1	Journal:	International Journal of Sports Physiology and Performance				
2						
3	Title:	Methodological considerations when quantifying high-intensity efforts				
4		in team sport using global positioning system technology				
5						
6	Submission Type:	Original Article				
7						
8	Authors:	Matthew C. Varley <sup>1</sup> , Arne Jaspers <sup>2</sup> , Werner F. Helsen <sup>2</sup> , James J.				
9		Malone <sup>3</sup>				
10						
11	Affiliations	<sup>1</sup> Institute of Sport Exercise and Active Living Victoria University				
12		Melbourne, Australia				
12	<sup>2</sup> Department of Kinesiology I aboratory of Perception and					
14		Department of Kinesiology, Eaboratory of Perception and				
14		Lucies and Lucies (KLL second) Lucies Delaiser				
15 16	University of Leuven (KU Leuven), Leuven, Belgium					
10	<sup>3</sup> School of Health Sciences, Liverpool Hope University, Liverpool,					
18		United Kingdom				
19						
20	Corresponding Author	or: Matthew C. Varley				
21	Corresponding Addr	ess: Aspire Academy, Aspire Zone, Doha, Qatar				
22	Corresponding Emai	l: <u>matthew.varley@gmail.com</u>				
23	Preferred running he	ad: Determining high-intensity efforts				
24	Abstract word-count	250				
25	Text only word-coun	t: 4018				
26	Number of figures:	5				
27	Number of tables:	2				

#### 28 Abstract

29

Purpose: Sprints and accelerations are popular performance indicators in applied sport. The 30 31 methods used to define these efforts using athlete tracking technology could affect the number of efforts reported. The study aimed to determine the influence of different techniques and 32 settings for detecting high-intensity efforts using Global Positioning System (GPS) data. 33 Methods: Velocity and acceleration data of a professional soccer match was recorded via 10-34 Hz GPS. Velocity data was filtered using either a median or exponential filter. Acceleration 35 36 data was derived from velocity data over a 0.2 s time interval (with and without an exponential filter applied) and a 0.3 s time interval. High-speed running ( $\geq$ 4.17 m.s<sup>-1</sup>), sprint ( $\geq$ 7.00 m.s<sup>-1</sup>) 37 and acceleration ( $\geq 2.78 \text{ m.s}^{-2}$ ) efforts were then identified using minimum effort durations (0.1 38 39 to 0.9 s) to assess differences in the total number of efforts reported. 40 Results: Different velocity filtering methods resulted in small to moderate differences (Effect

Size; 0.28 - 1.09) in the number of high-speed running and sprint efforts detected when minimum duration was <0.5 s and small to very large differences (ES; -5.69 - 0.26) in the number of accelerations when minimum duration was <0.7 s. There was an exponential decline in the number of all efforts as minimum duration increased, regardless of filtering method, with the largest declines in acceleration efforts.

Conclusions: Filtering techniques and minimum durations substantially affect the number of
high-speed running, sprint and acceleration efforts detected with GPS. Changes to how highintensity efforts are defined affect reported data. Therefore, consistency in data processing is
advised.

50

51 Key words: soccer, football, GPS, acceleration, sprint

#### 53 Introduction

Athlete tracking systems allow the quantification of athlete movement during training 54 or matches by measuring the distance, velocity and acceleration of an athlete. Semi-automated 55 tracking systems measure the displacement of an athlete over time from which distance, 56 velocity and acceleration are calculated. Global positioning system (GPS) devices measure 57 distance travelled via positional differentiation (the change in device location with each 58 received satellite signal). While velocity can be derived from this distance measure (distance 59 over time), a greater accuracy and lower error is found when velocity is calculated using the 60 Doppler-shift method (measured via the change in frequency of the satellite signal).<sup>1</sup> Thus, the 61 majority of GPS manufacturers calculate velocity via the Doppler-shift method from which 62 acceleration is subsequently derived. Athlete movements are typically recorded as the distance 63 64 covered or number of discrete efforts in specific speed or acceleration categories. These categories are defined using specific speed/acceleration thresholds which may vary between 65 users and sports. Practitioners and researchers use the distances and number of efforts 66 performed by athletes to monitor training load,<sup>2,3</sup> profile physical performance during 67 competition<sup>4-6</sup> and link these movements to injury<sup>7</sup> or match events such as scoring or 68 conceding points<sup>8</sup>. 69

70

Numerous validation studies have assessed the ability of GPS to measure distance and velocity which have been summarised in a recent review.<sup>9</sup> This is a continuous process as each new device or upgrade requires new validation. However, there is limited research regarding the various methods used to determine movement efforts. Typically, a movement effort is identified when GPS velocity/acceleration enters a specific threshold (e.g. sprint threshold) and lasts for a minimum duration, referred to as 'dwell time' or minimum effort duration (MED). Often the total count of efforts performed during a training session or match are reported. Movement efforts are determined independently of GPS distance information and are calculated using purely the velocity and acceleration data. The acceleration data is typically calculated based on the GPS-derived data and not from the inertial sensors within these devices which was the case in the present study. This is a common misconception from practitioners and may cloud judgement on the data reported (insert IJSPP black box review paper reference).

83

The most common movement efforts reported in research and by practitioners are highspeed, sprint and acceleration efforts.<sup>4,5,10,11</sup> A recent survey of practitioners from high-level football clubs around the world found that acceleration variables were ranked 1<sup>st</sup> as the most commonly used metric when monitoring athletes during training.<sup>12</sup>

88

89 There are several methodological considerations when identifying an effort that may substantially change the number of efforts identified when tracking athletes. To determine a 90 meaningful effort, practitioners should establish a minimum duration that velocity/acceleration 91 92 must exceed the specific movement threshold. For example, if a MED of 0.5 s is set to define a sprint effort then an athlete would need to maintain a speed greater than the sprint threshold 93 for at least 0.5 s for an effort to be recorded. This ensures that possible spikes in the GPS data 94 due to noise, which may last 0.1 s or lower depending on the sampling frequency, are not 95 96 recorded as discrete efforts. Additionally, as velocity/acceleration may oscillate around a set 97 threshold, selecting an appropriate MED will help to ensure that only meaningful efforts are recorded. The MED for a sprint may be longer than that for an acceleration, as a high rate of 98 acceleration is likely to be short.<sup>13</sup> These considerations will account for the inherent noise in 99 GPS velocity/acceleration data and increase the likelihood that any efforts identified are real. 100

102 Another consideration when using GPS to quantify athlete movement is the use of data filtering techniques within the manufacturer software. Due to the inherent noise in raw GPS 103 velocity data, manufacturers apply different filtering techniques to smooth velocity and 104 105 acceleration data. The type of filter is often chosen at the discretion of the manufacturer and may include median, exponential, Butterworth or other filters. Additionally, acceleration data 106 can be smoothed by widening or shortening the time interval over which it is derived from 107 velocity with a wider interval resulting in a greater smoothening of the data. Thus, acceleration 108 data can undergo substantial smoothing through a combination of manipulating the interval 109 110 over which it was derived and applying a filter to the data as demonstrated in Figure 1. The development of filtering techniques to improve accuracy is ongoing within the athlete tracking 111 industry via software and firmware updates. These updates may incorporate different filtering 112 113 techniques which can lead to substantial changes in the movement data reported. For example, following a software upgrade large decreases in the number of acceleration efforts were 114 detected when the same GPS data was processed.<sup>14</sup> Although this was not directly attributed to 115 changes in data filtering it is likely that these differences were partially due to a change in data 116 filtering. While some manufacturers will allow the user to customise the filter or the time 117 interval used to calculate acceleration, in other cases this is fixed and information regarding 118 these elements may not be available to the user. Alternatively, the raw data can be exported 119 and analysed in custom-based software such as Matlab or Microsoft excel allowing these 120 121 considerations to be defined by the user.

122

124

125 Currently it is unknown how changes to the data filtering and/or MED will directly 126 affect the number of efforts reported. In a sports setting, any changes to these settings may

<sup>123 ---</sup>Figure 1 here---

127 substantially alter the reported values which will affect athlete monitoring, training preparation and the practitioner's interpretation of these results. In research these details are often not 128 reported limiting both the ability to compare results across the literature and the reproducibility 129 130 of the research. The aim of this study was to determine the influence of varying MED to detect high-intensity efforts in an applied sporting context. This study also examined the influence of 131 different filtering techniques within GPS manufacturers' software on subsequent high-intensity 132 effort detection. The practical application of this study is to provide some recommended 133 guidelines for practitioners using such data for their daily practice. 134

135

### 136 Methods

137

# 138 Participants

Data were collected from six professional soccer players  $(23.0 \pm 1.8 \text{ years})$  competing in the highest league of the Netherlands (Eredivisie). As this study assessed the influence of different data analysis techniques a large sample size was not essential. Written informed consent was provided before participation in this study, which was approved by the ethics committee of KU in line with the requirements stipulated in the Declaration of Helsinki.

144

## 145 Design

To assess the differences of various MED methods and data smoothing filters, movement data were recorded in two different stages. The first was during controlled sprint tests of 10, 20 and 40 m under the assumption that during a maximal sprint from a static start a player should only register a single high-speed, sprint and/or acceleration effort. If more than one effort was recorded the MED could be adjudged to be too low. Only one trial for each sprint test (10, 20 and 40 m) was included in the analysis for each player (n=6). In the second 152 stage, movement data were recorded during a competitive match in order to demonstrate how 153 the different effort detection methods influenced the number of efforts identified in a practical 154 way. For both stages, GPS data was downloaded and processed using two versions of the 155 manufacturer's software, Sprint<sup>TM</sup> and Openfield<sup>TM</sup>, which each used different filtering 156 techniques.

157

#### 158 Methodology

159 GPS Data Collection

160 Data was collected using a commercial 10-Hz GPS device (Optimeye S5; firmware version 7.22, Catapult Sports, Melbourne, Australia) worn inside a custom made garment 161 positioned between the scapula. Previous research has found such devices to have acceptable 162 levels of reliability and validity for assessing velocity.<sup>15</sup> Prior to data collection, the devices 163 were left outside in an open area for 30 minutes to allow satellite connection and checked to 164 ensure a satellite 'lock' had occurred prior to placing on the soccer players. The sprint testing 165 was conducted on an outdoor natural grass pitch and the match data was collected in the team's 166 home stadium. The average  $\pm$  SD number of satellites and horizontal dilution of position during 167 the sprint testing was  $14.0 \pm 0$  and  $0.74 \pm 0.01$ , respectively, and for the match data collection 168 was  $15.0 \pm 0.6$  and  $0.70 \pm 0.10$ , respectively. These values have been suggestive of being 169 acceptable for good GPS signal coverage based on the manufacturer's recommendations.<sup>16</sup> 170

171

# 172 GPS Data Analysis

173 Subsequent data was downloaded and exported using two versions of the 174 manufacturer's software, Sprint<sup>TM</sup> (version 5.1.7) and Openfield<sup>TM</sup> (version 1.12.0, Catapult 175 Sports, Melbourne, Australia). The following describes the different filtering techniques 176 applied by the manufacturer's software in order to calculate the GPS velocity and subsequently GPS acceleration data that is used to quantify player movement. The raw GPS velocity data is
calculated using the Doppler-Shift method. The Sprint<sup>TM</sup> software filters the raw GPS velocity
data using a median filter (GPS Vel<sub>sprint</sub>), while the Openfield<sup>TM</sup> software filters the raw GPS
velocity data using an exponential filter (GPS Vel<sub>openfield</sub>).

181

The GPS acceleration data is derived from GPS velocity data. In the Sprint<sup>TM</sup> software 182 the user can select the time interval over which acceleration (GPS Accel<sub>sprint</sub>) is derived from 183 GPS Velsprint (referred to in the software as Smoothing Filter Width). In this study, time 184 intervals of 0.2 (Accel<sub>sprint 0.2</sub>) and 0.3 s (Accel<sub>sprint 0.3</sub>) were used. No additional filters are 185 applied to GPSAccel<sub>sprint</sub> after the time interval has been selected. In the Openfield<sup>TM</sup> software 186 GPS acceleration is derived from GPS Velopenfield using the 0.2 s time interval that is fixed 187 188 within the software. Data is then filtered further using an exponential filter (GPS Accelopenfield). All data was exported for analysis using custom-based software (Microsoft Excel). 189

190

# 191 Calculation of Movement Efforts

Movement efforts were determined from the aforementioned GPS velocity and 192 acceleration data using the following thresholds high-speed running ( $\geq$ 4.17 m.s<sup>-1</sup>), sprinting 193  $(\geq 7.00 \text{ m.s}^{-1})$  and acceleration  $(\geq 2.78 \text{ m.s}^{-2})$ . These thresholds were selected as they are 194 commonly used amongst the research literature.<sup>4,5,17</sup> High-speed running and sprint efforts 195 were identified using the following MED 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0,7, 0.8, 0.9 and 1 s. 196 Acceleration efforts were identified using the following MED 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 197 0.9 and 1 s. All data was analysed in Microsoft Excel duplicating the methods and output from 198 the respective software. It is worth noting that in the Sprint<sup>TM</sup> software although the minimum 199 duration for accelerations is an open option there is an error in the software that results in odd 200

numbers being 'rounded up' to the next decimal place (e.g. 0.1 becomes 0.2, 0.3 becomes 0.4
etc.), therefore practitioners who use this software will find 0.2, 0.4, 0.6, 0.8 and 1 s relevant.

### 204 Statistical Analysis

Data in the figures are presented as means and in tables as effect size and 90% 205 confidence limits (CL). All data were first log-transformed to reduce bias arising from non-206 uniformity of error. Differences in the number of efforts recorded between each MED and 207 differences in the number of efforts recorded between software filters were standardised using 208 209 Cohen's effect size principle with 90% CL. Uncertainty in each effect was expressed as 90% CL and as probabilities that the true effect was substantially greater than the smallest important 210 positive or negative difference. These probabilities were used to make a qualitative 211 212 probabilistic mechanistic inference about the true effect using the following scale: >25 - 75%, possibly; >75-95%, likely; >95 – 99%, very likely; >99%, almost certainly.<sup>18,19</sup> The magnitude 213 of a given effect was determined from its observed standardized value (the difference in means 214 divided by the between subject standard deviation) using the following scale; <0.20, trivial; 215 0.20-0.59, small; 0.60-1.19, moderate; 1.20-1.99, large;  $\geq 2.00$ , very large.<sup>18,19</sup> For clarity only 216 effects with a likelihood >75% are presented. 217

218

219 **Results** 

## 220 Efforts detected during 10 - 20 - 40m Sprint Tests

During the 10, 20 and 40 m sprints only one high-speed running effort was detected for each test regardless of the MED and filtering method. Similarly only one sprint effort was detected during the 40 m sprint regardless of the MED and filtering method, while no sprint efforts were detected during the 10 and 20 m sprints..

There were substantial differences in the number of acceleration efforts detected 226 between most of the different MED during the 10, 20 and 40 m sprints (Figure 2). Notably, 227 Accel<sub>openfield</sub> resulted in fewer differences across the MED (Figure 2C). A 0.2, 0.3 and 0.4 s 228 229 MED resulted in the identification of more than one acceleration effort per sprint when analysed using Accel<sub>sprint\_0.2</sub> and Accel<sub>sprint\_0.3</sub> as did a MED of 0.2 s when using Accel<sub>Openfield</sub> 230 (Figure 2). When comparing differences in the filtering methods, the number of acceleration 231 efforts detected were greater for shorter MED for both Accel<sub>sprint\_0.2</sub> and Accel<sub>sprint\_0.3</sub> compared 232 to Accel<sub>Openfield</sub> and lower for longer MED (Table 1). The number of acceleration efforts 233 determined using Accel<sub>sprint 0.3</sub> was lower for shorter MED compared to when using a 0.2 s 234 interval, however these differences became unclear as the MED increased (Table 1). 235

236

237 ---Figure 2 here---

238

## 239 *Efforts detected during a competitive match*

The number of high-speed running and sprint efforts identified during a match appeared to decline exponentially with an increase in the MED for both the Sprint<sup>TM</sup> and Openfield<sup>TM</sup> filtering (Figure 3). The number of high-speed running and sprint efforts identified during a match using the Openfield<sup>TM</sup> filtering were higher by a small to large magnitude which declined with increasing MED from 0.1 to 0.3 s, however, from 0.6 s on the differences were either unclear or clearly trivial (Table 2).

246

247 ---Figure 3 here---

248

There was an exponential decline in the number of acceleration efforts identified duringa match as the MED increased for all filtering methods (Figure 4). The number of acceleration

efforts identified using Accel<sub>Openfield</sub> were lower by a large to very-large magnitude for MED lower than 0.5 s compared to using both Accel<sub>sprint\_0.2</sub> and Accel<sub>sprint\_0.3</sub> (Table 2). A greater number of acceleration efforts were identified for a 0.2 and 0.3 s MED when using Accel<sub>sprint\_0.2</sub> compared to Accel<sub>sprint\_0.3</sub> and lower number for a 0.4 and 0.5 MED (Table 2).

255

256 ---Figure 4 here---

257

### 258 **Discussion**

The main finding of this study was that changes in the MED as small as 0.1 s substantially affected the number of accelerations, high-speed running and sprint efforts detected during matches. A secondary finding was that the use of different filtering methods used to smooth velocity and acceleration data changed the number of efforts identified.

263

Of all efforts, the number of accelerations were most affected by different MED and 264 filters. The analysis of individual sprints over 10, 20 and 40 m allowed the evaluation of 265 different MED for acceleration efforts from a practical perspective. The MED resulting in the 266 detection of more than 1 acceleration effort per sprint (0.2, 0.3 and 0.4 s when using Sprint<sup>TM</sup> 267 filtering and 0.2 s when using Openfield<sup>TM</sup> filtering) could be suggested to overestimate the 268 number of acceleration efforts occurring. However, in a competitive match MED greater than 269 0.5 s detected no more than 6 efforts regardless of the filtering method used (Figure 6). The 270 duration an athlete can sustain a high rate of acceleration is very short <sup>13</sup> and longer MED may 271 exclude maximal accelerations. An explanation for the detection of multiple accelerations 272 during the sprint tests is that the manufacturer's software defines the end of an acceleration 273 effort as when acceleration falls below the specific threshold for a single sample (0.1 s). As 274 GPS acceleration data is subject to noise, this could result in what would practically be termed 275

a single acceleration effort being classified as two separate efforts as can be seen in Figure 1. To test this assumption, the Accel<sub>sprint\_0.2</sub> and Accel<sub>sprint\_0.3</sub> data was reanalysed using previously established methods<sup>4</sup> where the end of an acceleration effort was defined as when acceleration fell below 0 m.s<sup>-2</sup> following the detection of an effort. As shown in Figure 5, this resulted in the detection of multiple acceleration efforts for a MED of 0.2 s only, while all other durations detected no more than a single effort, confirming the above hypothesis.

282

283 ---Figure 5 here---

284

The method used to identify the end of the effort is just as important as the MED, 285 however, this is often overlooked. Various methods can be used such as establishing a 286 287 minimum duration for velocity/acceleration to fall below the set threshold or requiring a drop in velocity/acceleration below a percentage of the set threshold. How the end of an effort is 288 identified should be based on the user's practical needs of the data. As an individual may 289 continue to accelerate until their rate of acceleration falls below 0 m.s<sup>-2</sup>, this may be a more 290 practical definition for identifying acceleration efforts than purely quantifying the extremely 291 short duration spent accelerating above the required threshold and may better represent the 292 perception of an acceleration held by a coach or other support staff. This method also allows 293 practitioners to use lower MED (e.g. 0.3 or 0.4 s) with confidence that single acceleration 294 efforts will not be detected as multiple efforts (Figure 5A and 5C). The limitation to this 295 approach is where an athlete accelerates maximally, their rate of acceleration falls below 296 threshold but not 0 m.s<sup>-2</sup> and then rises again, as this would only be considered a single effort. 297 Practitioners can either use both methods or choose one based on their needs. An endpoint 298 where acceleration falls below the maximum threshold may be more relevant for practitioners 299 interested in when athletes are only working at their most energetically demanding. An 300

endpoint where acceleration falls below 0 m.s<sup>-2</sup> may provide a more practical measure of 301 acceleration efforts allowing greater contextualisation of the movement. 302

303

The additional filtering used by the Openfield<sup>TM</sup> software resulted in a substantially 304 lower number of accelerations recorded during the match. A large change in the number of 305 accelerations detected has also been observed following a software upgrade using GPS from 306 other manufacturers (GPSports).<sup>14</sup> The results of this study suggest these changes were due to 307 the implementation of a more severe smoothing filter on the acceleration data. In this study, 308 309 absolute acceleration and velocity thresholds were used to demonstrate the methodological differences when analysing GPS data. While new filters may provide a more realistic 310 representation of acceleration and velocity efforts they may also require the user to re-evaluate 311 312 the thresholds they have used to define their movements. For example, Figure 1 demonstrates the different smoothing methods used to determine acceleration result in substantially different 313 peak acceleration values. Velocity would also show differences in the maximal values if a 314 smoothing filter is applied, such as the exponential filter used in Openfield<sup>TM</sup>. Thus, for a given 315 threshold the greater the smoothing applied to velocity and acceleration data, the less an athlete 316 would be expected to reach a given threshold. A possible way to address this issue may be to 317 develop device or filter specific thresholds. If movement thresholds are based on athlete 318 physical testing, athletes could wear the GPS during these tests allowing data to be processed 319 320 for each filtering technique. For example, if the sprint threshold is defined as percentage of Maximal Sprint Speed recorded by GPS during a 40 m sprint,<sup>20</sup> GPS data could be reprocessed 321 when/if a new data filter is used to maintain a consistent threshold. This will reduce the impact 322 of changing manufacturers/software on longitudinal monitoring. 323

Regardless of the methods used practitioners should be aware that there is no perfect 325 combination for detecting acceleration efforts. A lower MED will likely overestimate the 326 number of acceleration efforts while a higher MED will likely underestimate the number of 327 328 efforts. Further, applying a greater smoothing method to the data will allow lower MED to be used while a lower smoothing method may restrict the user to higher MED. Understanding the 329 advantages and limitations of each method will allow practitioners to choose the combination 330 that best suits their needs. It should also be acknowledged that this study has only considered 331 maximal acceleration efforts, which primarily occur at low velocities.<sup>4</sup> The effect of different 332 333 methods to identify low and moderate accelerations are likely to be even more pronounced as athletes are likely to have much greater oscillation around lower rates of acceleration. 334

335

336 The MED used to identify velocity based efforts showed smaller discrepancies than that of acceleration based efforts. Given that the 10, 20 and 40 m sprints were all maximal it is not 337 surprising that there was no difference in the number of high-speed running or sprint efforts 338 339 detected. However, during a match different MED resulted in the number of efforts decreasing in a somewhat exponential manner as duration increased (Figure 3). This is likely due to the 340 intermittent nature of match-running where players may oscillate around specific velocity 341 thresholds, whereas during sprint tests velocity is linearly increasing. Further, the exponential 342 filter used in Openfield<sup>TM</sup> resulted in a greater number of efforts being identified compared to 343 the median filter used in Sprint<sup>TM</sup>. Likewise, there were more and larger differences in the 344 number of efforts according to MED when analysed with Openfield<sup>TM</sup> compared to Sprint<sup>TM</sup>. 345 Similar to acceleration, different smoothing filters can have a substantial effect on velocity data 346 and efforts detected, an issue which is likely to occur regardless of manufacturer where 347 different filters are used. 348

350 Movement categories can be separated into a number of threshold bands such as running (e.g. 4.17 to 7.00 m.s<sup>-1</sup>). However, in this study, the thresholds for high-speed running 351 (>4.17 m.s<sup>-1</sup>) and sprinting (>7.00 m.s<sup>-1</sup>) were both open-ended, therefore high-speed running 352 353 efforts also included sprint efforts. The use of threshold bands may be more appropriate when determining the distances covered within each band rather than the number of efforts within 354 each band. It is difficult to determine a MED required within each band as an athlete will pass 355 through all bands when sprinting from a low speed. Depending on the rate of acceleration this 356 may result in multiple efforts for what is ultimately a single sprint effort. The use of efforts 357 358 according to threshold bands may have limited practical application for practitioners. A similar argument could be made when considering banded rates of acceleration effort, especially as 359 the higher the rate of acceleration, the shorter the maximal acceleration is likely to be. There is 360 361 currently no consensus on how the total number of high speed or high-intensity efforts should be defined. For example, if an athlete performs 30 sprint efforts (>7.00 m.s<sup>-1</sup>) and 50 running 362 efforts (4.17 to 7.00 m.s<sup>-1</sup>), 30 of which ultimately lead to sprints, should these be considered 363 364 separately (i.e. 80 independent high-speed efforts) or in combination (i.e. 30 sprints and 20 running efforts)? This is an important topic with regards to profiling high-intensity movements 365 and practitioners should make their decision based on how the information will be used. 366

367

#### 368 **Practical Applications**

Different data filtering methods and MED can substantially effect the number of high intensity movements detected using GPS devices

Practitioners and researchers should include detailed information regarding the filtering
 techniques and settings used to determine movement efforts in practical reports and
 research publications.

If velocity or acceleration thresholds are based on physical capacities, practitioners
 should establish a set of reference data which can be reprocessed using different
 smoothing filters to adjust these thresholds accordingly.

- When defining acceleration efforts practitioners may consider defining the end of an effort as when acceleration falls below 0 m.s<sup>-2</sup> to provide a more practical measure
- Practitioners should use a consistent method when analysing athlete velocity and
   acceleration data during a season, and any changes to this method should be done at the
   end of the season and may be applied to retrospective data
- 382

## 383 Conclusion

Different filtering techniques and MED substantially affected the number of high-384 intensity efforts detected with GPS. While this study provides novel insights into this area, it 385 is difficult to provide a recommendation for the appropriate filtering and MED to be used with 386 high-speed running, sprinting and acceleration efforts based on the results. It is unlikely that 387 practitioners using manufacturer software will be able to select the type of filter used, and may 388 be restricted in their choice of MED. Practitioners and researchers should be aware that changes 389 to filtering and MED are likely to affect reported data. The key recommendation is that 390 practitioners maintain consistency as much as possible in their data processing. Also following 391 a software or firmware update that affects data filtering, practitioners may consider re-392 analysing retrospective data to allow ongoing comparison of the data. Finally, the different 393 filtering of velocity and acceleration data will also effect the distances athletes cover at specific 394 thresholds and this should be explored in future research. 395





Figure 1. GPS velocity and acceleration data during a 40 m sprint effort. The graph demonstrates the smoothing
 effect when acceleration is derived from velocity using a different intervals (0.2 and 0.3 s) and when data is
 processed using an exponential filter (acceleration was derived using a 0.2 s interval). The threshold used to
 identify an acceleration effort is indicated by the line running parallel to the x axis at 2.78 m.s<sup>-2</sup>.





**Figure 2.** The number of acceleration efforts detected during 10, 20 and 40 m sprints when using different minimum effort durations and different filtering methods. The Sprint<sup>TM</sup> software derives acceleration from velocity data over a 0.2 (Figure A) or a 0.3 s interval (Figure B) and Openfield<sup>TM</sup> software derives acceleration from velocity data over a 0.2 s interval and then applies an exponential filter (Figure C). For each sprint test n=6.\_Quantitative chances of higher or lower differences between minimum effort durations are evaluated according to thresholds identified in statistical analysis; normal text = Likely, underlined text = Very likely, bold text = Almost certainly. T = Trivial effect size, S = small effect size, M = moderate effect size, L = large effect size, vL = very large effect size. 2, 3, 4, 5, 6, 7, 8 indicate an effect compared to a minimum

409 duration of 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, respectively.

Table 1. Differences in the number of acceleration efforts detected during 10, 20 and 40 m sprints according to
 the filtering method used. For each sprint test n=6. Data is effect size and 90% confidence limits

Sprint<sup>TM</sup> 0.2 Sprint<sup>TM</sup> 0.3 Sprint<sup>TM</sup> 0.2 vs Openfield<sup>TM</sup> vs Openfield<sup>TM</sup> vs Sprint 0.3 **Minimum duration Acceleration efforts** Acceleration efforts Acceleration efforts 10 m Sprint -0.64 (-1.85 to 0.57)\* -0.49 (-0.99 to 0.00)\* 0.2 -1.13 (-2.49 to 0.22)\* 0.3 -0.64 (-1.59 to 0.31)\* -0.12 (-0.29 to 0.04)\* -0.51 (-1.51 to 0.49) 0.4 0.32 (-0.37 to 1.01) -0.10 (-0.22 to 0.03) 0.42 (-0.23 to 1.07) 0.5 -0.05 (-0.15 to 0.06)\*\* 0.65 (-0.20 to 1.51)\* 0.70 (-0.11 to 1.52)\* 0.6 0.62 (-0.19 to 1.43)\* 0.31 (-0.35 to 0.97) 0.31 (-0.35 to 0.97) 0.7 0.99 (0.13 to 1.86)\* 0.66 (-0.20 to 1.53)\* 0.33 (-0.37 to 1.04) 0.8 1.18 (0.15 to 2.20)\* 0.78 (-0.24 to 1.81)\* 0.39 (-0.44 to 1.23) 0.9 NA NA NA NA NA NA 1 20 m Sprint 0.2 -1.74 (-2.32 to -1.17)\*\*\* -1.26 (-2.12 to -0.40)\*\* -0.48 (-1.00 to 0.03)\* 0.3 -1.99 (-2.48 to -1.50)\*\*\* -1.34 (-2.57 to -0.12)\* -0.64 (-1.70 to 0.41)\* 0.4 -0.39 (-1.23 to 0.44) -1.18 (-2.20 to -0.15)\* 0.78 (-0.24 to 1.81)\* 0.5 0.36 (-0.59 to 1.32) 0.43 (-0.48 to 1.34) -0.06 (-1.51 to 1.38) 0.6 0.78 (-0.24 to 1.81)\* 0.39 (-0.44 to 1.23) 0.39 (-0.44 to 1.23) 0.7 NA 0.51 (-0.57 to 1.58) NA 0.8 NA 2.02 (0.95 to 3.10)\*\* NA 0.9 NA 1.07 (-0.45 to 2.60)\* NA 1 1.07 (-0.45 to 2.60)\* NA NA 40 m Sprint 0.2 -2.26 (-3.19 to -1.33)\*\*\* -0.88 (-1.69 to -0.07)\* -1.38 (-2.19 to -0.57)\*\* 0.3 -2.06 (-2.95 to -1.18)\*\* -1.4 (-2.33 to -0.46)\*\* -0.67 (-2.1 to 0.76) 0.4 0.61 (-0.69 to 1.91) -0.18 (-0.42 to 0.06) 0.79 (-0.67 to 2.25)\* 0.5 0.77 (-0.23 to 1.77)\* 0.44 (-0.36 to 1.24) 0.33 (-0.53 to 1.19) 0.62 (-0.19 to 1.43)\* 0.31 (-0.35 to 0.97) 0.31 (-0.93 to 1.55) 0.6 0.7 0.99 (0.13 to 1.86)\* 0.33 (-0.37 to 1.04) 0.66 (-0.75 to 2.07) 0.8 0.99 (0.13 to 1.86)\* 0.66 (-0.75 to 2.07) 0.33 (-0.37 to 1.04) 0.9 0.64 (-0.20 to 1.48)\* NA NA NA 0.64 (-0.20 to 1.48)\* NA 1

412 Negative values indicate a lower number of efforts were reported using the second software name in each

column. Quantitative chances of higher or lower differences between filtering methods are evaluated according
to thresholds identified in statistical analysis; \* = Likely, \*\* = Very likely, \*\*\* = Almost certainly. NA indicates

that no efforts were detected during one of the filtering methods.



![](_page_19_Figure_1.jpeg)

Figure 3. The number of high-speed running (Figure A and B) and sprint efforts (Figure C and D) performed by
 players (n=6) during a competitive match when detected using different minimum effort durations and different
 filtering methods. The Sprint<sup>TM</sup> software uses a median filter and the Openfield<sup>TM</sup> software uses an exponential
 filter. Quantitative chances of higher or lower differences between minimum effort durations are evaluated
 according to thresholds identified in statistical analysis; normal text = Likely, underlined text = Very likely, bold

423 according to thresholds identified in statistical analysis; normal text = Likely, underfined text = Very likely, b 424 text = Almost certainly. S = small effect size, M = moderate effect size, L = large effect size, vL = very large

425 effect size, 2, 3, 4, 5, 6, 7, 8, indicate an effect compared to a minimum duration of 0.2, 0.3, 0.4, 0.5, 0.6, 0.7,

426 0.8, respectively.

427 Table 2. Differences in the number of high-speed running, sprint and acceleration efforts performed by players (n=6) during a competitive match when detected according to
 428 the filtering method used. Data is effect size and 90% confidence limits

Sprint <sup>TM</sup> vs Openfield <sup>TM</sup>			Sprint <sup>TM</sup> 0.2 vs Openfield <sup>TM</sup>	Sprint 0.3 vs Openfield <sup>TM</sup>	Sprint <sup>TM</sup> 0.2 vs Sprint <sup>TM</sup> 0.3
Minimum duration	High-speed running efforts	Sprint efforts	-	Acceleration efforts	-
0.1	1.09 (0.82 to 1.35)***	1.06 (0.41 to 1.70)**	NA	NA	NA
0.2	0.68 (0.5 to 0.85)***	0.50 (0.11 to 0.89)*	-5.69 (-6.51 to -4.88)***	-4.6 (-5.36 to -3.83)***	-1.09 (-1.25 to -0.94)***
0.3	0.39 (0.25 to 0.53)**	0.35 (-0.03 to 0.73)*	-5.30 (-6.12 to -4.47)***	-4.47 (-5.28 to -3.66)***	-0.82 (-0.92 to -0.72)***
0.4	0.28 (0.17 to 0.39)*	0.04 (-0.22 to 0.30)*	-2.26 (-3.03 to -1.48)***	-3.81 (-4.58 to -3.04)***	1.55 (1.33 to 1.77)***
0.5	0.17 (0.05 to 0.3)	0.008 (-0.21 to 0.37)	-0.78 (-1.29 to -0.26)**	-1.37 (-1.98 to -0.76)**	0.59 (0.24 to 0.95)**
0.6	0.04 (-0.03 to 0.12)**	-0.19 (-0.48 to 0.10)	0.55 (-0.09 to 1.20)*	0.30 (-0.48 to 1.07)	0.26 (0.02 to 0.49)
0.7	-0.04 (-0.09 to 0.01)***	-0.22 (-0.51 to 0.06)	0.44 (0.03 to 0.85)*	0.27 (-0.19 to 0.74)	0.16 (0.03 to 0.30)
0.8	-0.05 (-0.07 to -0.04)***	-0.31 (-0.59 to -0.02)	NA	0.18 (0.03 to 0.32)	NA
0.9	-0.05 (-0.15 to 0.05)**	-0.06 (-0.18 to 0.06)**	NA	1.06 (0.18 to 1.93)*	NA
1	-0.08 (-0.23 to 0.06)*	-0.22 (-0.45 to 0.01)	NA	NA	NA

429 Negative values indicate a lower number of efforts were reported using the second software name in each column. Quantitative chances of higher or lower differences

between filtering methods are evaluated according to thresholds identified in statistical analysis; \* = Likely, \*\* = Very likely, \*\*\* = Almost certainly. NA indicates that no
 efforts were detected during one of the filtering methods.

![](_page_21_Figure_0.jpeg)

Figure 4. The number of acceleration efforts performed by players (n=6) during a competitive match when detected using different minimum effort durations and different filtering methods. The Sprint<sup>TM</sup> software derives acceleration from velocity data over a 0.2 (Figure A) or a 0.3 s interval (Figure B) and Openfield<sup>TM</sup> software derives acceleration from velocity data over a 0.2 s interval and then applies an exponential filter (Figure C). Quantitative chances of higher or lower differences between minimum effort durations are evaluated according to thresholds identified in statistical analysis; normal text = Likely, underlined text = Very likely, bold text = Almost certainly. S = small effect size, M = moderate effect size, L = large effect size, vL = very large effect size. 2, 3, 4, 5, 6, 7, 8 indicate an effect compared to a minimum duration of 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, respectively.

![](_page_22_Figure_0.jpeg)

![](_page_22_Figure_1.jpeg)

Figure 5. The number of acceleration efforts detected during 10, 20 and 40 m sprints (Figure A and C)and a
competitive game (Figure B and D) when using different minimum durations. Acceleration is derived from
velocity using a 0.2 s (Figure A and B) and 0.3 s (Figure C and D) interval and the end of the acceleration effort

446 is identified when acceleration falls below or is equal to  $0 \text{ m.s}^{-2}$ 

448

### 449 References

- Townshend AD, Worringham CJ, Stewart IB. Assessment of speed and position during human
   locomotion using nondifferential GPS. *Med. Sci. Sports Exerc.* 2008;40(1):124-132.
- Gaudino P, Iaia FM, Strudwick AJ, et al. Factors Influencing Perception of Effort (Session-RPE)
   During Elite Soccer Training. *Int. J. Sports Physiol. Perform.* 2015;10(7):860-864.
- 4543.Malone JJ, Di Michele R, Morgans R, Burgess D, Morton JP, Drust B. Seasonal training-load455quantification in elite English premier league soccer players. Int. J. Sports Physiol. Perform.4562015;10(4):489-497.
- 4. Varley MC, Aughey RJ. Acceleration profiles in elite Australian soccer. *Int. J. Sports Med.* 2013;34(1):34-39.
- 459 5. Varley MC, Gabbett T, Aughey RJ. Activity profiles of professional soccer, rugby league and
  460 Australian football match play. *J. Sports Sci.* 2014;32(20):1858-1866.
- 461 6. Jones MR, West DJ, Crewther BT, Cook CJ, Kilduff LP. Quantifying positional and temporal
  462 movement patterns in professional rugby union using global positioning system. *Eur J Sport*463 *Sci.* 2015;15(6):488-496.
- 4647.Gabbett TJ, Ullah S. Relationship between running loads and soft-tissue injury in elite team465sport athletes. J. Strength Cond. Res. 2012;26(4):953-960.
- 4668.Gabbett TJ, Gahan CW. Repeated High-Intensity Effort Activity in Relation to Tries Scored and467Conceded during Rugby League Match-Play. Int. J. Sports Physiol. Perform. 2015.
- Scott MT, Scott TJ, Kelly VG. The Validity and Reliability of Global Positioning Systems in Team
  Sport: A Brief Review. *J. Strength Cond. Res.* 2016;30(5):1470-1490.
- 470 10. Murray AM, Varley MC. Activity Profile of International Rugby Sevens: Effect of Score Line,
  471 Opponent, and Substitutes. *Int. J. Sports Physiol. Perform.* 2015;10(6):791-801.
- 472 11. Di Salvo V, Baron R, Gonzalez-Haro C, Gormasz C, Pigozzi F, Bachl N. Sprinting analysis of elite
  473 soccer players during European Champions League and UEFA Cup matches. J. Sports Sci.
  474 2010;28(14):1489-1494.
- 475 12. Akenhead R, Nassis GP. Training Load and Player Monitoring in High-Level Football: Current
  476 Practice and Perceptions. *Int. J. Sports Physiol. Perform.* 2016;11(5):587-593.
- 47713.di Prampero PE, Fusi S, Sepulcri L, Morin JB, Belli A, Antonutto G. Sprint running: a new478energetic approach. J. Exp. Biol. 2005;208(Pt 14):2809-2816.
- 479 14. Buchheit M, Al Haddad H, Simpson BM, et al. Monitoring accelerations with GPS in football:
  480 time to slow down? *Int. J. Sports Physiol. Perform.* 2014;9(3):442-445.
- 481 15. Varley MC, Fairweather IH, Aughey RJ. Validity and reliability of GPS for measuring
  482 instantaneous velocity during acceleration, deceleration, and constant motion. *J. Sports Sci.*483 2012;30(2):121-127.
- 48416.Malone JJ, Lovell R, Varley MC, Coutts AJ. Unpacking the Black Box: Applications and485Considerations for Using GPS Devices in Sport. Int. J. Sports Physiol. Perform. 2016:1-30.
- 486 17. Aughey RJ. Increased high-intensity activity in elite Australian football finals matches. *Int. J.* 487 Sports Physiol. Perform. 2011;6(3):367-379.
- 488 18. Hopkins WG. Spreadsheets for analysis of controlled trials with adjustment for a predictor.
   489 Sportscience. 2006(10):46-56.
- Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports
  medicine and exercise science. *Med. Sci. Sports Exerc.* 2009;41(1):3-13.
- 492 20. Buchheit M, Mendez-villanueva A, Simpson BM, Bourdon PC. Repeated-sprint sequences
  493 during youth soccer matches. *Int. J. Sports Med.* 2010;31(10):709-716.