The OptimEye S5 device achieved 91% sensitivity and 91% specificity across all positions (front row, second row and back row) when the confidence level was at 50%. By making the algorithm specific to the scrum features, this study achieved a positive outcome compared to Reardon et al., (2017). However, this algorithm only accounts for the scrum count and future research could investigate the actual forces applied during the scrum to make feedback more specific. This advancement in IMU technology could help practitioners to determine the physical load associated with these non-locomotive movements, in order to improve athlete physical preparation and prevent against injury.

There are currently no studies investigating the non-locomotive actions of the goalkeeper position within football. Malone et al., (2018) investigated the training load practices of an elite GK using the OptimEye G5 GPS device (firmware version 717, OptimEye G5; Catapult Sports, Melbourne, Australia). The components of this device are the same as those used in the Catapult S5 model, which has shown to be a valid measure of velocity and distance based metrics (Roe et al., 2017). Results found a weak correlation between training load measures (duration, total distance, high deceleration efforts and load) and a subjective wellness response questionnaire over the course of one full season. This was a single participant case study, therefore it is difficult to make a comprehensive analysis to confirm if the results were true for all GKs. However, it was suggested that more meaningful correlations may be found if position-specific training load parameters are measured instead. Indeed more research into the ability of GPS to quantify GK specific movements within the training environment are required.

1.6 Conclusion

Despite the plethora of football focused literature, there is still very little known about the training practices of the goalkeeper position. The GK is vital to a football teams' success, being the last line of defence between the opposition and the goal, as well as communicating and organising the defensive positions to effectively defend the area around the goal. A potential explanation for the lack of GK research is the differences in the physiological demands. While the external demands of the outfield player are highly locomotive based, covering large distances and at high speed during matches and training, the GK demands are largely non-locomotive and instead focus on short, highly explosive specific movements. This has led to researchers removing or not including the GK position within their testing and results. As a result, there is still very little known about the training practices of the GK.

In the past, GK match demands have been quantified using motion-analysis technology such as manual observational analysis (De Baranda et al., 2002) computerised notational analysis (Di Salvo et al., 2008) and high speed cameras (Padulo et al., 2015). However, these methods are time consuming, labour intensive and sometimes restricted to match analysis only. The development of commercial GPS based IMU devices has not only allowed for accurate measurement of locomotive activities but has now been shown to measure non-locomotive movements for sports such as rugby union (Reardon et al., 2017) and volleyball (Gageler, Wearing & James, 2017) in a quick and easy way within the training environment. This is advantageous for coaches to reflect on training session content to optimise the training stimulus as well as sports scientists to monitor a more accurate external training load to reduce the chance of fatigue and injury.

Aim:

The present study will determine the ability of an IMU based GPS unit (firmware version 717, OptimEye G5; Catapult Sports, Melbourne, Australia) with a sensor infused GK specific algorithm to determine GK training content within a practical environment. The data collected will also allow for exploration of the GPS unit's ability to determine technical qualities of the GK movements in order to make informed decisions about physical preparation within the elite football club. This subject has not been previously investigated.

2. Introduction

Football is the most popular sport in the world. Due to its increasing commercialisation there has been extensive research and analysis applied to the physiological demands of match play for amateur and professional football (Stolen et al., 2005), particularly in methods of managing training loads and reducing injury risks. Surprisingly, the GK is often excluded from the literature, despite their importance to the team's success.

Goalkeepers are characterised by explosive, highly accelerated and technically demanding movements, requiring the ability to react quickly in response to an unpredictable stimulus (Ziv & Lador, 2011). Manual and computerised notational analysis methods have proven to be valid and reliable methods of analysis for locomotive demands of outfield players (Reilly & Thomas, 1976; De Baranda et al., 2002; Bradley et al., 2009), however, they can be labour intensive, require extensive installation processes and may lack the accuracy required to measure the demands of non-locomotive activities such as that of a goalkeeper (Padulo et al., 2015).

Previous GK literature has focused on isolated parameters such as technical match demands (De Baranda et al., 2002; Di Salvo et al., 2008), physical performance tests (Knoop, Fernandez-Fernandez & Ferrautifor, 2013), biomechanical analysis of specific actions such as the dive (Rebelo-Gonçalves et al., 2016; Spratford et al., 2009), cognitive demands during decision making actions (Obetko, Babic & Perácêk, 2019) or the effect of including GKs in outfield player training sessions (Babic, Holienka & Mikulič, 2018). These studies used either motion capture methods to account for the actions completed, force platforms to determine take-off mechanics or a combination of both (De Baranda et al., 2008; Ibrahim et al., 2018). While these studies produced novel information, they were conducted in controlled settings or during match play. Others have tried to conduct assessments of GK technical skills by mimicking match realistic scenarios (Rebelo-Gonçalves et al., 2016), however, these are time consuming and not always practical within the training environment.

Commercial GPS and IMU's have become popular in individual and team sports for real-time movement analysis due to its size and as an alternative to the labour intensive manual motion analysis. An IMU is a sensor containing a triaxial accelerometer, magnetometer and gyroscope; collectively known as a microelectronic mechanical system. Kalman filter-based sensor fusion on accelerometer, gyroscope and magnetometer is used to estimate the orientation of the human body and micro-movements to monitor physical activity (Chambers et al., 2015; Zihajehzadeh et al., 2014). This technology has been shown to accurately detect non-locomotive sports specific activities such as collisions in rugby league (Reardon et al., 2017), jumping in volleyball (Gageler, Wearing & James, 2017) and aerial acrobatics in skiing/snowboarding (Lee et al., 2015). In doing so practitioners can evaluate the true demands of a sport in a non-intrusive manor in order to assist in the technical analysis, physical preparation and longitudinal analysis of training content.

Training content and goals must be focused on match requirements, thus inflicting an appropriate training stimulus (Barry, 2009). The quantification of external training load is vital to understanding the influence of the training process. However, no previous study has dealt with the GK specific training demands. Malone et al., (2018) investigated the external training load of an elite GK using GPS derived parameters; duration, TD, average speed, high acceleration/deceleration efforts (ACCEL/DECEL; >3m·s^{-2}), PlayerLoad™, and PlayerLoad™ per minute. PlayerLoad™ was derived from the triaxial accelerometer during instantaneous change in accelerations giving an arbitrary value of athlete workload, independent of distance covered. Player-Load™ per minute was determined by dividing the total PlayerLoad™ value by the total session during in minutes. Analysis found small to moderate correlations between a subjective wellness questionnaire and GPS derived duration, total distance and number of decelerations of an elite football GK. However, these parameters are not specific to the GK training demands, thus underestimating the true physical demands of the athlete. Actions such as diving and jumping were not quantified due to limitations within the GPS device, thus practitioners were missing key biomechanical loading from their longitudinal training load monitoring. The following article presents the OptimEye G5 GPS unit coupled with an algorithm said to detect GK specific activities. We sought to investigate the validity, reliability and sensitivity of this GPS IMU to accurately detect GK training demands.

There were three aims of the present study; to determine if the OptimEye G5 system could show appropriate validity in deriving Dive, Dive Return and Jump counts. The second was to examine the intra-unit reliability for Dive, Drive Return and Jump counts. Thirdly, the sensitivity of the IMU derived Dive Return metric to changes in upper body and lower body physical performance tests.

3. Methods

3.1 Subjects

Six male full-time professional soccer goalkeepers, playing for a team in the Scottish Premiership, agreed to participate in this study during the 2017-2018 season. Average subject characteristics are shown in Table 1. All players were free from injury at the commencement of the study and received a clear explanation of the investigation. The body mass of the participants was measured on two portable force platforms (PASCO Pasport PS2142, Roseville, USA) as was the countermovement jump. The height of the participants was measured using a portable stadiometer (Seca Height Measure – 123, Hamburg, Germany). Within this practical environment, under General Data Protection Regulation and Legitimate Interest, as per the subject employment contracts, normal daily monitoring of the players over the course of the season allowed for data collection, storage and use of data without intervention.

Table 1: *Subject characteristics (Mean ± SD) for the Total Sample of Goalkeepers (n = 6).*

	Subject Characteristics
Age (y)	25 ± 7.50
Training experience (y)	15.5 ± 5.97
Height (cm)	190 ± 5.25
Body Mass (kg)	85.4 ± 6.10
Countermovement Jump (cm)	56.4 ± 3.00

3.2 Video Analysis:

Gold Standard reference criteria was met through the use of video recording (Panasonic HD 8.9 Mega Pixels) and subsequent manual analysis (Sportscode Pro; hudl; Agile Sports Technologies, Inc. United States) both of which were completed by the same investigator. For the purpose of manual analysis, criteria were set in order to determine one of the three movements of interest; diving, dive returns and jumps.

A dive was defined as a deliberate or reactive lateral propulsion from a vertical to horizontal plane, usually from 1 foot with one or both arms extended towards the ball trajectory. Reactive secondary dives were included. A dive return was defined as a reactive return from a horizontal to vertical plane following an initial dive. This also included secondary reactive dive returns. A jump was defined as a deliberate or reactive vertical propulsion of the body, which must have shown flight from the ground from one or two feet. Definitions were provided by the goalkeeper specific coach.

3.3 Inertial Movement Analysis

Each player wore a wireless OpimEye G5 GPS unit (GPS; OptimEye G5; firmware version 717; Catapult Sports, Australia). The GPS unit contained a built-in tri-axial accelerometer (sampling frequency of 100Hz), a tri-axial gyroscope (200-2000 $deg \cdot s_{-1}$) and tri-axial magnetometer (sampling frequency of 100Hz). The device was held within a Catapult designed vest, positioned between the scapulae, so that the Y axis of the IMU was situated along the horizontal plane. Each GPS unit sampled at 10Hz, providing information on speed, distance and acceleration. These IMU components are the same as those used by the Catapult S5 model which has shown acceptable levels of reliability and validity for velocity-based metrics (Roe et al., 2017). The IMU combined with Kalman filtering algorithms are able to identify specific micro movements (IMU Events).

The specific IMU algorithm identifies the start and end point of events from the acceleration curve. According to Catapult, in order to register as an IMU event there are two criteria that must be met; magnitude and direction. The magnitude is calculated from the area under the acceleration curve, based on the accumulation of antero-posterior and medio-lateral accelerations. The direction of an IMU event is measured according to the angle of the applied acceleration (Catapult, n.d.). These directions are categorised into left lateral (-135 to -45º), right lateral (45 to 135º), forward (-45 to 45º) and backward (-135 to 135º) movements (Fig. 4).

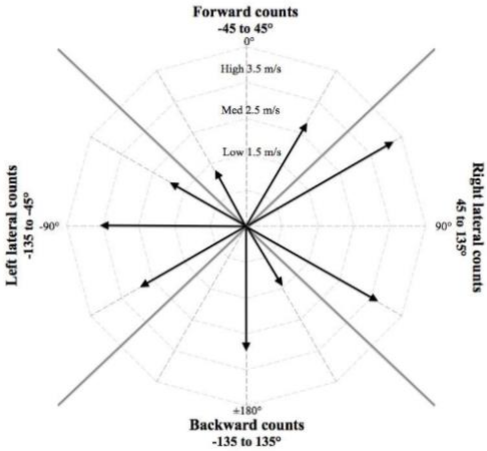


Figure 4: *IMU counts can be divided into forward, backward, left lateral and right lateral directions (Catapult Sports, 2013).*

3.3.1 GPS Event Count

The OptimEye G5 system uses a Catapult created algorithm based on the IMU platform to decipher goalkeeper specific movements. The three IMU events analysed in this study are; Total Dives (TD), Dives Right (DvR), Dives Left (DvL), Dive Returns (DR) and Jumps.

In order for a dive to be registered as an IMU event, the GPS unit must be accelerated right or left laterally for over 150ms for >0.5s so the Y axis of the IMU and gyroscope moves from a horizontal to vertical plane. Similarly, for a DR to be registered as an IMU event, a dive must first be registered, then the GPS unit must be accelerated right or left laterally for over 150ms for >0.5s so the Y axis of the IMU and gyroscope moves from a vertical plane back to a horizontal plane. For a jump to be registered as an IMU event, the IMU and accelerometer must be accelerated vertically along the z-axis for over 150ms for >0.5s.

3.4 Testing Procedure

The GK position is not often subjected to observation of this kind. Therefore, an initial period of familiarisation between the investigator and subjects and club practitioners was required to build a working relationship. This was necessary to limit the concern of the Hawthorn effect on the GK's.

The gold standard criterion was taken as video recording and subsequent manual analysis of recorded footage. Manual notational analysis is already accepted in the elite sporting environment as being a valid and reliable tool for counting athlete specific movements (Carling et al, 2005).

To record the training sessions included in this study, a video camera (Panasonic HD 8.9 Mega Pixels) was situated at a vantage point overlooking the goalkeeper training pitch. Video footage was manually analysed using SportsCode software on an Apple Macbook laptop. Only those actions resulting in a DvL, DvR, DR or Jump were coded.

In this study, each goalkeeper wore an OptimEye G5 GPS unit, within a Catapult designed vest, during each of their training sessions. Goalkeeper specific training sessions occurred on a separate pitch from the outfield players, led by a single goalkeeper specific coach. Training sessions included in this study occurred between the months of January to May and took place on a variety of pre and post-match days, therefore, training session content was varied. Players consistently used the same unit to decrease measurement error. GPS data was then downloaded using the manufacturer's software (Catapult Openfield, version 5.1.7) for the relevant metrics.

3.4.1 Inter-Unit Reliability

To test validity, the total counts from the OptimEye G5 GPS devices were compared to that obtained from the video analysis as a whole as well as separated into the five GK specific movements. All testing occurred as part of the participants usual training routine so did not require familiarisation sessions.

3.4.2 Intra-Unit Variability

As per our observations in the validity study, we mainly sought to monitor GPS and video derived counts for Dives, DR and Jumps, to ensure their reproducibility for longitudinal analysis. As this study was conducted in a practical setting, it was impossible to replicate training sessions in order to derive reproducibility of results. Therefore, we sought to monitor GPS and video derived counts for any reproducibility or trends within the difference between GPS and video counts over time. In order to achieve more meaningful results, only metric counts >10 were included in this section of the study. Lower counts caused greater error and bigger percentage differences.

3.4.3 Inter-Unit Sensitivity

This investigation did not have the capacity to measure jump height, dive intensity or dive return time from video footage. In order to test the sensitivity of the Catapult OptimEye G5 IMU to a gold standard measurement, we sought to relate DR to Countermovement Jump (CMJ) and Ballistic Press-up (BP) performance.

Each participant was required to perform a testing battery consisting of a CMJ and BP, involving triple extension and arm force production respectively which are both physical components of the DR action. Performances were measured via a pair of PASCO PS-2142 portable force plates (37cm x 37cm; PASCO Pasport PS2142, Roseville, USA) situated within a metal frame for stability. Each plate collected data at a sample rate of 1000Hz using five beams: four corner beams and one central beam to measure normal and parallel force respectively. This allowed for the assessment of bilateral force production, velocity and power measurements. The participants were required to perform 3 CMJs and 3 BPs, the maximum of which was taken as the final result.

Firstly, the participant performed 3 CMJs. CMJ was performed from a standing position with the knee extended at 180◦ and with the plantar surface of the foot contacting the ground. The participant was informed to flex the knees down to a self-selected depth before performing a maximal vertical thrust, making sure to land back on the force plates with the knees extended at 180 degrees. All jumps were performed with the hands positioned on the pelvis and the trunk upright. The hands were placed on the pelvis to maximally relate the power output of the lower limbs alone. When the arms are utilised in a swinging motion, they can assist in elevating the centre of mass via the transfer of momentum, increasing jump height, increasing maximum force and altering biomechanics of the jump (Akl, 2013).

Secondly, the participant performed 3 BPs The movement was performed from a press-up position with the hands placed on the force plates and feet paced on the ground, with the body suspended in between the two points of contact. The participants were reweighed in this position. They were informed to perform a concentric flexion of the elbows to a self-selected depth, followed by a maximal vertical thrust, making sure to land the hands back down onto the force plates with the elbows extended at 180 degrees.

Three attempts of each movement were allowed with at least 10 seconds of recovery between each attempt and three minutes between each set of jumps. The best jump in terms of velocity at peak power (m/s) were used for analysis. All participants were familiar with the CMJ and BP techniques, so no familiarisation sessions were required. All jumps were administered by the same investigator on the same day.

3.4.4 Dive Return Calculations

Dive return performance was monitored via a wireless, Catapult OptimEye G5 tracking device, as summarized above. In order for a DR action to be recognized by the IMU device, an initial dive must first be registered. Following the completion of the initial dive action, the IMU gyroscope and accelerometer must move from a lateral horizontal plane (dive) to a vertical plane (standing). DR times of the IMU were documented manually from the data files displayed on the Catapult software.

3.5 Statistical analysis

Descriptive statistics were expressed as means and standard deviations (SD) and Pearson's Coefficient of Variation (r) of GPS and VA derived counts. The magnitude of correlations were considered as trivial ($r \leq 0.1$), small ($r > 0.1$–0.3), moderate ($r > 0.3$–0.5), large ($r > 0.5$– 0.7), very large ($r > 0.7$–0.9), nearly perfect ($r > 0.9$), and perfect ($r = 1.0$) in accordance with Hopkins et al. (2009). The inter-unit reliability between GPS and VA derived counts for each metric was expressed as error percentages and illustrated using Bland Altman 95% Limits of Agreement (LOA) and mean bias. A one-way analysis of variance (ANOVA) plus a multiple comparisons Tukey's honestly significant difference (HSD) analysis was used to evaluate the differences between movements. The intra-unit variability, level of agreement and accuracy between GPS and VA derived metrics was acquired by calculating 95% LOA and mean bias. The relative error was acquired from the coefficient of variation (CV%) of the difference. The CV% was rated as good when CV <5%, as moderate when CV was 5–10% and as poor when CV was >10% (Jennings et al, 2010). A second one-way AVOVA and Tukey HSD test was used to evaluate the differences between the metrics between the GPS units. A minimum of 3 sessions and >10 counts had to be achieved per subject to be included in this section of analysis. Pearson's rank correlation (r) was used to investigate the relationship between DR and CMJ, BP and CMP + BP. All statistical analysis was conducted using SPSS (IBM SPSS Statistics Version 26, Inc., Chicago, USA).

4. Results

4.1 GPS derived total counts vs Video Analysis derived total counts

In total there were 14 goalkeeper specific sessions included in analysis, with 1-4 goalkeepers in each. Descriptive values of the subjects are summarized in Table 1. The total GK specific IMU events counted by the GPS were compared to the total GK events manually counted via VA. No significant difference was found, and a nearly perfect correlation was obtained ($n = 123$; $r = 0.903$; $p > 0.05$; Fig. 5). This is illustrated by the linear pattern of points on Figure 5, following the line of equality. The line of regression sits just under the line of equality indicating a general under-estimation of VA counts compared to GPS counts.

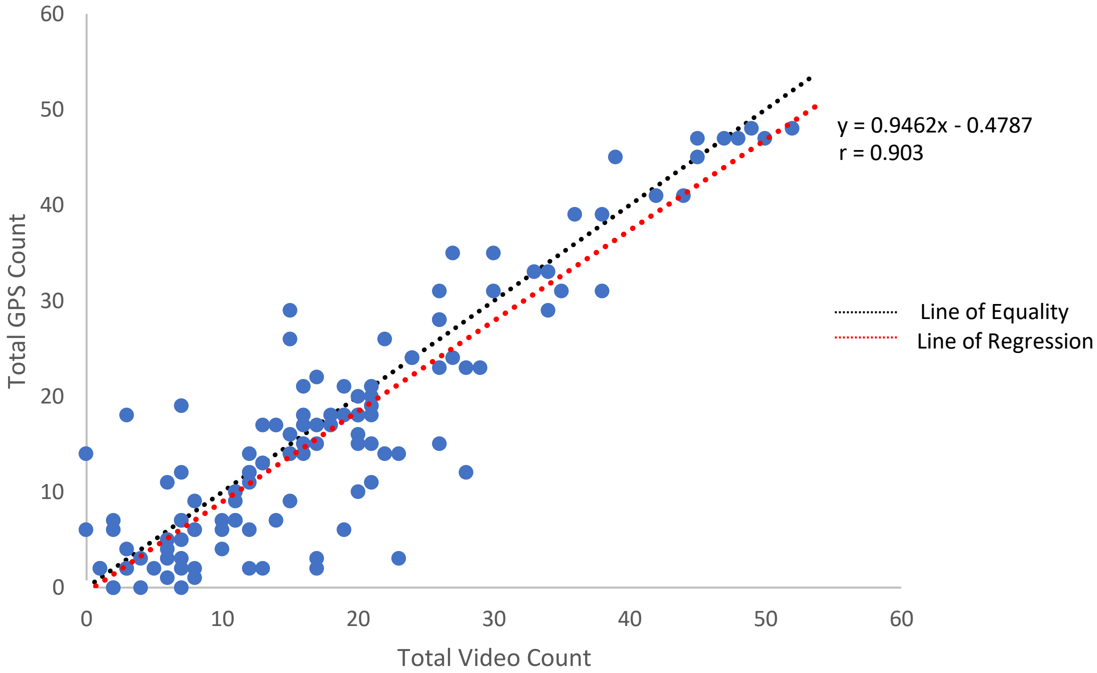


Figure 5*: Scatterplot graph displaying the total GPS counts vs the total video analysis counts recorded over the 14 sessions.*

4.2 Inter-unit Variability.

The total counts for both GPS and VA were separated into GK specific metrics and the accuracy of IMU detection for each are shown in Table 2. Pairing up the corresponding movements in the video with the IMU data indicated that Jumps were the only metric that was significantly different ($p<0.05$) with 18% of the 280 Jumps correctly registered, while 16% were false negatives. This meant that 67% of jumps were registered as false positives.

On the other hand, TD, DvR, DvL and DR showed no significant difference ($p>0.05$) between detection methods with >78% correctly registered. However, TD and DvR had greater false positives (7% and 12% respectively) compared to false negatives (2% and 1% respectively), while DvL and DR had greater false negatives (6% and 11% respectively) compared to false positives (5% and 10% respectively).

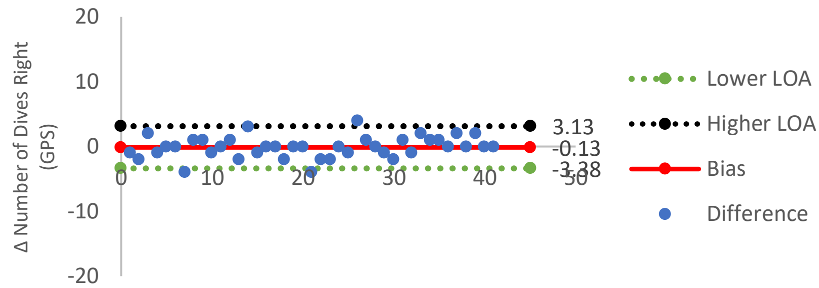
Table 2: *GPS vs VA count showing true positives, false positives and false negatives. The error percentage as calculated as a percentage of the number of counts which should have been found. * = (p<0.05)*

	True Positive	False Positive	False Negative
Total Dives	801/877 (91%)	59/877 (7%)	17/877 (2%)
DvR	387/444 (87%)	52/444 (12%)	5/444 (1%)
DvL	384/433 (89%)	22/433 (5%)	27/433 (6%)
DR	673/861 (78%)	90/861 (10%)	98/861 (11%)
Jumps	49/280 (18%)*	187/280 (67%)	44/280 (16%)

Bland Altman 95% limits of agreement are used to further illustrate the count variability and the potential for over and under-estimation between GPS and VA for all metrics (Fig. 6). As can be seen, Dives Right (-3.38 to 3.13; Fig. 6A), Dives Left (-1.75 to 4.04; Fig. 6B) and Total Dives (-3.6 to 5.6; Fig. 6C) have very narrow LOAs indicating the lowest variability.

While there was no significant difference between GPS and VA for DR counts, the wider limits of agreement (-13 to 12.6; Fig. 6D) show there is greater discrepancy and potential for under estimation by the GPS. Jump counts also had large limits of agreement (-8.8 to 15.7; Fig. 6E) along with the highest mean bias (3.49) of the five metrics.

A.



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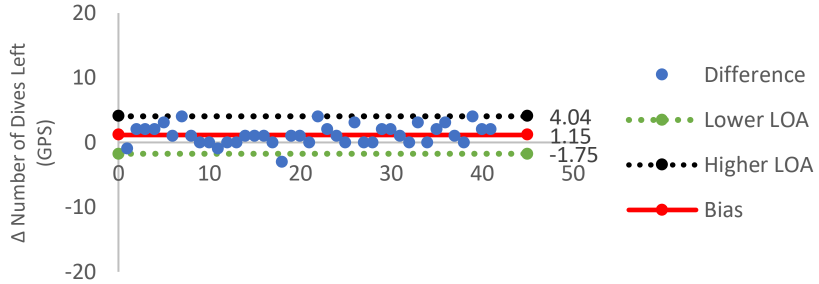

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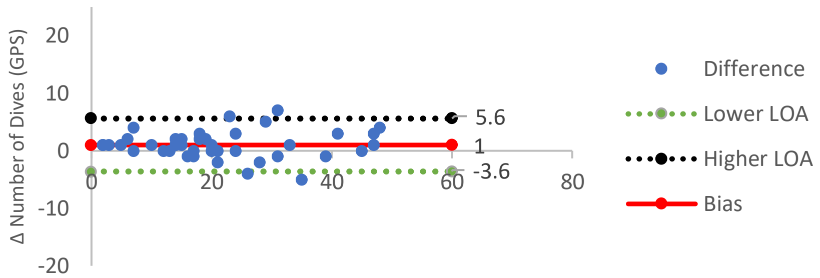

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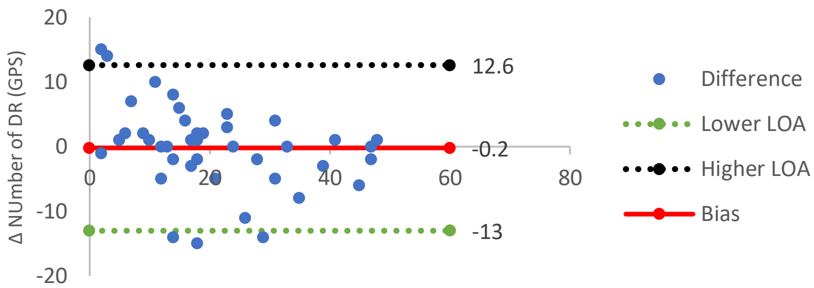

E.

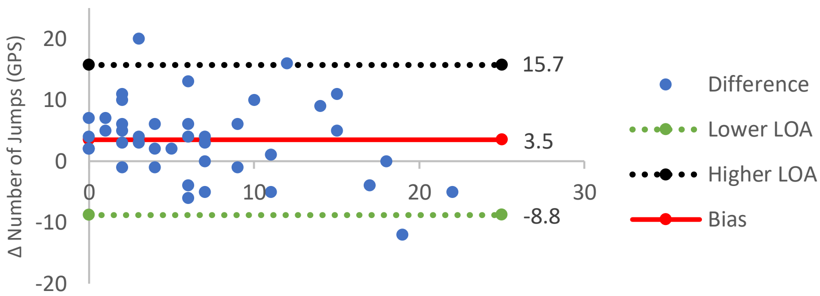

Figure 6: *Bland-Altman plots (n=41) of Video derived versus GPS IMU derived A) Dives Right B) Dives Left C) Dives D) Dive Returns E) Jumps. X-axis represents players observed. Y-axis represents bias observed between Video and IUM derived counts. Positive difference signifies IMU measure produces a greater count.*

4.3 Intra-Unit Variability.

In order to assess the intra unit variability, the difference between GPS derived counts and VA derived counts for TD, DR and Jumps were calculated for each session and individual GPS units if they met the inclusion criteria (see methods).

It appears the GPS units consistently over estimated total counts of all metrics. Dives showed the lowest over estimation across all units on average (mean bias 1.5 ± 2; 95% of LOA -2.5 to 5.4; CV 8.1%; Table 3).

While DR difference had a slightly greater Mean Bias ± SD compared to Dives, the GPS over estimated slightly more so with a greater day to day count variance compared to VA on average (mean bias 1.65 ± 5.91; 95% of LOA -8.97 to 11.27; CV 50.9%; Table 4).

Jumps showed the greatest day to day variance on average compared to VA (mean bias 5.32 ± 4.92, 95% of LOA -4.33 to 14.96; CV 93.5%; Table 5). No Significant differences were found between methods across all three metrics and four GPS units ($p>0.05$).

Table 3: *Intra-unit variance for all subjects (N = 4) for the difference in Total Dive counts between GPS and Video Analysis. (>2 days of testing, >10 counts). SD: Standard Deviation. LOA: Limits of Agreement. CV%: Coefficient of Variation.*

Subject	**1**	**2**	**3**	**4**	**Average**
Number of Sessions	3	8	8	10	7
Mean Bias ± SD	2.7 ± 1.5	0 ± 1.31	0.75 ± 3.11	2.4 ± 2.12	1.5 ± 2
Upper 95% of Mean	14.08	37.85	32.88	29.09	28.47
Lower 95% of Mean	1.63	-21.26	-20.85	-8.78	-12.32
CV%	8.6	5.1	7.8	10.9	8.1

Table 4*: Intra-unit variance for all subjects (N = 4) for the difference in DR counts between GPS and Video Analysis. (>2 days of testing, >10 counts). SD: Standard Deviation. LOA: Limits of Agreement. CV%: Coefficient of Variation.*

Subject	**1**	**2**	**3**	**4**	**Average**
Number of Sessions	3	8	9	10	8
Mean Bias ± SD	1.67 ± 1.15	0.63 ± 6.19	-0.33 ± 6.38	2.64 ± 6.92	1.65 ± 5.91
Upper 95% of Mean	3.93	12.75	12.18	16.2	11.27
Lower 95% of Mean	-0.6	-11.5	-12.85	-10.92	-8.97
CV%	6.9	103	26.2	67.5	50.9

Table 5: *Intra-unit variance for all subjects (N = 4) for the difference in Jump counts between GPS and Video Analysis. (>2 days of testing, >10 counts). SD: Standard Deviation. LOA: Limits of Agreement. CV%: Coefficient of Variation.*

Subject	**1**	**2**	**3**	**4**	**Average**
Number of Sessions	3	4	5	6	5
Mean Bias ± SD	2.5 ± 2.12	1 ± 4.69	10.6 ± 5.73	7.17 ± 7.14	5.32 ± 4.92
Upper 95% of Mean	6.66	10.19	21.83	21.16	14.96
Lower 95% of Mean	-1.66	-8.19	-0.63	-6.83	-4.33
CV%	33.12	33.06	218	89.6	93.5

4.4 Inter-Unit Sensitivity

The current study also investigated the sensitivity of the IMU Dive Return metric to changes in derivatives of the dive return action; the ballistic press-up as the equivalent of the initial explosive arm press from the ground and the countermovement jump as the secondary triple extension of the legs to get the lower body under the rising torso and center of mass. Subjects were ranked 1-4 based on their average DR times over the course of the 14 sessions included in the study (Table 6). Using Pearson's Rank Correlation, subjects were then ranked again based on their BP (Fig. 7A), CMJ (Fig. 7B) and CMJ + BP (Fig. 7C) results.

Table 6*: Subject ranking according to average DR times ± Standard Deviation (SD).*

Subject Ranking	Average DR Time (s)	Body Mass (kg)
GK1	1.39 ± 0.75	79.7
GK2	1.43 ± 1.04	76.9
GK3	1.48 ± 0.75	85.3
GK4	1.54 ± 0.84	90.8

Pearson's Rank Correlation found that BP and upper body velocity at peak power had the smallest relationship with average DR time (r = 0.684; Fig. 7A) as measured by the GPS IMU. Subject 1 achieved the lowest velocity at peak power (1.99m/s) while Subject 2 achieved the greatest velocity at peak power (3.09m/s).

CMJ and lower body velocity at peak power production had a nearly perfect correlation with average DR time (r = 0.992; Fig. 7B). Subject 1 had the greatest average DR time (1.39 ± 0.75) as well as the greatest velocity at peak power (2.71m/s) while Subject 2 had the second lowest velocity at peak power (2.57m/s) followed by Subject 4 (2.46m/s) who also had the lowest average DR time (1.54 ± 0.84s).

When combining lower body (CMJ) and upper body (BP) peak power performance, Rank Correlation found Subject 1 again has the lowest total (4.71m/s) and Subject 2 had the greatest total (5.66m/s) with an overall correlation of r = 0.603 (Fig.7C).

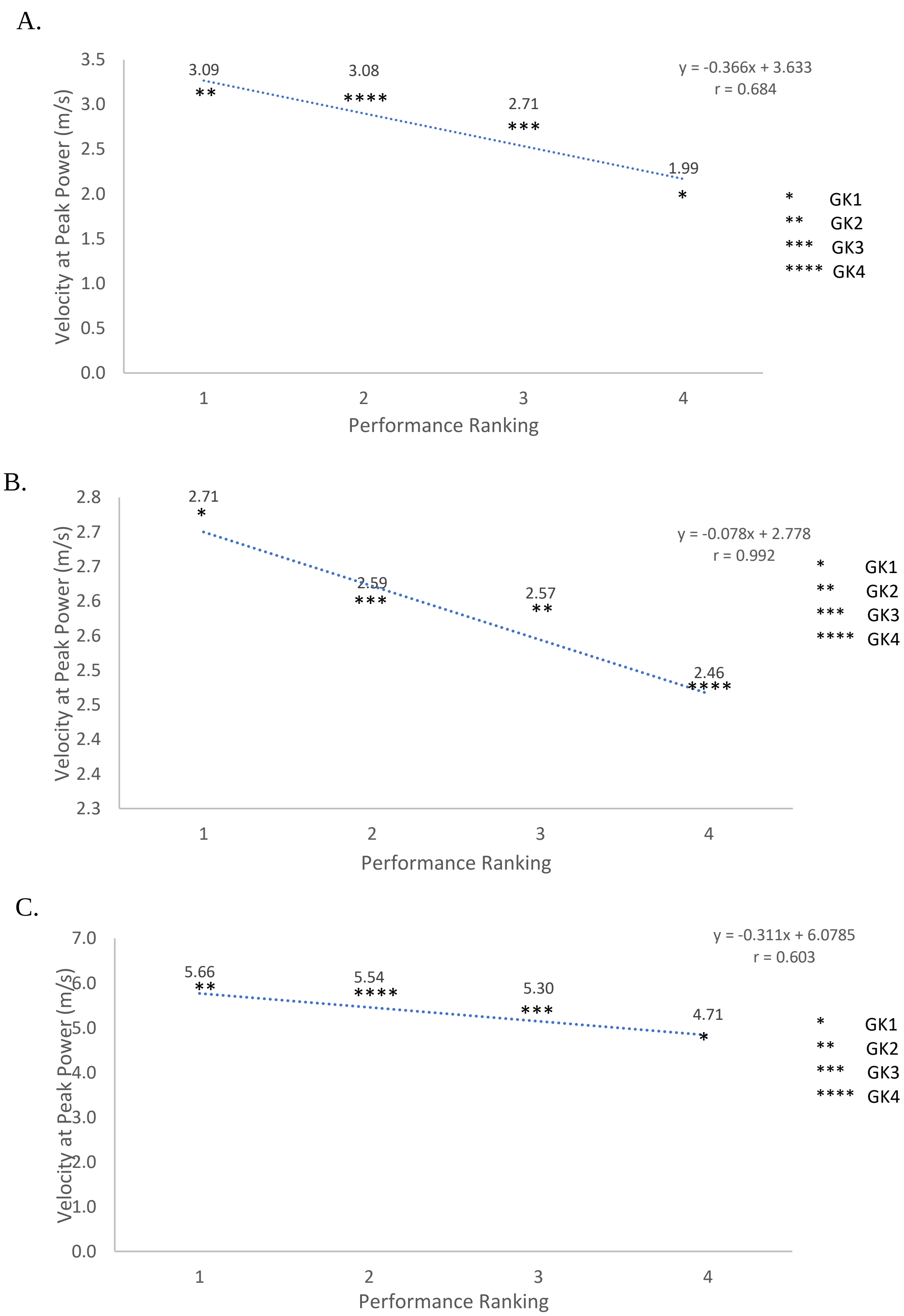

Figure 7: Pearson's Rank Correlation of average DR time vs relative peak power from: A) Ballistic Press-Up B) Countermovement Jump C) Ballistic Press-up + Countermovement Jump. * = GK1, ** = GK2, *** = GK3, **** = GK4

5. Discussion

The aim of the present study was to establish the ability of an IMU based GPS unit to accurately count goalkeeper specific IMU events compared to the gold standard criterion of video analysis and subsequently establish the sensitivity of the IMU derived dive return times to lower and upper body performance tests.

While the present study confirmed the ability of the IMU and algorithm to accurately count GK specific movements as a whole (Fig. 5), it appears the type of movement performed influences inter-unit validity of the algorithm (Table 2). There were no significant differences between GPS and VA methods of measuring TD, DvR, DvL and DR counts but this was not the case for Jump counts. Intra-unit analysis found no significant difference across all metrics and GPS units ($p>0.05$). In addition, the IMU derived average DR time showed an almost perfect correlation with lower body velocity at peak power ($r=0.922$; Fig. 7B) compared to upper body velocity at peak power ($r=0.684$; Fig. 7A) and lower and upper body combined ($r=0.603$; Fig. 7C) suggesting the lower body dominance during this action. This study provides novel data on GK training demands using the OptimEye G5 GPS unit, the first MEMS technology to carry a filtering algorithm specific to GK specific movements.

5.1 Inter-Unit Variability

5.1.1 Dives

One of the most critical movements involved in goalkeeping is the diving action, characterized by large ground reaction forces upon take-off, and often without prior knowledge of ball location (Ibrahim et al., 2018). The OptimEye G5 automatically detected GK dives within a non-significant difference from VA with a 91% true positive result (Table 2) and narrow limits of agreement (-3.6 to 5.6; Fig. 6C). In order for a dive to be recognized, it must fit the algorithm threshold produced by the IMU based accelerometer, gyroscope and magnetometer; a horizontal-vertical force applied either right (45º to 135º) or left (-135º to -45º) resulting in the orientation of the GPS unit rotating around the x-axis so the z-axis of the gyroscope moves from vertical to horizontal along the earth's magnetic field. Only IMA events ≥ 150ms were included. This is a complex movement, providing the algorithm with a specific acceleration and gyroscope trace every time a GK initiates a Dive and lands horizontally (Reardon et al., 2017) making the IMU count ability robust and valid.

As there is a greater over estimation of total dives (7% False Positive) rather than underestimation (2% False Negative), it seems the IMU tends to recognize movement patterns similar to that of a dive rather than missing the dive altogether. This may be the case, given the practical training environment of a GK involves excessive torso movement and the GPS unit is situated between the scapulae of the torso. For example, bending to pick up a football may be recognized as an appropriate acceleration and gyroscope rotation from the vertical to the horizontal plane and thus be registered as an IMU Dive event (Malone et al., 2017). However, these are not significant differences and in the grand scheme of longitudinal training load monitoring this small over estimation will not make a significant difference.

Within the practical environment, ideally the GPS unit would produce consistently accurate results. However, Sports Science practitioners may prefer an over estimation of Dives rather than an underestimation when monitoring longitudinal biomechanical loading in order protect the GKs from injury risk. Ekstrand, Hagglund & Walden, (2009) found 4483 injuries occurred during 566,000 hours of exposure within football, giving an injury risk of 8.0 injuries/1000h.

During the Diving action, there is a risk of upper body and lower body injuries. During a dive landing, the GK's hip is exposed to forces of 4.2–8.6kN times body weight and vertical impact velocities up to 3.25m.s^{-1} depending on diving technique (Schmitt, Schlittler & Boesiger, 2010). The GKs upper limb strength and stability is also challenged during the dive when reaching to block a ball which could be moving up to 80mph. A third of shoulder injuries sustained by professional football players are sever, leading to them being removed from training for >28 days (Ekstrand, Hagglund & Walden, 2009). The current study saw GKs performing up to 50 Dives in a single training session. This raises concerns over the physical and mental load of the GKs and the possible risk of injury as a result of such loads. Thus, monitoring a slightly over-estimated Dive count may act as an additional level of caution for injury risk management. Additionally, it is something to be aware of during the delicate stage of returning a GK from injury when they were not prescribed any diving within rehabilitation sessions, but the post training GPS analysis says otherwise.

While the study showed that the IMU could reliably detect Dives to the left and right, there are still various errors that must be examined. There seemed to be an imbalance in the detection of DvR and DvL with 12% and 5% false positives respectively but a 1% and 6% false negative respectively. This suggests that DvR were slightly underestimated while DvL were slightly over estimated by the IMU (Fig. 6A, Fig. 6B). Albeit speculative, as these differences were not reported, the imbalance between right and left side dives within this study could be due to the use of each GK's preferred side of the body to dive, the dive height required to block a ball or a combination of both. GKs must be able to dive to both sides of their bodies and to various heights to block the ball, however, natural imbalances exist within the musculoskeletal system (Demura et al., 2001). This has been found to influence the movement pattern of an elite GK (Spratford et al., 2009; Rebelo-Gonçalves et al., 2016) which can create differences between both sides and could therefore affect the ability to fulfil the IMU event threshold in order to detect a dive.

Spratford et al., (2009) found significant differences in dive times (0.04-0.14s slower) to the non-preferred side compared to the preferred side at heights of 30cm, 90cm and 150cm (although not significantly different) in Under-20 Australian national team GKs. This was due to a greater lateral rotation of the pelvis and torso at the initiation event, leading to less hip-extension and a slower traveling centre of mass at take-off, when diving towards the non-preferred side. Contrastingly, Ibrahim et al., (2018) conducted a similar study with 10 elite GKs ranging from the top Dutch division to the top under-17s Dutch division (age 18.4 ± 2.6 years). They found no significant difference in dive times to 30cm or 90cm heights but a significant difference in between dominant and non-dominant diving sides. Lower dives were characterised by greater horizontal linear momentum (side-step followed by a side dive) and frontal plane angular momentum, while high dives were characterised by greater vertical linear momentum (side-step followed by a side jump) (Ibrahim et al., 2018; Knoop, Fernandez-Fernandez & Ferrauti, 2013). They indicated their contradictive results were due to the higher level of GKs participating in their study compared to Spratford et al., (2009). It has been shown that older, more skilled and experienced GKs dive faster and with more precision (Suzuki et al., 1987). Skill level is determined by additional factors such as tactical understanding, placing, perception and anticipation (Sorencen, Ingvaldsen & Whiting, 2001). If this is the case, the older elite GKs within the present study can be assumed to have faster, more accurate dives with less noticeable performance differences between their preferred and non-preferred sides compared to younger, less experienced GKs. Never the less, both studies were conducted in controlled settings with stationary balls positioned either laterally or 1m in front of the goal, potentially restricting natural take-off mechanics. When diving in an unrestricted situation, GKs prefer to dive diagonally (sideward and forward), so they can reach the ball at a better angle, reducing the goal area they need to cover (Ibrahim et al., 2018). Within the current practical setting, the GKs were unrestricted and able to dive at various heights, intensities and within game realistic situations. However, we speculate a large variation in take-off mechanics, creating variability in the accelerometer and gyroscope movement trace from which the IMU algorithm recognises a Dive initiation, thus leaving potential for miscounts or false positives (Gageler, Wearing & James, 2017). Rebelo-Gonçalves et al., (2016) found differences between right and left side dives in GKs (12-15years) during two tests involving a sprint or a lateral shuffle prior to diving towards a stationary ball at ground level. The results and dive mechanics would therefore be influenced by the components beforehand (acceleration, deceleration, jumping, change of direction). However, this study used timing gates to measure the movements as a whole, rather than the dive events individually. Further research on diving technique within the practical environment as well as the ability of the IMU based GPS unit to differentiate between dives of various directions, heights and intensities must be conducted.

While the instrumental testing apparatus used in previous literature (Spratford et al., 2009; Knoop, Fernandez-Fernandez & Ferrauti, 2013) are good practical tools for coaches to identify weaknesses and design specific training programmes (e.g. prescription of strength or plyometric training for the non-dominant side), it is not easily accessible to practitioners and could also potentially alter the diving technique compared to saving a moving target. Therefore, the use of an IMU based GPS to identify dive counts to a reliable level and thus monitor the specific longitudinal training demands of a GK could be hugely beneficial to practitioners (Malone et al., 2018).

5.1.2 Dive Return

Diving across the goal to block an incoming shot leaves the rest of the goal vulnerable to secondary rebound shots, therefore, returning upright from a dive and in to an athletic position as fast as possible is crucial to GK performance and match winning events. Goalkeeping coaches will implement game realistic dive and dive return scenarios within the training session drills to train this reactive movement. The results of this study found no significant difference ($P<0.05$) between the IMU count and VA count of DR (78% true positive; Table 2). The DR action descriptor begins when a Dive (initiation) and Dive landing (momentary pause in acceleration) is registered by the IMU device. Similar to the Diving action threshold, from this momentary static horizontal position, a vertical-horizontal force is applied either right (45 to 135º) or left (-135 to -45º) resulting in the orientation of the GPS unit rotating around the x axis so the z-axis of the gyroscope moves from horizontal to vertical away from the earth's magnetic field. This specific accelerometer and gyroscope pattern every time a GK dives and returns to feet provides the IMU algorithm with distinct descriptors to register these IMU events, making the IMU count ability more robust and valid.

There was a noticeable degree of over and under-estimation (-13 to 12.6; Fig. 6D) by the IMU device that must be discussed. The IMU underestimated 11% of all DR and overestimated 10% (Table 2). If the DR movement does not fit the threshold set by the IMU and the algorithm, it is not counted. For example, if the initial Dive was not registered for reasons discussed previously, then the return from the dive will also not be registered. This explanation mirrors that of Chambers, Gabbett & Cole, (2018) who validated a microsensor-based algorithm for the automatic detection of scrum events during training and match-play. While scrums could be automatically detected, false negatives occurred when the activity duration was insufficient to satisfy the algorithm's minimum requirements; e.g. when scrums collapsed or were re-set, or when players did not maintain a horizontal position for an adequate time period. Within the present study, training scenarios involved game realistic situations requiring the GK to make an initial dive followed by a reactive secondary dive and DR in quick succession to block another immediate shot on goal. If the gyroscope y-axis does not return to within the horizontal threshold and the x-axis does not return to within the vertical threshold to complete the DR algorithm requirements, before the secondary Dive and DR occur, the movement may not fulfil the algorithm criteria of an IMU Dive event leading to underestimation or false negatives. Similarly, if initial Dives were not counted for reasons discussed above, the DR may not be counted leading to false positives and overestimation. However, if this were the case Dive (91% true positive) counts and DR counts (78% true positive) would be relatively similar.

As far as we are aware, this is the first study to analyse the DR action in any respect. The IMU and algorithm's ability to count DR actions in the practical setting to within a significant level is obviously very helpful in assessing performance and informing exercise prescription. However, in order for us to make an accurate assessment of the DR action and the algorithm threshold for successive actions, greater clarity and transparency of the software used are required from the manufacturer. Unfortunately, this software is subject to intellectual property protection and manufacturers do not disclose details to users (Malone et al., 2017). This has hindered our ability to validate this metric and give informed analysis of its discrepancies. Until this issue has been resolved we would recommend exercising caution when using this metric and continue using adjacent video analysis.

5.1.3. Jumps

Jumping performance is considered as one of the key qualities of a goalkeeper (Hervéou et al., 2018). It is important that this movement is monitored for individual levels of workload and performance. Results found that Jumps were extremely over estimated (67% false positive) by the IMU with only 18% of Jumps registered as true positives (Table 2). Unlike the Dive and DR actions, which require both the accelerometer and gyroscope to provide orientation descriptors, the Jump primarily uses accelerometer data to provide the IMU algorithm with z-axis and y-axis magnitude and direction descriptors potentially making it less robust and unreliable than the events requiring both the accelerometer and gyroscope. Acceleration applied in the z-axis is smoothed at a known frequency and overlaid with the original acceleration trace, so the start and end points can be identified (Catapult, n.d.).

These results contradict that by Gageler, Wearing & James, (2017) who found 95% of jumps during a volleyball training session were correctly detected, only 5% being missed as false positives and 4% false negatives. They found that by applying a low pass filter to inertial sensor data then calculating the magnitude of the anterior-posterior and vertical axis, all movements which met these criteria were automatically detected as jumps. While this system performed to a satisfactory level, it was still affected by the accuracy to detect the start and end of flight which could cause the possible jump to be incorrectly classified. There are several reasons within the practical environment that could affect take-off and landings causing false positives. GKs perform split-steps before diving or jumping to stop a ball. While this movement gives the GK better muscular pre-activation and reactivity just before extension, enhancing jump and dive performance (Hervéou et al., 2018), it may interfere with the acceleration trace from which the algorithm recognises a Jump take-off phase. In addition, different types of jumps (e.g. single leg take off, double leg take off), may cause different IMU traces based on their take-off and landing forces which is made even more variable depending on the relative hardness of the grass training pitch conditions, affected by factors such as seasonal weather changes and over-use (Rennie et al., 2016).

On the other hand, the various offensive and defensive aspects performed by GKs, characterised by explosive and highly reactive adjustments of their body (Ibrahim et al., 2018), may be falsely recognised as vertical accelerations and Jumps thus over-estimating the total count (Fig. 6E). Previous research has advocated the use of accelerometers to measure peak impacts and highly accelerated movements in team sports (Wundersitz et al., 2015). However, it was suggested that metrics based on acceleration-based thresholds such as that of the G5 OptimEye, may be unreliable, especially during unpredictable, multi-plane movements such as jumping, diving and rotations. It has been determined that horizontal accelerations must reach 150ms for at least half a second to be counted (Bradley et al., 2009; Ingebrigtsen et al., 2015; Dalen et al., 2016). It is assumed that this criteria for horizontal acceleration is also applied to vertical acceleration (i.e. a Jump). GKs are characterised by explosive and highly reactive adjustments of their body (Ibrahim et al., 2018) and so the large majority of GK Jumps and key performance variables may exceed this threshold within the practical setting. Nicolella et al., (2018) determined that accelerations applied in the z-axis (up and down) were more reliable that accelerations applied in the x-axis (side to side) and y-axis (front to back) for the Catapult OptimEye S5. With a 67% false positive result, it is possible that the default threshold of 150ms for the vertical Jump metric may be too low, thus picking up high levels of noise and false positives from unimportant movements. For example, in addition to split-steps, GKs often perform a “pre-set” movement such as a small reactive hop of the feet before catching an incoming ball. However, given that 50% of an outfield players accelerations reach 300ms when initiated from standing (Sonderegger et al., 2016), Aughey, (2010) suggested that a higher acceleration threshold of >300ms may be more suitable for field sports. For example, during small sided games (SSGs) in football, there is a greater frequency of high intensity accelerations due to a low starting velocity thus requiring greater initiation forces to react and change speed (Guard, 2017). It is therefore important to be able to distinguish between intentional accelerations by outfield players for tactical reasons or simply a change in torso and GPS unit orientation. By increasing the acceleration threshold of the IMU from 150ms to >278ms, Guard, (2017) decreased the number of false positive accelerations in 4v4 (150m$_2$), 5v5 (153m$_2$) and 6v6 (151m$_2$) SSGs and even further when the threshold was increased to 300ms. Goalkeepers spend the majority of their training drills within penalty box sized areas (672m$_2$). By increasing the acceleration threshold of vertical Jumps to 300-400ms, this may provide a solution to differentiate between lower intensity accelerations (split steps) and higher intensity accelerations (Jumps), potentially improving the validity of IMU Jump counts.

Future research should investigate an optimal threshold and cut off frequency to improve the specificity of the algorithm. If it's too high, the accelerometer will maintain high levels of noise and possibly overestimate IMU event counts. Conversely, if it's too low the filter may eliminate important characteristics of the signal and underestimate IMU event counts.

5.2 Intra-Unit Variability

As this study was conducted in a practical setting, training sessions were impossible to replicate in order to test true reliability. As a result, we sought to monitor GPS and VA derived counts for any reproducibility or trends within the difference between GPS and VA counts over time. From this, the science and medical staff could take into consideration any individual over or underestimation of GPS units for accurate longitudinal analysis of training demands. However, across all metrics and all four GPS units which met the inclusion criteria, there were no consistent day to day differences with coefficient of variations ranging from 5.1% (Table 3) to 218% (Table 5) and the GPS over estimating the total counts of all metrics in an inconsistent manner.

A previous validity and reliability study by Nicolella et al., (2018) found the portable accelerometers within the Catapult OptimEye S5 to have excellent intra-device reliability with the majority of CVs <2.0%. They found differences varied according to the direction of acceleration with larger variability measured in the x-axis and y-axis compared to the z-axis suggesting a device calibration discrepancy. This is different to the current study in which Jumps (z-axis and y-axis dominant) appeared to have the greatest day to day variance compared to Dives and DR (x-axis and y-axis dominant). The accelerometer, gyroscope and magnetometer within the OptimEye G5 GPS unit work together with a sensor fusion algorithm to estimate the orientation of the human body segments and thus monitor the GKs physical activities (Zihajehzadeh et al., 2014). It is thought that when diving and returning from the dive, the IMU provides the algorithm with rotational as well as acceleration data, creating a more detailed placement estimation compared to vertical acceleration of a jump involving minimal orientation and rotational input. This may explain the lower intra-unit variation for Dives and DR compared to Jumps. High error rates for inter-unit reliability have been presented across a variety of GPS models, particularly for velocity and acceleration-based metrics (Malone et al., 2017). However, considering the OptimEye S5 contains the same technology as the OptimEye G5 used in this study, thus demonstrating the reliability of the accelerometer, the GPS intra-unit performance is most likely affected by the manufacturer's algorithm and prescribed thresholds. This trend is consistent with the validity results discussed previously, and supports our lack of specificity outcome. Perhaps the algorithm thresholds for each metric require calibration as well as the devices themselves.

During a practical training session, the GPS units are held within a vest which moves and accelerates along with the movements of the athlete, introducing an additional level of variability between individual units (Rantalainen et al., 2018). On the other hand, the GPS units of Nicolella et al., (2018) were mounted into a shaker table and tested in a highly controlled setting, aimed at isolating the accelerometer and focussing on one direction of acceleration at a time. While rigorous investigations such as these provide an important performance baseline, these benefits are lost if the technology is not tested within the practical environment as well or it is forces the athlete to alter their performances and movement patterns as a result (Spratford et al., 2009; Sorensen et al., 2008).

None-the-less, it is appreciated that the outcome of this part of the investigation is not comprehensive and further enquiries into the reliability of the G5 OpimEye are required. For example, conducting closed GK specific drills similar to that of Rebelo-Gonçalves et al., (2016) which are closer to a practical environment and give more realistic feedback for practitioners. Other studies have used sports specific movement circuits (Wundersitz et al., 2015), however, studies involving human participants will always be limited due to their inability to replicate movements on multiple occasions. Due to the GPS units inconsistent over and under estimation from day to day, it is recommended that practitioners ensure each GK wears their own device at all times for accurate within athlete longitudinal monitoring.

5.3 Inter-Unit Sensitivity

The goalkeeper has a very different role to play in a football team in opposition to their outfield teammates. They can use their whole body, including upper and lower limbs to jump, dive, dive return, sprint, kick and throw the ball to prevent the ball ending up in the goal. However, the Dive Return action has not been investigated in precious literature. Results of individual tests of lower and upper limb velocity at peak power showed a nearly perfect correlation of Dive Return times with lower body velocity at peak power (r=0.922; Fig. 7C) compared to upper body velocity at peak power (r=0.684; Fig. 7A) and lower and upper body combined (r=0.603; Fig. 7C) suggesting lower body dominance during this action. During the DR, the arms push into the ground laterally, lifting the torso up while the legs simultaneously move underneath the body bringing it back to vertical and ready to react again if necessary. Only specific muscular training will allow a GK to optimise their muscular capabilities, therefore, it was important to investigate the key features of this critical movement.

The OptimEye G5 GPS was able to do this automatically by providing analysis of each DR completed within training. Subject 1 had the fastest average DR time of the four GKs (Table 6), as well as the greatest velocity at peak power during a CMJ (Fig. 7A). However, GK1 had the lowest velocity at peak power of the four GKs during the ballistic press-up indicating that upper body force velocity was not limiting the subjects DR performance. On the other hand, GK2 (ranked second in average DR time, Table 2) was only ranked third in velocity at peak power during the CMJ but had the greatest velocity at peak power during the ballistic press-up (Fig. 7B). This suggests that while GK2 had greater upper limb velocity, GK1 still had the greatest average DR time during training indicating the lower limb dominance in the DR action compared to the upper body. To the best of our knowledge, this is the first study to investigate the physical components of the Dive Return action within goalkeeping.

On the training pitch, short explosive lower limb movements are a primary focus; positioning of the body, sprinting short distances, side-stepping before diving or jumping for a ball as well as ball distribution. This is made evident in the plethora of lower body based performance tests within the already small cohort of GK based literature (Sorensen et al., 2008; Schmitt, Schlittler & Boesiger, 2010; Rebelo-Gonçalves., 2016; Ibrahim et al., 2018). Hervenou et al., (2018) was one of very few studies to investigate both the upper and lower body muscular profiles of GKs. They found that both the lower and upper limbs force velocity (F-V) profiles were more orientated towards velocity, rather than force. Lower limb F-V profiles of GKs (-11.5 ± 4 N.s.m^{-1}.kg^{-1}) were closer to that of an outfield soccer player (-11.6 ± 7.36 N.s.m^{-1}.kg^{-1}) (Samozino et al., 2010) and high level sprinters and jumpers (-8.06 ± 1.91 N.s.m^{-1}.kg^{-1}) (Jiménez-Reyes et al., 2014) compared to high level rugby players (-24.1 ± 9.7 N.s.m^{-1}.kg^{-1}) (de Lacey et al., 2014). This suggests that GKs present lower body muscular profiles similar to that of athletes of whom velocity is prominent in their training compared to the resistance and force training involved within rugby. On the other hand, the upper limb force velocity profile of GKs (-3.7 ± 1.1 N.s.m^{-1}.kg^{-1}) (Hervenou et al., 2018) has been compared to that of shot-put throwers (-4.7 N.s.m^{-1}.kg^{-1}) and the significant relationship between maximal power and the throwing performance (Bourdin et al., 2010). Differences could be explained by the difference in weight between the shot and that of the football. It seems the focus towards release velocity of the ball during throwing and distribution of the ball has orientated the UL towards a velocity profile. This is in accordance with the specificity of their activates (Ziv & Lidor, 2011).

The upper body and lower body F-V profiles support the notion of the IMU derived DR metrics sensitivity to lower and upper body physical performance tests with the outcome of lower limbs being the more dominant factor within the DR. However, it must be kept in mind that the subjects used within this study are elite level GKs while subjects used by Hervenou et al., (2018) and the majority of GK based literature are younger and/or sub-elite. For example, Hervenou et al., (2018) reported CMJ performances of 41.6 ± 5.5cm while the current study reported higher values of 56.4 ± 3cm. Jumping performance is considered one of the key qualities of a GK and depends on intrinsic physiological capacities as well as training experience and frequency (de Villareal et al., 2009). Therefore, the highly trained GKs of this study (1st Scottish division) are assumed to have force velocity values greater than those of the well trained (4th French division) GKs used by Hervenou et al., (2018). Consequently, these results are restricted to the elite population and this must be taken into consideration when applying this knowledge to younger cohorts. It must also be kept in kind that IMU DR counts had a mean bias of -0.2 and wide variation compared to VA counts and although this is not a significant difference, results should be interpreted with caution.

With regards to this study, practitioners are encouraged to create training programs targeting the F-V profile of the upper body, finding a compromise between the enhancement of velocity and maintenance of optimal force, in order to improve overall DR times (Samozino et al., 2010). This would include both plyometric exercises (e.g. ballistic medicine ball throws) and resistance training to compliment specific training on the pitch. Further performance testing would indicate whether the changes in ballistic press-up ability were having a positive effect on the average DR times provided by the IMU based GPS.

5.4 Limitations & Practical Implications

In terms of the practicality of these investigations, the limited data from the small GK cohort and the limitations surrounding collecting data from a practical environment made it difficult to draw conclusions. While the IMU has excellent levels of validity, the algorithm lacks specificity and reliability for monitoring GK training demands. I would suggest that when using the GPS units to observe the day to day training content of GK sessions, practitioners should exercise caution, especially when monitoring Jump counts, as well as being rigid in each GK wearing their own unit.

Many of the validity and reliability research papers mentioned previously have been conducted in a closed environment and controlled as much as possible. This study was conducted within an elite football training environment with very little room for intervention. This hindered the research process in that we were unable to interrupt the training and competition process nor subject the participants to testing measures out with that prescribed by the science and medical staff. For example, we would ideally like to have conducted a repeatability test to scrutinise the intra-unit reliability of the IMU. This was definitely a limitation of the study, as our results did not show any consistent variance across all GPS units and metrics analysed. It is therefore appreciated that the research outline in this part of the thesis is not comprehensive and does not answer the question raised. Future research would seek to determine true reliability of the OptimEye G5 IMU and algorithm in a more robust manner. By doing so, this would help clarify if the system does have a place for monitoring longitudinal goalkeeper demands and subsequent training load monitoring. By doing so practitioners could determine if any changes from normal variance are attributed to training stimuli as opposed to variability within the units or metrics analysed.

In determining the reliability of the OptimEye G5 in an ideal environment, future researchers could conduct closed tests in order to control the conditions as well as the number of movements the subjects would conduct. As outlined by Ibrahim et al., (2018), the diving action and dive return action can be analysed using force plates and high speed cameras to capture the kinetics and full body kinematics of the movements to compare with that of the IMU output. Perhaps this would also give us a greater insight into the ability of the IMU to detect changes in dive onset, flight direction and DR times. Future investigations could consider the IMUs ability to detect GK jumps by comparing the IMU to force plate and motion capture outputs (Nielsen et al., 2018). They could also analyse the reliability of the IMU within a more training realistic scenario but with a controlled number of desirable GK actions using a simulated GK circuit (Singh et al., 2010; Wundersitz et al., 2015).

Due to the practical environment and equipment available, investigations into the sensitivity of the IMU to changes in DR times could also have been improved. Ideally, we would have liked to have measured each GKs true DR time using force plates and infra-red motion analysis instead of the derivates of the DR action (i.e. CMJ and BP). Additionally, when a dive is completed on the training pitch, the GK is coached to land on their side, keeping their frontal plane facing the front of the goal, thus having visibility of any secondary threats on goal from the opposition. In doing so, the DR is initiated by a lateral ballistic arm press, unlike the bilateral ballistic press-up used within this study, potentially reducing the specificity of the test. As an alternative we could have used a single arm bench press.

A common limitation within GK research seems to be the small sample size, as there are usually only three or four GKs within a professional team, of which only one is required to play in competitive games. This narrows down the participant pool available. For example, Boone et al., (2012) conducted a physical fitness assessment on first division Belgian soccer players; 272 of which were outfield players and only 17 were goalkeepers. Previous literature have also used youth GKs from sub-elite clubs or national set-ups to increase the volume of subjects and reliability of results. Rebelo-Gonçalves et al., (2015) focused on the anthropometric and physiological profiling of youth football players using Portuguese U13s – U19s players, 74 of which were outfield players and 71 of which were goalkeepers. While the larger subject pool makes the results more robust, goalkeeper abilities change with age and maturation status, playing experience and subsequent physiological abilities. Therefore, any results from this study should be interpreted with caution when applying to younger GKs as the reliability and sensitivity of the IMU may change.

The novel approach of monitoring the training demands of GKs is very appealing, especially with regards to reducing analysis time, a limitation noted of other methods outlined in the literature review. In saying that, DR times for each session had to be collected manually from the flagged Dive events on the GPS velocity trace. Given there were up to 48 dives in a session by a single GK alone, this was very time consuming and not ideal within a fast paced working environment. However, a single IMU was able to provide insight in the training demands of the GK without the need for cumbersome invasive methods.

5.5 Conclusion

In conclusion, the validity of the GPS based IMU to count GK movements compared to the criterion measure of VA was almost perfect ($r = 0.903$). However, our data suggests the specificity of the IMU based algorithm to distinguish different GK metrics was questionable. The IMU could detect Total Dives and DvR or DvL with minimal discrepancies, was able to distinguish between right and left dives and possibly any physiological imbalances within these actions. While there was also no significant difference between DR count and the criterion method, it showed large limits of agreement and variability. The metric algorithm is not fully understood so caution must be taken when monitoring this action until further analysis is undertaken. Jumps were significantly over-estimated and, in the meantime,, we would suggest using video analysis along with the GPS analysis for accurate longitudinal analysis.

This study provided novel information regarding the DR action, of which the lower body muscular profile plays the dominant part in. Although there are limitations within this study, these investigations should only act as the first step in understanding if the GPS coupled IMU has a place in accurately determining the training demands of a goalkeeper for practitioners to make informed decisions.

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