# USE OF ACCELEROMETERS IN AUSTRALIAN FOOTBALL TO IDENTIFY A KICK

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The use of inertial measurement units (IMUs) is growing in elite sports such as Australian Football (AF). The purpose of this study was to identify ball contact (BC) and ball release (BR) of an AF kick and its intensity on the basis of IMU accelerometer data. A mechanical kicking limb, designed to replicate an AF kick, performed six punt kicks at six different angles. The acceleration dataset of each kick was analysed with Matlab and the characters BC and BR of the kick were obtained from high speed video footage and just over 43% was correct identified in the acceleration data. The kicks were correctly identified by Matlab as a kick. Kick intensity was obtained from the acceleration data. An AF kick identifier arose from this study. According to the findings, further analysis should analyse a kick with an accelerometer with a higher acceleration range.

**KEY WORDS:** IMU, punt kick, mechanical kicking limb, high speed video.

**INTRODUCTION:** An inertial measurement unit (IMU) measures multi-dimensional acceleration, angular velocity and positional data and provide real time movement data without using labour intensive (three-dimensional) video analysis (Cunniffe, Proctor, Baker, & Davies, 2009; Cummins, Orr, O'Connor, & West, 2013; Gabbett, 2013). With video analysis, unlike IMUs, the use of the second derivative from position data is required to estimate acceleration and is limited to one location for testing. IMUs are not restricted to a lab or location and can be used outdoors in field setting for testing.

Kicking is one of the most important skills in Australian Football (AF) because it is the only way to score a goal and is the most common form of passing between players. Current studies involving AF using IMU accelerometer data have investigated a broad spectrum of the sport such as external load during a match (Boyd, Ball, & Aughey, 2013), impact detection (Gastin, Mclean, Breed, & Spittle, 2014) and activity profile (Varley, Gabbett, & Aughey, 2013). However, none have used IMU acceleration data to evaluate and identify a pattern in the acceleration data that represents a kick. Further, monitoring the number of kicks during training is a key element in both skill development and load management of players. However, as monitoring is done via manual means only, it is time and labour intensive so the ability to monitor kick numbers automatically has utility.

In previous studies, the IMU unit was worn on the posterior side of the torso between the scapula's to collect data. However, putting an IMU on the lateral side above the ankle joint of a kicking limb might be a method that leads to automatically calculating the number and intensity of kicks when in field settings. A second potential use of the IMU worn on the lateral part of the kicking limb is to identify ball contact and ball release of a kick, this data can be useful for analysing the kick signal. The purpose of this study was to (i) develop a code to automatically identify a kick, (ii) identify ball contact and ball release and (iii) calculate the intensity of the kick from acceleration data.

**METHODS:** A mechanical kicking limb (Peacock & Ball, 2016) was used to perform drop punt kicks (most common kick in AF) with a standard AF ball (Match ball, Sherrin, Australia) inflated to a recommended pressure by the Australian Football League (AFL) of 69 KPa. The mechanical kicking limb provides the ability to kick a ball multiple times at the same speed. For each kick trial the ball was positioned at the same angle and location on a kicking tee (Moose Kicking Tee Pty Ltd, Australia) and all impact characteristics were controlled. The tee allowed a typical AF kick, straight swing through of the leg (Ball, 2011). Six different foot speeds were produced by starting the kick leg at six different backswing positions (90°,80°,70°,60°,50°,40°). Two systems were used in this study. The first system contained a high speed video camera (Photron SA3, Photron Inc., USA) capturing the impact phase at 2000 Hz and one 2-axis(X,Y) analog accelerometer (AD22037, Analog Devices Inc., USA) ±15g data logging at 2000 Hz. The second system was a 3-axis(X,Y,Z) IMU accelerometer (IMeasureU Blue Thunder, Auckland , New Zealand) ± 16g, 12 grams, 40x28x5mm; data logging at 1000 Hz. Both sensors were fixed at the same location of the mechanical limb above the approximate ankle joint.

Data from the IMU was logged on the internal 4GB SD card and controlled using the IMU Research application for iPhone (IMeasureU, Auckland, New Zealand), imported on a computer with Lightning Desktop App (IMeasureU, Auckland, New Zealand) then exported to Matlab (The Mathworks Inc., USA).

To identify ball contact (BC) and ball release (BR) in the IMU acceleration dataset, data of the first system were synchronized with each other using Photron FASTCAM Viewer (Photron Inc., USA). The frame numbers of BC and BR, identified from the high speed video (HSV) footage, are synchronized with the frame numbers of the analog accelerometer. To synchronize this with the second system (IMU dataset), the frame number of the analog accelerometer data and IMU accelerometer data where the first change in acceleration (leg is starting to move) occurred is identified. The IMU and analog accelerometer can now be synchronized to determine BC and BR in the IMU acceleration dataset.

Two reflective markers were attached in line with the IMU, one above and one below the IMU. To determine footspeed at ball contact the two reflective markers were analysed using ProAnalyst (Xcitex Inc., USA). Speed was calculated by averaging the speed of five data points before BC. Data was smoothed using a low pass Butterworth filter of 130 Hz that was based on a spectral analysis.

Matlab was used to analyse the data, perform frequency analysis with Fast Fourier Transform (FFT) and to create a trainedClassifier with the Classification Learner App to create a program which can possibly identify the kick. The frequency domain signal gained through FFT for the six different speed datasets showed a peak around 200 Hz. This peak occurred in the signal around BC and BR. Due to this peak it was chosen to not use a filter in the dataset. The maximum acceleration value of the x-axis and y-axis for every footspeed dataset was used to determine kick intensity.

Three steps were taken to create a trainedClassifier. Firstly, the training dataset was chosen. In this study every footspeed dataset was used as training dataset to explore the effects of every footspeed dataset on the trainedClassifier. Six different trainedClassifiers arose. The second step was pre-processing the data to selected features from the used datasets. The used features are the acceleration in the x-axis and y-axis. The last step was to develop a predictive model which was most accurate, in this case a simple decision tree.

**RESULTS:** All kicks were correctly identified by the developed code up to a footspeed of 5.9 m/s (Table 1). An average offset of the identified BC and BR of 4.8 frame numbers was found for all the trainedClassifiers together (Table 2). A descending kick intensity in x and y-axis was found for descending footspeed (Graph 1).

**Table 1**
**Identification of kicks**

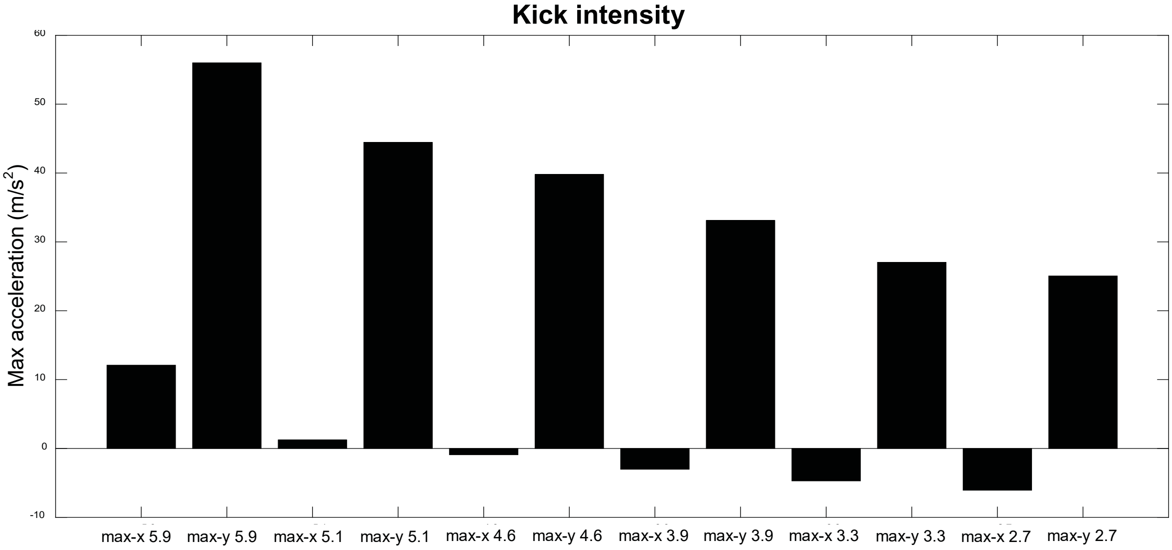
| Footspeed m/s | Angle of mechanical limb | Identification of the kick Used footspeed dataset for trainedClassifier (m/s) 5.9 | 5.1 | 4.6 | 3.9 | 3.3 | 2.7 |
|---|---|---|---|---|---|---|---|
| > 5.9 | > 90° | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| 5.9 | 90° | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 5.1 | 80° | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 4.6 | 70° | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 3.9 | 60° | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 3.3 | 50° | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2.7 | 40° | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

- ✓=correct identified; ✗=incorrect identified

**Table 2**
**Frame number offset of identified BC and BR**

| Footspeed | Average offset in frame numbers of identified ball contact and ball release (1 frame number = 1ms) Used footspeed dataset for trainedClassifier (m/s) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 5.9 | | 5.1 | | 4.6 | | 3.9 | | 3.3 | | 2.7 | |
| m/s | BC | BR | BC | BR | BC | BR | BC | BR | BC | BR | BC | BR |
| 5.9 | 0 | 0 | 0 | **+29** | **-6** | **+7** | **-13** | **+28** | 0 | **+70** | **-8** | **+53** |
| 5.1 | 0 | 0 | 0 | 0 | 0 | **+3** | **-9** | **+18** | 0 | **+40** | **-7** | **+40** |
| 4.6 | 0 | 0 | **+3** | 0 | 0 | 0 | **-7** | **+4** | 0 | **+20** | **-6** | **+34** |
| 3.9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **-3** | **+11** |
| 3.3 | **+3** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2.7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **-3** | 0 | 0 | 0 |

**Graph 1**
**Kick intensity**




## DISCUSSION:

The first aim of this study was to provide a code to automatically identify a kick. Findings indicate that kicks can be identified by the produced trainedClassifier algorithm. Kicks for foot speeds from 2.7-5.9 m/s were classified with 100% accuracy. This indicated that the classifier was suitable for use in identifying kick counts for foot speeds up to 5.9 m/s. However, kicks over 5.9 m/s were not accurately identified this was due to the accelerometer range being too low for the values generated through impact. As a result, classification was being conducted on a signal with clipping. Use of a higher range accelerometer is needed to determine if the classifier will work for higher foot speeds.

The second aim was to identify ball contact and ball release from acceleration data. According to the findings, identification of BC and BR produced less accurate results. The identification of BC and BR was correct identified for just over 43% of the kicks. A visual inspection of the acceleration graphs showed noise in the data. This noise could possibly be created by the mechanical limb. The limb executed an automated movement which could create vibrations whereof noise arose that affected the data. Higher footspeed datasets on low trainedClassifiers tend to be less accurate findings, this could possibly be explained by the noise in the data. The lower footspeed datasets had a less steep curve during BC/BR which entailed that some noise around BC or BR had the same frequency as BC/BR. This caused a faulty recognition of BC/BR of the kick. Whether higher foot speed kicks tended to be less accurate in identifying the instant of ball contact, this was not consistent across all trainedClassifiers. To determine if the noise affected the data a filter should be included in the trainings dataset, excluding the area from BC to BR to not affect this data, to smooth the data to reduce frequency similarities with BC/BR and the noise.

The third aim was to calculate the intensity of the kick from acceleration data. The kick intensity was found through calculating the maximum acceleration and there seems to be a linear regression for the maximum x-axis intensity values ($R^2$=0.81) and the y-axis ($R^2$=0.97). Kick intensity increased with increasing footspeed. This indicates that the kick intensity can be obtained through accelerometer data.
The z-axis of the accelerometer is excluded from the datasets because the mechanical limb was not designed to move in the frontal plane. After analysing the data some movement in the frontal plane was seen, but it was too small (< 0.1m/s$^2$) to be included in the training dataset to create a trainedClassifier.
This small IMU unit can provide meaningful data and be a valuable tool for assessing performance data of ball sport players. It can be useful for both coaches and players. According to the first findings (further testing is planned) the identified kick pattern can be used to identify the kick and may be useful to assess the quality of kick performance, particularly when shooting for goal and monitor and track the number of kicks/ types during training and games. This deducts the need of any additional staff member or additional equipment to analyse kicks.
The analysis up to now are done with a small sample size and an accelerometer with an acceleration range that is too low. Further testing will be done with a greater sample size to apply statistical analysis and an accelerometer with a greater acceleration range.

**CONCLUSION:** The present study indicates that the developed code was able to identify kicks, identify BC and BR for just over 43% of the kicks and calculate kick intensity out of acceleration data gained from an IMU sensor with an acceleration range of ±16g. The designed kick identifier code was found to be valid for identifying a pattern in the acceleration data that represents an AF kick up till 5.9 m/s. Further analysis should analyse a kick with an IMU accelerometer with a higher acceleration range. It is an interesting part for future research to investigate if the identification of the kick pattern also applies on data gained from real AF players kicking a ball.

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