Development and validity of an accelerometer-based velocity profile using Playermaker

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1. Introduction

Time motion analysis data has been used extensively throughout different sports in order to quantify the external loads of an individual athlete (Cardinale & Varley, 2017; Malone et al., 2020; Vanrenterghem et al., 2017). These metrics have been calculated using manual coding, video analysis (Reilly, 1976), semi-automated camera systems (Di Salvo et al., 2007; Bradley et al., 2009) and global positioning system devices (GPS; Aughey et al., 2010; Harley et al., 2010; Malone et al., 2020). Positioning data from GPS worn within a manufacturer vest between the scapulae commonly measure variables such as total and distances covered in a variety of locomotor classifications or speed zones (Rampinini et al., 2007; Reilly & Thomas, 1976). Using these data points is simple and easy to use. However, GPS derived data can be interfered with in poor satellite coverage areas such as large stadiums and indoor sessions.

Inertial measurement units (IMU) containing tri-axial accelerometers within some GPS devices, have been able to provide alternative methods of monitoring external training load (Barrett et al., 2014; Boyd et al., 2011; Gomez-Carmona et al., 2019). Vector magnitudes have commonly been used and provide an arbitrary unit that is derived from three-dimensional measures of the instantaneous rate of change of acceleration (Barrett et al., 2014; Boyd et al., 2011; Gomez-Carmona et al., 2019). However, these vector magnitudes have large within and between athlete differences from the same activity (Barrett et al., 2016) and can make it difficult for practitioners to interpret this information and feedback to coaches. Time motion analysis metrics have been derived from IMU devices predominately from the accelerometer via the detection of an individual's stride length and cadence (Potter et al., 2019). Using IMU's to derive time motion analysis metrics, depending on the location of the device, may provide a more valid and reliable method then using GPS systems (Godfrey et al., 2015; Potter et al., 2019). Furthermore, it would allow practitioners to use it in multiple training environments. Therefore, the aim of the current study was to develop and assess the validity of time motion analysis data using foot mounted IMU's.

2. Methods

Participants

40 well-trained team sports players (age: 20.1 ± 2.1 years; height: 178 ± 4 cm; body mass: 75.1 ± 5.4 kg) volunteered to partake in the study, giving verbal consent.

Experimental Design

Each participant was instrumented with two Playermaker devices (**Figure 1**; Playermaker A1, Playermaker™, UK; 1000 Hz), wearing one on each foot. Video recordings were filmed to assess the participants movements (GOPRO hero 5, GOPRO, USA; 120Hz – 1080x720). An analysis process was developed were the player's position was tracked on a video data (Figure 3) and later camera lens un-distortion and perspective transformation (Figure 2) was applied on the, pixel based, position to obtain a metric based position. The video transformation method was accuracy tested at 45º angled camera and low total error rates of 0.36%± 0.2 was recorded (Figure 2). The video reference position velocity profile was extracted as gold-standard to compare with Playermaker's results. Prior to starting the trial, participants performed a standardised 10 min soccer specific warm-up (see **Appendix 1**), followed by a 5-min passive recovery period. Before undertaking the $SAFT_{90}$ protocol (Lovell et al., 2008), a maximal velocity test (50m) was performed.

Figure 1. An image of the Playermaker device and how it is fitted to the lateral malleolus of the foot

The $SAFT_{90}$ is a field based soccer simulation, designed to mimic the movement characteristics of elite soccer match play, which incorporates multi-directional movements and replicates the time motion analysis data typical of English Championship soccer match play (Lovell et al., 2008; Marshall et al., 2014). The 90-min activity profile consists of 1332 changes of direction and

1269 changes in speed over a 90-min period performed within a 20m free running protocol (See **Figure 2**).The activities performed during SAFT$_{90}$ include standing (0.0 $km.h^{-1}$), walking (5.0 $km.h^{-1}$), jogging (10.3 $km.h^{-1}$), striding (15.0 $km.h^{-1}$) and sprinting (>20.4 $km.h^{-1}$; Small et al., 2008) which are controlled via an audio recording. In the current study, participants completed 5 min of activity, comprising ~70 changes in speed and 75 changes in direction over the 5 min period. The video and the Playermaker velocity profile were synced using a tap gesture at the beginning and end of each session and were later compared (see example on **Figure 3**).

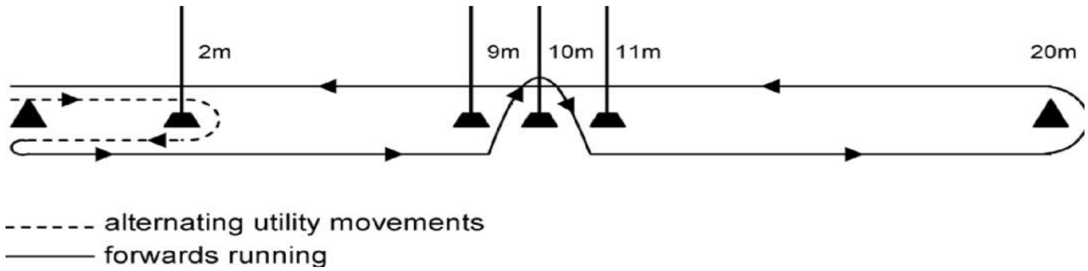

Figure 2. A diagram to show the course design of the SAFT$_{90}$

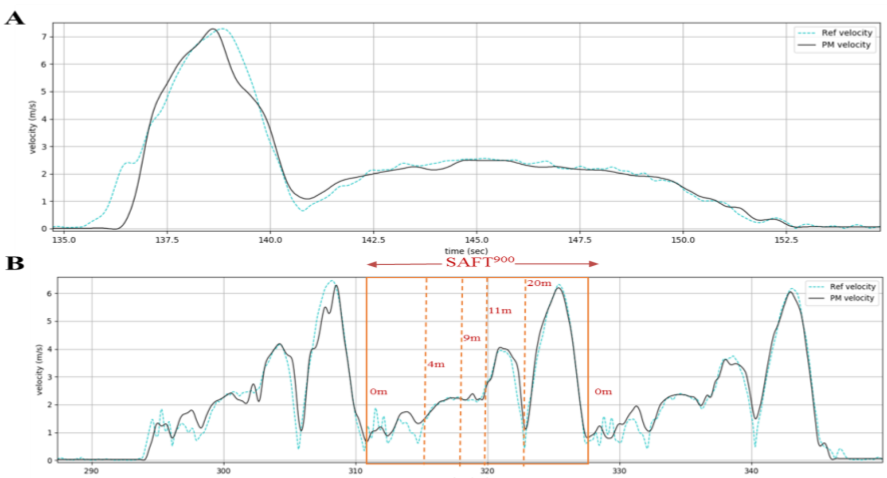

Figure 3. A Diagram to show the velocity profile of the video (Ref.Velocity) against Playermaker (PM Velocity) during, A) The 50m maximum sprint and B) during the SAFT90.

The velocity profile from Playermaker was calculated whole-body velocity using a combination of the inertial sensors within the unit. This permits gait tracking algorithms to detect the orientation and translation of the subject's lower limbs during gait cycles (heel strike, toe-off). Utilising Kalman filters together with the gait events, the resulting output provides the velocity profile of the individual wearing the sensors. An explanation and details of these calculations can be seen in **Figure 4**.

Statistical Analysis

To determine the concurrent validity between the velocity profile from the camera and Playermaker for each session, a Pearson product moment-correlation coefficient (r_2), the coefficient of variation (CV) and the root mean squared error (RMSE) were calculated. The level of agreement between the Playermaker and the video measurement was compared by the velocity distribution according to typical team sports velocity zones. Magnitude of the correlation coefficients was deemed as trivial (r_2<0.1), small (0.1< r_2 < 0.3), moderate (0.3< r_2<0.5), large (0.5< r_2< 0.7), very large (0.7< r_2< 0.9), nearly perfect (r_2 > 0.9) and perfect (r_2=1; Hopkins et al., 2009). Analyses were completed using IBM SPSS Statistics for windows software (release 20; SPSS Inc., Chicago, IL, USA).

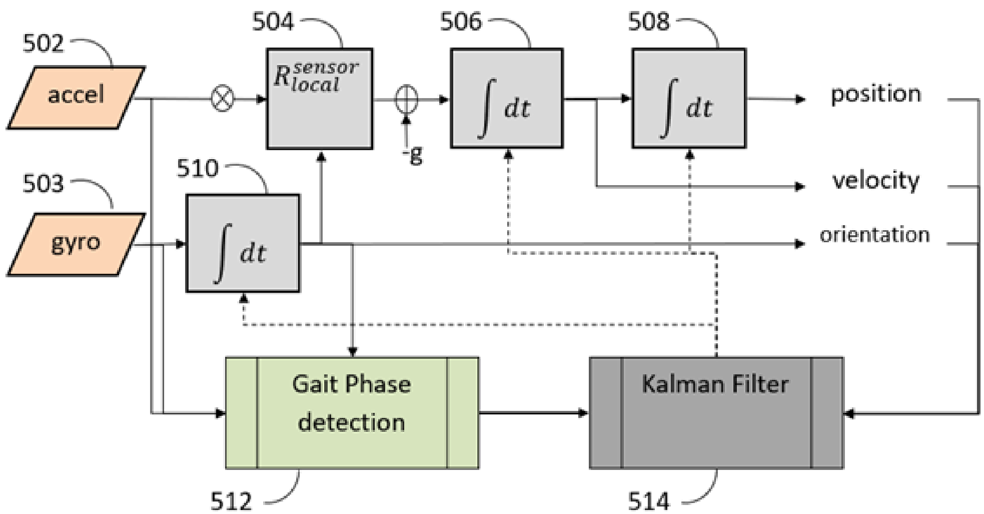

Figure 4. Playermaker™ gait tracking flowchart. 502 - accelerometer, 503 - gyroscope, 504 – "R" rotation matrix (sensor relative to local frame), 506,508,510 – numeric integration of raw inputs, 512- proprietery machine learning for gait phase detection, 514 - proprietary Kalman Filter design to calculate position, velocity and orientation. "+" sign indicates a sum, the "X" indicates a cross product. The rotation matrix transforms the accelerations from the sensor frame to the local frame. At block 502, the processor receives sensor data from the accelerometer. At block 503, the processor receives the sensor data from the gyroscope. At block 504 the acceleration data rotated to the local frame and then subtracted by *g* on the local z-axis. At block 506, the processed acceleration data is integrated and the velocity vector is formed at block 508. The velocity is integrated and the position vector, along with the velocity vector, is used at block 514, with the Kalman Filter. At block 510 the gyroscope data is integrated for calculation of R (that is used in block 504) and for the detection of zero-velocity update and stance, along with the raw acceleration and gyroscope

data, at block 512. (Solid lines = feedforward to gait phase detection or Kalman Filter; dashed lines = feedback

3. Results

The velocity profile correlation parameters are presented in **Table 1**. Correlations were nearly perfect between the Playermaker and video calculations for the $SAFT_{90}$ (r_2- 0.943 to 0.968) and between 50m sprints (r_2- 0.977 to 0.985). The coefficient of variation (CV) ranged between 0.14% to 0.17% for the $SAFT_{90}$ protocol and between 0.19% to 0.25% for the linear sprints. The root mean squared error (RMSE) ranged between 0.34 to 0.46 for the $SAFT_{90}$ protocol and between 0.3 to 0.4 for the linear sprints. Overall, the Playermaker velocity profile presented a very high correlation with the video tracking velocity profiles (r_2- 0.96-0.98; see example in **Figure 3**), differences are discussed in the discussion section. In the max velocity test, the Playermaker system showed a range of -6.4% to 6% difference in comparison to the camera system, with an average of -1.7±3.8%, for $SAFT_{90}$ protocol.

Table 1. Concurrent validity of the velocity profiles, all tests averaged result and the 1 STD range for the $SAFT_{90}$ protocol and the linear sprints

	$SAFT_{90}$	LINEAR SPRINTS
Pearson (r_2)	0.96±0.01	0.98±0.003
CV (%)	0.16±0.01	0.21±0.02
RMSE	0.4±0.05	0.35±0.03

CV (%)- Coefficient of variation; RMSE- Root mean squared error

4. Discussion

Time motion analysis data is commonly used to calculate the external training load of individual and team sport athletes (Cardinale & Varley, 2017; Malone et al., 2020; Vanrenterghem et al., 2017). The current study found that the use of a foot mounted IMU (Playermaker), derived near perfect correlations to the foot velocity profile of a criterion measure (video platform) during soccer specific simulation. This allows practitioners and scientists to understand the noise within the data set to identify the signal:noise data. This will have interpretations for understanding a meaningful change in velocity profiles of players during tasks of similar nature.

Locomotor activities have typically been measured by following the players centre of mass via a GPS unit between the shoulder blades (Malone et al., 2020) or by a multi-camera system (MCS; Bradley et al., 2009). Within the current study the use of a foot mounted IMU, when compared to a criterion measured derived from a high frame camera, was a valid measure of time motion analysis data. While there are obvious differences between the technologies (GPS, IMU and MCS) and their algorithms to derive the time motion analysis data, the current study has shown Playermaker to be a valid measure during a soccer simulation and linear sprinting. When comparisons are made between different anatomical locations for measuring the device, differences will be apparent due to the anatomical location itself. These changes are more apparent within change of direction activities, when the foot moves to reach out (for example, touching a line), during which time a device placed at the centre of mass, would not detect that additional movement (Waldron et al., Unpublished). Further research should look to examine the differences between measure locomotor activities at different anatomical locations and different types of measuring systems.

5. Conclusion

Foot mounted IMU (Playermaker) derived time motion analysis provide a valid measure of monitoring an athlete’s velocity profile. With limited difference observed between the motion capture and Playermaker, the Playermaker can provide a mobile/less time-consuming method of monitoring velocity derived metrics.

6. References

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A. Appendix

Warm-Up procedure

Over a 10 metre course (Cones placed down at 0, 5 and 10 metres). Participants perform each exercise as instructed by the researcher. Diagram of the circuit can be seen below the exercises.

1) 4 sets*Light Jogging (8 times)
2) 2 sets*Side stepping (1 way there 1 way back)
3) 1 sets*Backwards Jogging (There and back)
4) 2 sets*Heel Flicks & Up at front; On way back Outsides, Insides (5 on each leg; 10 in total)
5) 2 sets*Skipping (On way back shake off)
6) 2 sets*Jumping (Calf jumps up, Headed jumps back) every time at a cone
7) 2 sets* Jockeying (Forwards and backwards up and down); 2 jockeys each way
8) 2 sets*Adductors (Over gates up, Close gates back)
9) 2 sets*Kicking through & Stamping (Up and Down)
10) 2 set* Donkey Kicks (1/2 pace on way back)
11) 2 set* Squats & Lunges
12) 2 set* 5m sprint (5m up, 5m back)
13) 3 set* 10m sprint competitions (Facing, Jumping & Down; Walk on way back)
14) 2 set* 10m sprint multi-direction (Zig-Zag)

(This should take about 8 mins; Half of the warm-up)