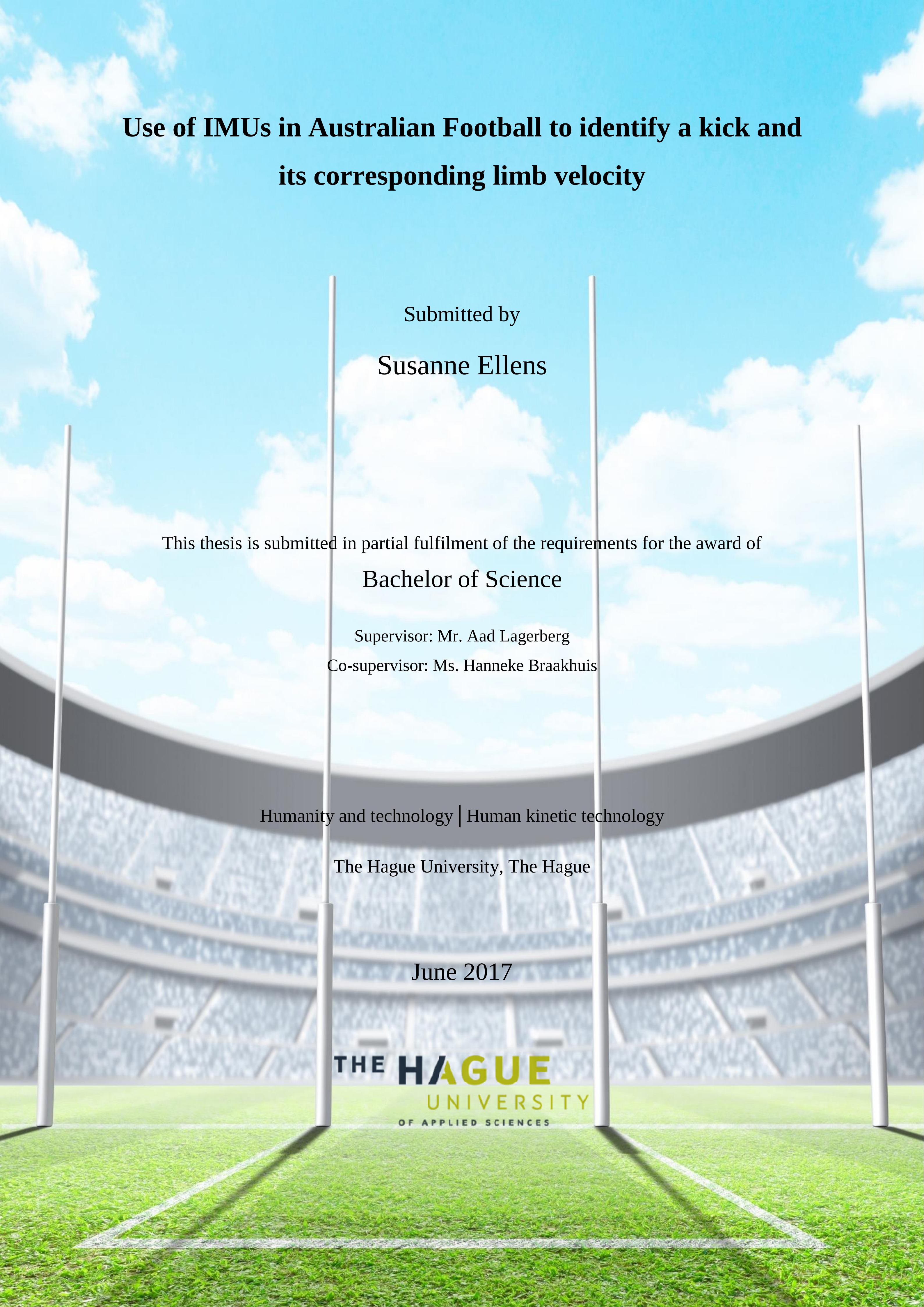

Use of IMUs in Australian Football to identify a kick and its corresponding limb velocity

Submitted by

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Use of IMUs in Australian Football to identify a kick and its corresponding limb velocity

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Kicking in Australian Football (AF) has been reported as the most important skill of the game. Nevertheless, no study has investigated kicking with IMU units. These units could be used to gain kicking data through an easy and assessable way. The purpose of this study was to analyse a kick executed by a mechanical limb to evaluate the accuracy of machine learning identification of an Australian Football kick out of IMU data and evaluate the validity of a method to calculate IMU foot velocity against the reference foot velocity derived from high speed video. A mechanical limb, designed for producing drop punt kicks, performed twelve different kicks at different foot velocities. The IMU datasets were analysed with Matlab to calculate the foot velocity and create a classification system to identify kicks. The classification of correctly identified kicks provided an accuracy of 99.3% for the best produced classification system. The method to calculate IMU foot velocity demonstrated good validity ($CV < 0.25$, $r > 0.96$) with the reference. Not reaching 100% accuracy is possibly due to saturation (clipping) in the acceleration signal. To keep count for this an IMU unit with a higher dynamic acceleration range or the application of a saturation compensating smoothing algorithm should be used. This could possibly lead to a more accurate classification system. The use of a mechanical limb with one rotation axis created extra undesired centripetal acceleration in the y-axis acceleration data of the IMU, resulting in higher calculated foot velocity. Usage of a mechanical limb with an extra element and rotation axis in its chain of motion is needed to minimalize the centripetal acceleration in the y-axis. The classification system in combination with the valid method for calculating foot velocity holds the potential to be used in field settings, assisting coaches and trainers with the performance analysis and load management of players.

Key words: IMU, machine learning, drop punt kick, high speed video, mechanical kicking limb

Introduction

The use of inertial measurement units (IMUs) is growing in the field of sports. An IMU measures multi-dimensional acceleration, angular velocity and magnetic field data to capture 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). Unlike IMUs, video analysis requires the use of the second derivative from position data to estimate the acceleration, the position angle and time to estimate angular velocity and it is not possible to gain magnetic field data. Besides this, video analysis 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. It is cost efficient and asks for less qualified personnel and effort to analyse the data. The ease in use and amount of data an IMU is producing results in a growing popularity of IMU use in elite sports such as the Australian Football League (AFL). Currently 17 out of the 18 AFL teams are using IMUs to monitor their athletes during training and games ("The safe choice for sport science", 2017)

Australian Football (AF) is a popular sport in Australia with a total domestic participation of 1,404,176 in the year 2016 according to the Australian Football League 120th Annual Report 2016 (Fitzpatrick, 2017). An AF match is divided into four quarters of 30 minutes (min) which equals 120 min in total, this is more than other field sports such as hockey 70 min, rugby 80 min and soccer 90 min

(Boyd, Ball, & Aughey, 2013; *Rules of hockey*, 2017). The playing surface of AF ranges from 15,000 to 18,000 square meters (m^2) this equals 436-516 m^2 per player compared to 7,000 m^2 (233 m^2 per player) for rugby and 8,250 m^2 (375 m^2 per player) for soccer (Ball, 2006). As a result of the larger playing surface players from the AFL covered the greatest relative running distances (129 ± 17 metres per minute (m.min−1)) compared to Rugby League (97 ± 16 m.min−1) and soccer (104 ± 10 m.min−1) (Varley, Gabbett, & Aughey, 2013). All these factors together make AF to a physiological and physically demanding sport (Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004; Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004b; Norton, Craig, & Olds, 1999).

Current studies involving IMUs in AF and similar sports such as Rugby League/Union, investigated a broad spectrum of the sport such as external load during a match (Boyd et al., 2013), impact identification (Gastin, Mclean, Breed, & Spittle, 2014) and activity profile identification (Varley et al., 2013). However, none have used IMU data to evaluate kicking in AF. Kicking is one of the most important skills in AF because it is the only way to score a goal and is the most common form of passing between players. IMU data can be used to capture and analyse the movement of an AF kick in order to automatically classify and detect performed kicks. This kick classification system presents an easy an accessible method to monitor and track kicks. Monitoring the kicks is a key element in both load management and skill development of athletes. As monitoring the amount of kicks is done via manual means only it is time and labour intensive, so monitoring this automatically has utility.

To develop a kick classification system, machine learning procedures applied on the captured IMU data are required. Machine learning is a valuable tool for predicting human movements such as skateboard tricks (Groh, Kautz, Schuldhaus, & Eskofier, 2015) and kicks in AF. Explained in a simple way, machine learning uses features of captured data and predicts what these features represents. Features include the captured signal itself and characteristics of it such as maximum amplitudes and frequency domain. Machine learning with IMU data has proven to be able to identify contact based activities such as tackle events in AF with a 78% accuracy (Gastin et al., 2014), collision events in rugby with a 97.2% accuracy (Hulin, Gabbett, Johnston, & Jenkins, 2017) and tennis strokes with a 90% accuracy (Connaghan et al., 2011). Based on the fact that an AF kick is also a contact based activity, machine learning presents a method to identify AF kicks.

Foot velocity is an important parameter in AF kicks. An increase in foot velocity causes an increase in kicking distance and performance (Ball., 2008). The data can also assist coaches and trainers in AF with the physical preparation for this physically demanding sport to mitigate injury risk (Rogalski, Dawson, Heasman, & Gabbett, 2013). IMU acceleration data can be used to calculate instantaneous velocity (Dadashi, Crettenand, Millet, & Aminian, 2012) and can be a tool to calculate the foot velocity of an AF kick.

To systematically explore the characteristic of an AF kick, mechanical testing is required. This will allow the generation of a range of foot velocities while keeping other impact characteristics of the kick constant. Peacock & Ball (2016) validated a mechanical kicking limb that produced AF kicks similar to drop punt kicks executed by a human performer. This mechanical kicking limb creates a methodical exploration to calculate foot velocity and classify AF kicks and is the first step towards automatically counting kicks in field settings.

Therefore, the aim of this study was to analyse a kick executed by a mechanical limb to evaluate the accuracy of (i) machine learning identification of an Australian Football kick out of IMU data against the criterion value identified from high-speed video footage. (ii) Evaluate the validity of the method to calculate foot velocity out of IMU data against the criterion velocity derived from a high-speed video camera.

Methods

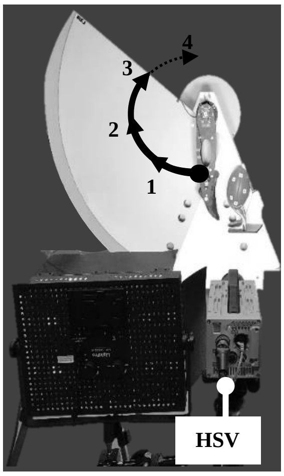
Study design

Kicks were performed by a mechanical kicking limb (Peacock & Ball, 2016). For a test setup see figure 1. This limb performs drop punt kicks (most common kick in AF) with a standard AF ball (Match ball, Sherrin, Australia) inflated to a recommended pressure by the AFL of 69 KPa. The mechanical kicking limb provides the ability to systematically explore the effects of an impact of the ball on the shank. For each kick trial the ball was positioned at the same angle and the same place on a kicking tee (Moose Kicking Tee Pty Ltd, Australia), this was controlled with ProAnalyst software (Xcitex Inc., USA). The tee allows a typical AF kick, straight swing through of the leg (Ball, 2011). Twelve different mechanical limb foot velocities were produced by manipulating the starting point of the limb (figure 1b). Half of the kick datasets were used for creating the classification system and the other half for testing the sytem.

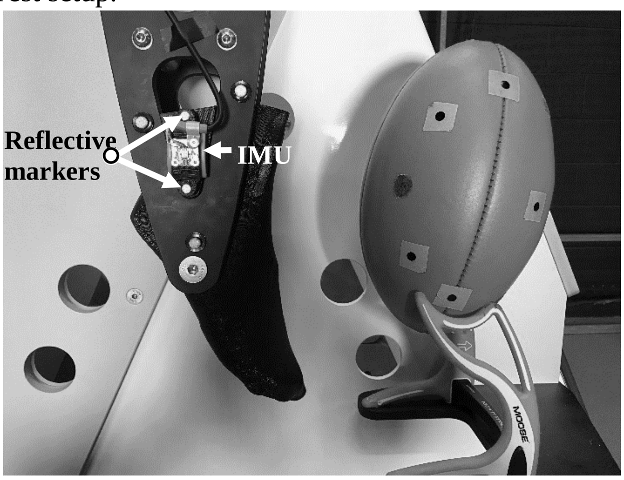
Sensor hardware

Kicks were measured with an IMU sensor (IMeasureU Blue Thunder, Auckland, New Zealand) containing a 3-axis (X, Y, Z) accelerometer ±16g, 3-axis gyroscope ±2000º/s, 3-axis magnetometer ±1200μT, 12 grams, 40x28x5mm. Previous studies showed that higher sample rates (>100 Hz) and usage of acceleration data plus gyroscope, without magnetometer, improved classification (Wundersitz et al., 2015). Therefore, data log was set at 500 Hz (instead of the 100 Hz function) and use the IMU acceleration and gyroscope data. The sensor was attached on the lateral side of the mechanical limb, above the approximate ankle joint (figure 1a). Data of the IMU was logged on the onboard 4GB SD card and this was controlled using the IMU Research application for IPhone (IMeasureU, Auckland, New Zealand). The data was imported on a computer with Lightning Desktop App (IMeasureU, Auckland, New Zealand) then exported to MATLAB.

Figure 1. Starting position of the limb, example of start positions *1, 2, 3, 4*, of the limb to produce the different foot velocities **(a)**. Placement of the IMU and reflective markers on the side of the mechanical limb **(b).** Test setup.



(a)



(b)

A high-speed video (HSV) camera (Photron SA3, Photron Inc., USA) data logging at 1000 Hz was used to identify ball contact (BC), ball release (BR) and calculate foot velocity of the mechanical limb. Two reflective markers (figure 1a) were attached on the mechanical limb, one above and one below the IMU. Both markers were in line with the IMU y-axis (figure 2).

Data processing

To determine the criterion velocity the two reflective markers of the mechanical limb were analysed using ProAnalyst (Xcitex Inc., USA). Velocity in the x-/y-axis at BC was calculated by averaging the gained velocity of the two reflective markers of five time samples before BC (Ball, 2008). Data was smoothed using a low pass Butterworth filter of 130 Hz as used by Ellens, Blair, Peacock, Barnes, & Ball (2017) in a similar study.

Instantaneous IMU limb velocity of five data points before BC was calculated by using the equation of motion (see equation 1) on the x-/y-axis acceleration data. No use has been made of the z-axis IMU data because the data of interest is located in the sagittal plane. $V0$ is zero before the mechanical limb starts to move, as soon as the limb moves $V0$ changes to the previous calculated V. The axis orientation of the IMU (IMUa) velocity data is changed to the HSV axis (HSVa) (figure 2) by equation 2 and 3 to compare the velocity dataset of the IMU and HSV.

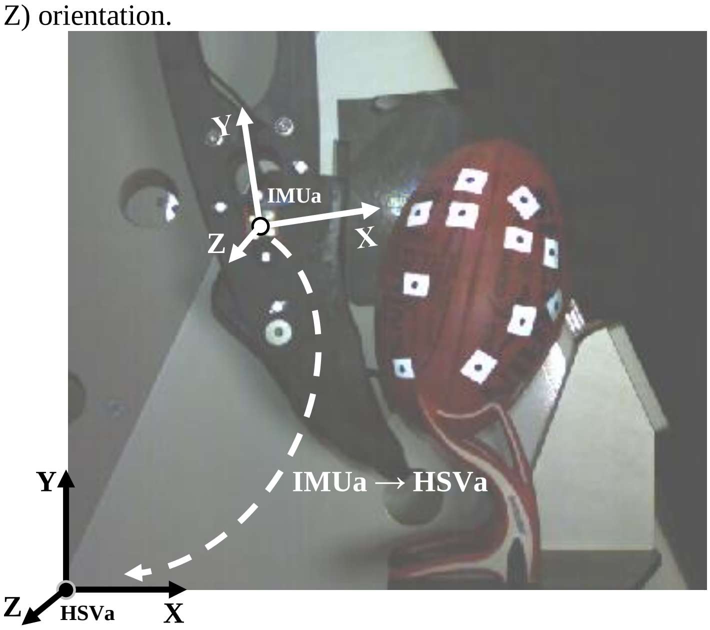
$$V = V0 + a * \Delta t \tag{1}$$

$$VHSV_x = VIMU_x * \cos(\alpha) - VIMU_y * \sin(\alpha) \tag{2}$$

$$VHSV_y = VIMU_x * \sin(\alpha) + VIMU_y * \cos(\alpha) \tag{3}$$

Where VHSV is the velocity of the high-speed video and VIMU the calculated velocity of the IMU. Subscripts x and y represent the x-axis and the y-axis. Alpha (α) is the angle between the HSV y-axis (vertical orientated) and the IMU y-axis.

Figure 2. IMU axis (IMUa X, Y, Z) orientation and its change towards the HSV axis (HSVa X, Y, Z) orientation.



MATLAB was used to analyse the acceleration data to calculate the velocity as described above, perform frequency analysis with Fast Fourier Transform (FFT) and to create a kick classification system with the Classification Learner App to identify a kick. After visual inspection and FFT analysis of the acceleration data it was chosen to not use a filter in the dataset.

In the Classification Learner App, Supervised machine learning was used to create the kick classification system. Supervised learning is based on a known input dataset (in this case x-/y-axis acceleration and z-axis gyroscope) and responses to the data (kick or non-kick) and trains a model (classifier) to generate predictions for responses to new data. The method is described in detail in the e-book 'Getting started with Machine Learning' (2016), and the classifiers by Zaki and Meira (2014).

Data analysis

To evaluate the quality of the classifier, the accuracy is calculated by 5-fold cross-validation (Fushiki, 2011). Sensitivity and specificity (table 1) of the classifier outcome were calculated using formula 4 and 5 as described by Whelan, O'Reilly, Ward, Delahunt, & Caulfield (2016).

Table 1: Definition of the events used to evaluate the quality of the classifier.

	Sensitivity (Kick occurred)		*Specificity (No kick occurred)*	
	True Positive (TP)	**False Negative (FN)**	**True Negative (TN)**	**False Positive (FP)**
True event	Kick occurred	Kick occurred	No kick	No kick
Classifier	√ Kick identified	X No kick identified	√ No kick identified	X Identified a kick

• √*: Classifier identified the correct event.* ***X****: Classifier identified the wrong event*

$$Sensitivity = \frac{TP}{TP+FN}\ [\%] \tag{4}$$

$$Specificity = \frac{TN}{TN+FP}\ [\%] \tag{5}$$

Similar classification studies stated an accuracy of 97.43%, 97% sensitivity and specificity for hitting load in tennis (Whiteside, Cant, Connolly, & Reid, 2017) and a 97.8% accuracy, 94.2% sensitivity, 99% specificity for skateboard tricks (Whiteside, Cant, Connolly, & Reid, 2017). The implementation of this study with a mechanical limb is more controlled than studies involving human, so it is desired to get results higher than studies involving humans. This means a classification accuracy of ≥ 97.8%, sensitivity ≥ 97% and specificity ≥ 99%.

Validity of the IMU velocity and the criterion HSV velocity was assessed using mean and standard deviations (SD), Pearson's correlation (r), mean bias, typical error of the estimate expressed as raw units (CV m/s2) and 90% confidence limits (90% CL) (Blair, Robertson, Duthie & Ball, 2016).

Results

The most accurate classification system was a Fine K nearest neighbor (KNN) with an accuracy of 99.3%. The details of the classification system are show in table 2. Kicks were correctly identified for 93% (sensitivity) and the non-kick events were correctly identified for > 99% (specificity).

Validity of the method to calculate IMU velocity in the x and y-axis is presented in table 3. Foot speed in the x-axis (mean bias 0.35) and foot speed in the y-axis (mean bias 15.11), was higher for the IMU compared to HSV. Mean bias was found trivial for foot speed in the x-axis (0.16) and y-axis (27.89). Both parameters showed strong correlation (r > 0.96) and low measurement errors (CV < 0.25) between the two methods.

Table 2: Confusion Matrix of the best performing kick classification system, KNN.

True Class	Predicted Class: Kick	Predicted Class: No-Kick		
			True Positive	False Negative
Kick	93%	7%	93%	7%
No-Kick	<1%	>99%	>99%	<1%
			True Negative	False Positive

Table 3: Validity of method for calculated parameters measured with an IMU unit and HSV (n=12).

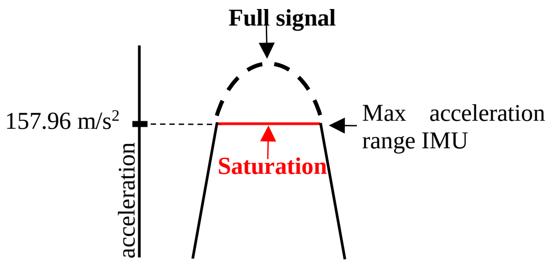
Foot velocity	Mean ± SD		Mean Bias ± SD	90% CL		r	CV m/s^2	90% CL	
	Reference HSV	IMU		Lower	Upper			Lower	Upper
x-axis	12.1 ± 2.3	12.5 ± 3.8	0.35 ± 1.6	-0.28	0.6	0.99	0.25	0.18	0.45
y-axis	-0.6 ± 0.5	14.6 ± 4.3	15.11 ± 4.79	22.76	33.02	0.96	0.16	0.12	0.28

Discussion

The first aim of this study was to determine the accuracy of machine based learning to identify an Australian Football kick out of IMU data. The results demonstrate that accurate kick identification using IMU accelerometer and gyroscope inputs is achievable with the use of a mechanical kicking limb. In detail, results showed that the best performing classification system for this purpose was Fine K nearest neighbour with an overall accuracy of 99.3%. This was consistent with the desired accuracy of ≥ 97.8%. Further, the classification system reached a sensitivity (i.e. the ability to identify a kick when a kick occurred) of 93% and specificity (i.e. the ability to *not* identify a kick when a kick did *not* occur) of >99%. The specificity was in accordance with the desired ≥ 99%. Notably, the sensitivity was lower than the desired ≥ 97%.

During data collection of the kick the IMU acceleration signal reached values larger than its maximum dynamic range of ±16g (=157.96 m/s^2) around the true kick event. This caused saturation (clipping) of the signal, see figure 3 for a visual example of saturation. The saturated IMU acceleration signal happed to be the same pattern as IMU acceleration signals of a not moving IMU units (recording a flat line due to no occurring acceleration). A part of the signal of non-kick events included a not moving IMU unit, thus the same pattern as the saturated signal (representing a kick), what could cause a prediction by the classification system of non-kick, although the true class was a kick. This affects the ability of the classification system to identify a kick when a kick occurred and could possibly explain the lower sensitivity than desired. Whiteside, Cant, Connolly, & Reid (2017) reported saturation in their IMU acceleration signals of tennis shots. They used a 'sensor saturation compensating smoothing algorithm (Dang and Suh, 2014)' to reconstruct the saturated signals, reaching a sensitivity of 97.5%. This is higher than the sensitivity in this study, which makes it a promising method to keep count for the saturation and could possibly lead to higher sensitivity values. Another solution to keep count for the occurring saturation is the usage of an IMU unit with a high dynamic acceleration range. This ensures that the recorded acceleration does not exceed the dynamic acceleration range of the IMU unit.

Figure 3. Occurring saturation in the IMU acceleration signal. Full signal is the signal that would have been captured if the IMU unit did not reach its maximum dynamic range resulting in saturation.



In reviewing the literature, no study was found on the ability of machine based learning to identify an Australian Football kick. Gastin et al. (2014), identified tackle and impact events in AF with an accuracy of 78%, this is lower than the reached accuracy of 97.8% for this study. The low accuracy in Gastin et al. (2014) was due to the used algorithm, developed primarily for rugby and was not suitable for AF. They suggested that the underlaying sensor data (IMU data) may have the potential to identify a range of events in AF. This study has shown that the underlaying sensor data can be used in AF to identify kick events.

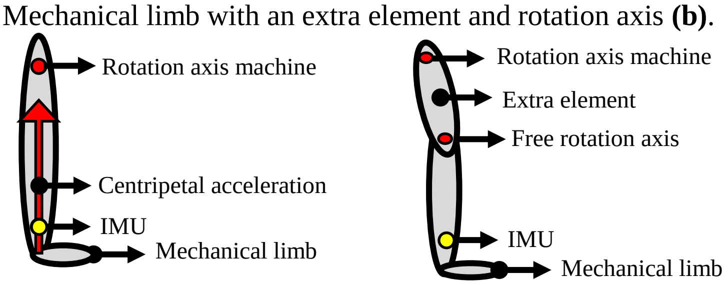
The findings of this study are comparable to previous, similar contact based, machine learning identification work (Hulin, Gabbett, Johnston, & Jenkins, 2016; Connaghan et al., 2011). Hulin, Gabbett, Johnston, & Jenkins (2017) reported a 97.2% accuracy, 97.6% sensitivity and 91.7% specificity for collision events in rugby. Connaghan et al. (2011) reported a 83% accuracy, 89% sensitivity and 95% specificity for stroke events in tennis. The results of this study are higher than the reported results of Hulin, Gabbett, Johnston, & Jenkins (2017) and Connaghan et al. (2011), except the sensitivity reported in Hulin, Gabbett, Johnston, & Jenkins (2017) which is probably due to the occurring saturation or may be due to differences in methodology. Specifically, Hulin, Gabbett, Johnston, & Jenkins (2017) used lower frequency sampled data, 100 Hz instead of 500 Hz used in this study, and also identified collision events which is a different event from kicking. Wundersitz et al. (2015) suggested that an increase in sample frequency (>100 Hz) could aid identification performance. According to higher accuracy values of this study it could be suggested that an increase in sample frequency aid identification performance. Wundersitz et al. (2015) also suggested that the higher sample frequency may have a negative effect on processing time. Processing time is not investigated in this study and forms an interesting part for future research.

The produced classification system in this study achieved superior accuracy if compared to previous studies. Next to this it is as relevant to say that IMUs can provide a more practical option for collecting data of training sessions and games than video based data to assist coaches and trainers. It asks for less personnel than video based analysis and the data analysis is faster than video based data analysis. The system would also offer a genuine advancement for counting kicks automatically, currently done by manual means only.

The second aim was to evaluate the accuracy of the method to calculate foot velocity out of IMU data. The calculated IMU foot velocity demonstrated good validity with a correlation of $r > 0.96$ and a typical error of $CV < 0.25$ for both the x-axis and y-axis parameters compared to the HSV velocity. The results suggest that the method overestimated the IMU y-axis velocity (mean bias 15.11).

The high correlation value (r = 0.96) of the y-axis foot velocity suggests that the difference in foot velocity, foot velocity is calculated out of the acceleration data, between IMU and HSV is due to a standard offset in the acceleration data. This offset might be due to the usage of a mechanical limb. The mechanical limb is rotating around one axis (this will be the knee axis in the human body) shown in figure 4a. The rotation of the mechanical limb around one axis results in the production of centripetal acceleration, which is facing towards the centre of the rotation axis, making it an extra acceleration in the y-axis acceleration data of the IMU. This could possibly explain the standard offset in the calculated y-axis foot velocity. The HSV velocity does not take the centripetal acceleration into count when estimating the velocity. To calculate the y-axis velocity with less centripetal acceleration influence, the mechanical limb needs an extra degree of freedom in its chain of motion (two instead of one). This creates more movement possibilities for the part of the limb where the IMU is attached, resulting in less centripetal acceleration. This can be created by adding an extra element and rotation axis, shown in figure 4b, in its chain of motion. Through this way the movement of the limb will be more similar to the human leg movement, with less influence of the centripetal acceleration.

Figure 4. Mechanical limb with one rotation axis and the occurrence of centripetal acceleration **(a)**. Mechanical limb with an extra element and rotation axis **(b)**.



(a) **(b)**

The occurring saturation in some of the IMU datasets could also possibly lead to a standard offset in the y-axis foot velocity. If the IMU reaches its maximum dynamic acceleration range during ball contact, resulting in saturation, the calculated foot velocity (calculated by taking the average of five data points before ball contact) will be the average of the saturated signal. Resulting in an average of the maximum values. To keep count for this, the usage of an IMU unit with a high acceleration range or the use of a sensor saturation compensating smoothing algorithm, both described above, should be used.

The findings of this study are comparable to a previous study estimating velocity out of IMU data (Dadashi, Crettenand, Millet, & Aminian, 2012). Dadashi, Crettenand, Millet, & Aminian (2012) reported low measurement errors (CV < 0.6) and strong correlation (r = 0.94) for front-crawl velocity estimation using IMU data. No differences were found between the calculated x-axis and y-axis velocity, this is due to difference in methodology. Dadashi, Crettenand, Millet, & Aminian (2012) estimated the velocity of a human swimmer in a 3D plane, they did not need to deal with occurring centripetal forces. The similarities between the studies suggest that IMU data can be used to calculate velocity with the proposed method.

The method to calculate velocity out of IMU data can be of practical value for quantifying load and kick intensities. It could possibly assist coaches with pointing out the weakest kick of a player and help with improving their kick intensity. In combination with the classification system it could highlight players who kick too much (kick count) to minimalize injury risks.

The data of this study is only collected of a mechanical limb kicking the ball. It is an interesting part for future research to investigate if the classification system also works on real AF players kicking a ball. If this results in high accuracy values, the classification system could possibly be used during training and games. To this end, the high accuracy values reached in this study together with the valid method to calculate foot velocity is encouraging. These results are promising for further research where real-time identification of kicks during training and games is investigated.

Conclusion

This study indicates that the classification system was able to identify kicks with an accuracy of 99.3%, sensitivity of 93% and a specificity of > 99%. The validity of the calculated IMU foot velocity demonstrated good validity with the high-speed video foot velocity, advocating the use of IMU units for calculating foot velocity. Further analysis should analyse a kick with occurring saturation with a sensor saturation compensating smoothing algorithm or an IMU unit with a higher acceleration range. Next to this, the used mechanical limb should have an extra element and rotation axis in its chain of motion. Resulting in a mechanical limb that is more comparable to the human limb and less influence of centripetal acceleration.

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