Automatic Classification of Locomotion in Sport: A Case Study from Elite Netball.

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Abstract

In team sport Human Activity Recognition (HAR) using inertial measurement units (IMUs) has been limited to athletes performing a set routine in a controlled environment, or identifying a high intensity event within periods of relatively low work load. The purpose of this study was to automatically classify locomotion in an elite sports match where subjects perform rapid changes in movement type, direction, and intensity. Using netball as a test case, six athletes wore a tri-axial accelerometer and gyroscope. Feature extraction of player acceleration and rotation rates was conducted on the time and frequency domain over a 1s sliding window. Applying several machine learning algorithms Support Vector Machines (SVM) was found to have the highest classification accuracy (92.0%, Cohen's kappa $K = 0.88$). Highest accuracy was achieved using both accelerometer and gyroscope features mapped to the time and frequency domain. Time and frequency domain data sets achieved identical classification accuracy (91%). Model accuracy was greatest when excluding windows with two or more classes, however detecting the athlete transitioning between locomotion classes was successful (69%). The proposed method demonstrated HAR of locomotion is possible in elite sport, and a far more efficient process than traditional video coding methods.

KEYWORDS: HUMAN ACTIVITY RECOGNITION; LOCOMOTION; MACHINE LEARNING; NETBALL; SUPPORT VECTOR MACHINES

Introduction

Understanding the movement of athletes is an essential part of team sport analysis. Traditionally performed by sport specific experts undertaking time-motion studies during the event, or using video coding software post-event, this process is restrictive due to the subjective classification of movement, and time required to complete the process (Barris & Button, 2008; Colyer, Evans, Cosker, & Salo, 2018; Randers et al., 2010). Many elite sports teams now wear micro-electrical-mechanical-systems (MEMS) to provide sports scientists an additional tool to analyse athlete movement. Positional data gathered by GPS has enabled the calculation of player velocity and acceleration (Coutts & Duffield, 2010; Jennings, Cormack, Coutts, Boyd, & Aughey, 2010), however its use is limited to outdoor sports. Recent developments in ultra-wideband-frequency (UWB) tracking have made recording athletes position in indoor sport possible (Luteberget, Spencer, & Gilgien, 2018; Serpiello et al., 2018), however like radio frequency identification (RFID) (Foina, Badia, El-Deeb, & Ramirez-Fernandez, 2010), and automated computer vision (Moeslund, Thomas, & Hilton, 2017; Xing, Ai, Liu, & Lao, 2011) remain price restrictive for its wide use.

Within team sports the application of accelerometers and gyroscopes contained in inertial measurement units (IMUs) has generally concentrated on wide scale metrics such as overall mechanical work load (Bourdon et al., 2017; Boyd, Ball, & Aughey, 2011; Walker, McAinch, Sweeting, & Aughey, 2016). By disregarding the fine-scale information collected from IMUs, potentially a vast amount of movement data is being ignored that may provide finer detail of athlete movement and performance (Chambers, Gabbett, Cole, & Beard, 2015; Wundersitz et al., 2015) or physical condition (Buttfield & Ball, 2019). With IMU logging rates typically faster (100Hz) than GPS (10Hz) and UWB (6Hz) systems, IMUs have the potential to provide a more detailed analysis of physical movement through the process of Human Activity Recognition (HAR), a statistical process that attempts to classify the activity or movement the subject is performing (Ermes, Parkka, Mantyjarvi, & Korhonen, 2008). Researchers have utilised this process by analysing IMU data from accelerometers (Khan, Ahamed, Rahman, & Smith, 2011; Lee, Mellifont, Burkett, & James, 2013; Mitchell, Monaghan, & O'Connor, 2013), accelerometers with gyroscopes (Hsu, Yang, Chang, & Lai, 2018; Lee, Mellifont, James, & Burkett, 2007), accelerometers, gyroscopes with magnetometers (Ustev, Incel, & Ersoy, 2013; Valenti, Dryanovski, & Xiao, 2015), and accelerometers with GPS (Ofstad, Emmett, Szcodronski, & Choudhury, 2008; Sadi & Klukas, 2012). Placement of the sensors has also varied between studies including waist (Capela, Lemaire, & Baddour, 2015), hip (Karantonis, Narayanan, Mathie, Lovell, & Celler, 2006; Wang, Chen, Sun, She, & Wu, 2011), arm (Jaitner & Gawin, 2010), hand (Bulling, Blanke, & Schiele, 2014), ankle (Hsu et al., 2018; Schmidt, Rheinländer, Wille, Wehn, & Jaitner, 2016) or multiple locations (Ahmadi et al., 2015; Altun, Barshan, & Tunçel, 2010; Moran et al., 2015). To date the main application of HAR has been in the health and leisure industries targeting detection of activities including sleeping, laying, sitting, walking, climbing stairs, and falling (Ahmadi et al., 2015; Karantonis et al., 2006), and leisure activities including star jumps, cycling, driving, or playing football (Cust, Sweeting, Ball, & Robertson, 2019; Ermes et al., 2008; Hsu et al., 2018; Long, Yin, & Aarts, 2009).

HAR using IMUs in sports has primarily focused on identifying a high intensity event (HIE) from periods of relatively low work load. This has included detecting a bowling event in cricket (McNamara, Gabbett, Chapman, Naughton, & Farhart, 2015), tackling in Australian football (Gastin, McLean, Breed, & Spittle, 2014) and rugby (Gabbett, 2013), detecting a scrum or tackle in rugby (Chambers, Gabbett, & Cole, 2019; Kelly, Coughlan, Green, & Caulfield, 2012), phases of a tennis serve (Ahmadi & Rowlands, 2010) shots and passes in

football (Schuldhaus et al., 2015), or jump detection in snow sports (Chardonens et al., 2012; Roberts-Thomson, Lokshin, & Kuzkin, 2014; Sadi & Klukas, 2012). Automatic locomotion classification in sports using IMUs however has been limited to subjects performing a set routine in a laboratory environment (Mitchell et al., 2013; Moran et al., 2015; Wundersitz et al., 2015). Although achieving high prediction accuracy these studies required participants to perform an activity for an extended period before moving to the next activity. In one of the few studies to be performed outside a lab environment Ermes' (2008) study of activity recognition of daily activities and sports achieved a prediction accuracy of 72%, but similarly participants would spend an extended period of time performing the activity.

To date there have been no published research using IMUs to classify all locomotion of the athletes within an elite sports match, where subjects perform rapid changes of movement in a non-controlled manner. If the application of HAR in elite sport was shown to be successful this would have wide implications on the analysis of team performance. This may include a more detailed understanding of the composition of athlete external work load, player movement profile change due to tactical changes, fatigue or injury, or provide a more detailed movement analysis of training sessions. Despite the inherent complexity of activity recognition in competitive sports, where IMU devices are employed it should be both possible and feasible to use accelerometer and gyroscope data to accurately classify sporting activities (Wundersitz et al., 2015). Chambers (2015) stated further research is required to determine if movement patterns can be detected during competitive matches using a single sensor, as it would be advantageous to understand the demands of elite sport in greater detail. Similarly, Wundersitz (2015) stated further development of algorithms in sport is required, and once developed, should be validated for their ability to classify team sport activities.

The aim of this paper is first: to determine if HAR using an IMU can successfully identify athlete locomotion within an elite sports match, and test using a selection of machine learning algorithms which method provides the greatest accuracy; second: to determine the individual contributions of the accelerometer and gyroscope data sets to classification accuracy; Third: determine what effect using extracted features sets on the time and frequency domain has on classification accuracy; and finally: to determine the ability for the algorithm to detect the athlete transitioning from one movement class to the next. Ultimately, this paper outlines a methodology that will save analysts potentially thousands of hours undertaking motion analysis over the length of a season.

Method

Participants

Data collected from six elite female netballers with a mean ($\pm$ SD) age, height and mass of 29.0 ± 2.2 , $178\text{m} \pm 12$, $74 \pm 10\text{kg}$, was collected for this study. All players were from the Sunshine Coast Lightning netball team competing in the 2018 Australian Suncorp Super Netball league (SSN) season. The subjects had no known injuries or physical limitations during the reference match that would restrict or alter their natural movements. The match was played on a sprung wooden floor overlaid on concrete. Ethics approval was granted by the university research ethics committee prior to the commencement of research (A/16/885).

Design

A single regular season match from the 2018 SSN was analysed. The six athletes wore an IMU containing a tri-axial accelerometer and gyroscope logging at 100 Hz (Catapult s6, Catapult Sports, Australia). The unit was located between the shoulder blades in a dedicated pouch on

their vest that was worn underneath their dress (Game Clothing) (Figure 1). To provide familiarity with the device each player had an IMU allocated to them several months prior to the match. The unit was worn for all training sessions and matches throughout the season and was standard practice, and did not interfere with any natural movement. The match was recorded by a stationary video camera (Panasonic HC-W580M HD @25 frame/second) placed five metres behind the goal post and seven metres above court level.

Figure 1. IMU accelerometer and gyroscope placed in a pocket worn underneath the athlete's game dress between the shoulder blades.

Data Processing

Video taken during the match was imported into video coding software (Coding - Nacsport Elite, 2019). Notational analysis was performed by a trained expert recording the locomotion of a player for one quarter of the match. Locomotion categories were based on the definitions used by Mayhew (Mayhew & Wenger, 1985) and Doherty (Doherty & Neary, 1988). These were; stand, no locomotion activity performed; walk, strolling locomotion in any direction; shuffle, a sideways, forward/back, on-the-spot movement requiring shuffling of the feet; run, fast locomotion with elongated stride with purpose; jump, vertical displacement of the body where both feet are off the ground for an extended period. A jump was recorded from the start of the eccentric phase of take-off, and concludes at the end of the eccentric phase after landing. If the athlete is performing any of the other locomotion classes during jumping, only a jump was recorded. The analyst noted the start and stop time of the movement to the nearest video frame (0.04 seconds). This was repeated for each test subject. This process is quite time consuming at, on average, 10 hours per athlete per quarter. This equates to, for a given game, approximately 280 hours of analysis.

Acceleration and rotation rates were downloaded from each sensor using the manufacturer's software (Openfield, Catapult Sports, Australia) then exported into Matlab (2018b, version 9.3, The MathWorks Inc., Natick, Massachusetts, USA). In addition to the tri-axial acceleration and gyroscope recordings, resultant acceleration and rotation vectors were calculated for the medio-lateral/antero-posterior, medio-lateral/vertical, antero-posterior/vertical and medio-lateral/antero-posterior/vertical axes. To minimise signal noise a Savitzky-Golay filter was applied to the acceleration data. This method has been shown to provide a good balance between smoothing data while preserving the high frequency components of the signal. To

remove the low frequency gravitational acceleration components a 0.5Hz high pass filter was applied to the acceleration data. This value is consistent with other studies in accelerometry which generally range between 0.1 and 1Hz (Bouten, Koekkoek, Verduin, Kodde, & Janssen, 1997; Fahrenberg, Foerster, Smeja, & Muller, 1997; Mathie, Coster, Lovell, & Celler, 2003).

Feature extraction for the data set was conducted on a 1 s sliding windows. This epoch was used as it has been shown to achieve a good balance between being long enough to capture one cycle of walking cadence, but short enough to minimise the chance of including multiple movement categories that would be expected in normal match play (Bailey, Gastin, Mackey, & Dwyer, 2017; Bulling et al., 2014; Fox, Spittle, Otago, & Saunders, 2013; Karantonis et al., 2006; Mathie et al., 2003). To evaluate classification accuracy of a model built exclusively with features from each sensor the data was partitioned into three sub-sets; the first consisting of features derived through the accelerometer sensor ($n = 592$), the second features derived through the gyroscope sensor ($n = 592$), and a third set using the combined accelerometer and gyroscope features ($n = 1184$). A second set of data was also prepared to evaluate the effect of mapping to the time and frequency domain. It consisted of three parts; the first containing features derived on the time domain ($n = 450$), the second on features derived on the frequency domain ($n = 734$), and the third being a combined set of time and frequency domain features ($n = 1184$). To maximise the number of window samples that could be used to build the model, the combined accelerometer and gyroscope data were used in this data set.

Three methods were tested to understand the effects of modifying the video notated classifications within the window (Figure 2). The first window conditioning method (WC1) involved excluding any window that contained two or more movement classes. This is common practice in HAR in an attempt to isolate the movement classes from each other and establish the optimal conditions for algorithm development by using only windows containing the movement of that class (Bao & Intille, 2004; Capela et al., 2015; Ermes et al., 2008; Khan et al., 2011; Preece, Goulermas, Kenney, & Howard, 2009; Zhang, Werner, Sun, Pi-Sunyer, & Boozer, 2002). The second window conditioning method (WC2) allocated the class that was performed the longest in each window. This method was implemented to test a real world system that could be utilised for real-time classification. Window conditioning method 3 (WC3) allocated a “transition” class to the window if it included two or more movement classes. This was used to not only analyse the ability of the algorithm to detect the pure locomotion movement classes of stand, walk, shuffle, run, and jump, but also the transitional state as the athlete changed from one movement class to the next.

Feature extraction was conducted using self-developed code (Matlab 2018b, The Mathworks Inc., Natick, Massachusetts, United States) for the accelerometer and gyroscope signal. This was conducted for each of the three sensor axes and resultant vectors, with jerk values also calculated to include the rate of change of the vector. The feature set included twelve time domain features (maximum amplitude, minimum amplitude, mean amplitude, variance of amplitude, standard deviation, mean absolute deviation, interquartile range, skewness, kurtosis, correlation). To assist in differentiating epochs of low and high activity, signal magnitude area was calculated. Additionally four features were calculated on the frequency domain. Spectral entropy was used to measure the power distribution in the epoch. To calculate energy distribution across the frequency spectrum, features were created from discrete energy bins. These were calculated from 0Hz to the Nyquist frequency (50Hz) in 5Hz bins (0-5, 5-10, 10-15, 15-20, 20-25, 25-30, 30-35, 35-40, 40-45, 45-50); 10Hz bins (0-10, 10-20, 20-30, 30-40, 40-50); 1-15Hz, 15-30Hz, 30-50Hz bins; 1-20Hz, 20-50Hz bins; and 1-50Hz bin. The first five spectral peaks were found with the frequency and amplitude recorded as features. To negate the effect of a large range between inter-feature values influencing the classification model the feature sets were mapped to a new range using standard max-min normalisation.

Figure 2. Overview of the window conditioning processes.

Statistical Analysis

Feature sets were joined to the video notated classifications for each window and imported into the classification software (Matlab 2018b, The Mathworks Inc., Natick, Massachusetts, United States). To protect from over fitting, the data set was partitioned into ten folds and accuracy was estimated using a cross-validation technique on each fold. Six machine learning techniques were employed to assess their ability to classify athlete locomotion undertaken during the match. These were: classification tree, discriminant analysis, k-nearest neighbour (kNN), support vector machines (SVM), artificial neural networks (ANN), and ensemble techniques. Classification tree uses a binary recursive partitioning to split the feature set into two branches. This process is repeated until the node has all the values the same as the target class. Within this study Gini's Diversity index was used with a maximum numbers of split set at 100. kNN is an algorithm that classifies the data on a distance measure. Each case is classified by the majority vote of its distance to its k nearest neighbours. For this study

Euclidean distance was used with nearest neighbours set to 1. Linear discriminant classification estimates the parameters of a Gaussian distribution for each class so it minimises the expected classification cost of the class. SVM provide a classification model by mapping high dimensional data to another feature space then calculating the most optimal hyperplane that separates the data. To maximise accuracy of the model that was not linearly separable kernel transforms were conducted by a quadratic, cubic, and Gaussian transform to the hyperplane. ANN consist of an input layer of m neurons equal to the number of features in the data set, a hidden layer of 50 neurons, and an output layer equal to the number of movement classes. The hidden layer consists of connected nodes or neurons with a processing element that acts as a non-linear activation function. Using conjugate gradient back-propagation it calculates the decision region boundaries until the network achieves an acceptable level of convergence and minimises the average sum of errors for the training vectors. Accuracy is calculated for each algorithm with a confusion matrix presented. To measure inter-rater reliability between the ground-truth video classification to model classification, Cohen's kappa coefficient (K) is shown for key algorithms. Refer to figure 3 for modelling overview and appendix 1 for pseudo code of classification model.

Results

The total amount of data used for evaluating the models was 5,558 one second windows. Standing was the most frequently performed classification and had the longest average time per event as presented in Table 1.

Table 1. Total time spent (%) performing each classification as identified by video notation analysis for each window conditioning method.

Window conditioning method	Classification					
	Stand	Walk	Shuffle	Run	Jump	Transition
WC1	31	46	10	13	0.4	
WC2	26	40	18	15	1.6	
WC3	17	25	5	7	0.2	45

WC1, Window conditioning method 1 where windows containing more than one class are excluded ($n = 3075$); WC2, Window conditioning method 2 where the class with the greatest amount of time in each window is included ($n = 5558$); WC3, Window conditioning method 3 where windows containing more than one class in a window are re-labelled "Transition" ($n = 5558$).

The accuracy of each algorithm for the three tested window conditioning methods is presented in Table 2. SVM outperformed all other modelling methods regardless of the window conditioning method, with SVMcubic producing the greatest accuracy (92%) using WC1. Locomotion classifications ranged from 88% (run) to 93% (walk), however jump detection was significantly lower at 63% (Table 3). The next highest performing classification model for each group were EnsembleSubspace discriminate 89.4%, ANN (88.9%), Linear Discriminate 86.8%, Treemedium 84.5%, kNNfine 84.2%. When all data windows were included (WC2) SVMcubic again showed the greatest accuracy (79.9%). SVM outperformed the other methods using WC3 (SVMquadratic 73.8%), however introducing the transition category decreased all models accuracy. The addition of the transition classification had little effect on classification precision for standing and walking (80%) when compared to WC2, however shuffling precision decreased from 70% to 57% (Table 4).

Figure 3. Overview of the modelling process.

Table 5 presents the accuracy for the model using WC1 and built exclusively on the accelerometer, gyroscope, and the combined accelerometer and gyroscope data set. The accelerometer provided the highest accuracy of the two sensors (90% compared to 84%, $K = 0.85/0.78$). The highest accuracy however was achieved using the combined data set (92%, $K = 0.88$). The greatest reduction of classification accuracy for each locomotion class occurred using the gyro. Of these shuffling suffered the greatest reduction of precision for the ambulatory modes compared to the full data set (88% to 74%). This compared to the accelerometer model showing only a 6% decrease in precision for shuffling classification. The

greatest accuracy reduction was seen in the jump category from 63% using the combined data set, to 45% for the accelerometer, and 36% using the gyro.

Table 6 presents the accuracy when the model is built on features mapped on the time and frequency domain using WC1. Overall predictive accuracy marginally decreased when using either the time and frequency domain features (91%, $K = 0.86/0.87$) compared to using the combined feature set (92%, $K = 0.88$). Ambulatory class predictive accuracy was similar between each domain.

Table 2. Accuracy (%) of classifiers for each of the tested window conditioning methods for a data set derived from the accelerometer ($m = 592$) and gyroscope ($m = 592$) sensor data mapped to the time and frequency domain using a 10-fold leave-one-out cross validation.

Classifier		Window conditioning method		
		WC1	WC2	WC3
		$n = 3075$	$n = 5558$	$n = 5558$
Tree	Fine Tree	83.5	72.2	66.5
Discriminant	Linear	86.8	77.0	68.2
SVM	Linear	90.5	78.8	73.1
	Quadratic	91.8	79.7	73.8
	Cubic	92.0	79.9	72.6
	Fine Gaussian	46.5	79.5	51.2
	Medium Gaussian	91.1	79.5	73.4
	Course Gaussian	86.7	75.9	69.0
	Weighted	83.6	73.5	67.4
kNN	Fine	84.2	71.1	63.0
	Medium	82.7	73.5	67.5
	Course	75.5	68.7	63.0
	Cosine	79.4	70.0	66.0
	Cubic	78.7	70.5	64.2
	Weighted	83.6	73.5	67.4
	Weighted	83.6	73.5	67.4
ANN	Cross Entropy	88.9	57.3	72.5
Ensemble	Boosted Trees	88.7	75.5	70.7
	Bagged Trees	89.0	77.7	72.0
	Subspace	89.4	78.9	71.1
	Discriminant			
	Subspace KNN	85.5	73.0	65.0
	RUS Boosted Trees	83.1	72.0	52.3

Table 3. Confusion matrix (%) for WC1 (n = 3075) and WC2 (n = 5558) for the data set derived from the accelerometer (m = 592) and gyroscope (m = 592) sensor data mapped to the time and frequency domain modelled using SVMCubic and a 10-fold leave-one-out cross validation.

Notated Class	Predicted Class									
	Stand		Walk		Shuffle		Run		Jump	
	WC1	WC2	WC1	WC2	WC1	WC2	WC1	WC2	WC1	WC2
Stand	91	81	6	11	2	7	1	1	0	10
Walk	8	6	93	84	2	6	1	2	13	0
Shuffle	1	4	1	2	88	70	5	15	25	18
Run	<1	1	<1	2	7	13	93	80	0	18
Jump	<1	<1	0	<1	1	4	<1	2	63	55
Positive Prediction	91	81	93	84	88	70	93	80	63	55
False Discovery	9	19	7	16	12	30	7	20	38	45
Overall Accuracy	WC1: 92, WC2: 80									
K	WC1: 0.88, WC2: 0.71									

Table 4. Confusion matrix (%) for WC3 for the full data set (n = 5558) derived from the accelerometer (m = 592) and gyroscope (m = 592) sensor data mapped to the time and frequency domain modelled using SVMQuadratic and a 10-fold leave-one-out cross validation.

Notated Class	Predicted Class					
	Stand	Walk	Shuffle	Run	Jump	Transition
Stand	80	2	1	1	0	8
Walk	2	80	0	<1	0	10
Shuffle	0	<1	57	1	0	8
Run	<1	0	2	76	50	5
Jump	0	0	2	0	50	<1
Transition	2	18	39	22	0	69
Positive Prediction	80	80	57	76	50	69
False Discovery	20	20	43	24	50	31
Overall accuracy	74					
K	0.62					

Table 5. Accuracy (%) of SVMCub classifier model built using WC1 and a data set derived from the accelerometer (n = 592), gyroscope (n = 592) and a combined (n = 1184) features data set mapped to the time and frequency domain using a 10-fold leave-one-out cross validation.

Class	Model built on sensor features		
	Accelerometer	Gyro	Combined (Acc+Gyr)
Jump	45	36	63
Run	86	88	93
Shuffle	82	74	88
Stand	89	80	91
Walk	93	90	93
Overall	90	85	92
K	0.85	0.78	0.88

Table 6. Accuracy (%) of SVMCub classifier model built using WC1 on accelerometer and gyroscope a features data set mapped to the time domain (n = 450), frequency domain (n = 734) and the combined features data set of (n = 1184) using a 10-fold leave-one-out cross validation method.

Notated Class	Model build on feature set		
	Time Domain	Frequency Domain	Combined (time+frequency domain)
Jump	100	50	63
Run	91	90	93
Shuffle	86	86	88
Stand	90	90	91
Walk	92	92	93
Overall	91	91	92
K	0.86	0.87	0.88

Discussion

The purpose of this study was to assess the accuracy of using IMU devices with machine learning to classify human locomotion activities in an elite sport application. There is a growing body of research within the field of HAR but to our knowledge all have been tested in controlled environments and/or the subjects performing each activity for extended periods of time, or to detect a high intensity event during periods of low activity. By using the elite sports environment, specifically netball as a test case, this study is the first to show the feasibility of using IMUs to successfully classify locomotion where subjects are undertaking rapid changes of locomotion modalities through three-dimensional space.

Specifically, this study showed SVM to be the most successful modelling algorithm to classify each movement activity. Of all modelling algorithms tested, SVMcubic had the greatest overall

accuracy for WC1 (92.0%, $K = 0.88$) and WC2 (79.9%, $K = 0.71$) and SVMquadratic for WC3 (72.6%, $K = 0.62$). This agrees with previous research finding SVM have a great ability to differentiate human locomotion and movement type. Lau (2009) and Fida (2015) found that SVM were superior in classifying different walking and sitting conditions than other machine learning methods including decision trees, kNN, Naive Bayes, ANN, and Radial Bias Function Neural Networks. Similarly, in a study of shot and passing detection in football SVM were able to classify these events with greater precision than Classification and Regression Tree, and Naive Bayes algorithms (Leutheuser, Schuldhaus, & Eskofier, 2013). Although this study did not classify locomotion, it did show SVM ability to detect high intensity activity when performed in sequence with other movements that generate high signal energy. Similarly, SVM have been shown to identify high energy events and four locomotion types in basketball (Nguyen et al., 2015). This study however did not test multiple algorithms, so it is unknown if SVM were the most optimal in terms of sensitivity. Conversely, Erdas (2016) and Wundersitz's (2015) HAR study both found Random Forest to outperform SVM, with Wundersitz finding Logistic Model Trees providing the superior result. Although direct comparison between studies is difficult, particularly with Erdas employing a lower sampling rate (5Hz) to our and Wundersitz's work (100Hz), notably both these studies relied on subjects performing the actions isolated from other movement types for extended periods of time. This may be the reason why these algorithms outperformed SVM due to the greater dissimilarity of the response classes may have been more suited to random forest and logistic regression trees in these specific cases. Fida (2015) speculated that SVM are also able to better deal with variability in the speed that the subject is performing the movement. Notably when testing on an artificially generated data set, Amancio (2014) found that when assessing classifiers on higher dimensions SVM were highly successful. The findings from our research support this and suggest that higher order SVM have a great ability to separate highly complex relationships between predictors and responses, particularly with smaller data sets and several response classes.

Effects of Conditioning the Data Window

Conditioning the data by selective modification of the video notated classifications in each window (Table 2) is common in HAR studies in an attempt to isolate each movement class (Ermes et al., 2008; Khan et al., 2011; Preece et al., 2009; Zhang et al., 2002). Excluding windows from the data set if it contained multiple classes (WC1) provided the highest accuracy with the model built on the most ideal signal characteristics in the context of real world data. Despite this, the highest accuracy recorded was 92% ($K = 0.88$) using the SVMcubic algorithm. This indicates that noise is still present within the signal caused from movement that would not be expected under controlled conditions. This could include rotation of the thorax or change of direction of the athlete within the epoch.

WC2 had a detrimental effect on classification accuracy (SVMCubic 80%, $K = 0.71$). The reduced accuracy of each locomotion class is seen as a function of the model including windows where data from the preceding or subsequent movement of the main movement in that window are included, thus decreasing the dissimilarity of each class. Although this process decreases prediction accuracy, its acceptance will depend on the specific application as it may be an efficient trade-off between prediction accuracy and processing computational time. This is particularly important when considering a near real-time classification system where the data can be more easily broken into regular epochs without missing any time frames.

WC3 included the addition of a transition category. We believe one of the weaknesses of existing investigations in the HAR field is they assume a discrete change of movement from one category to the next. We propose that neglecting transitional changes and the time to do so

may neglect key movement strategies of the subject. By including a transition category in this form was seen as the first step to understanding the transition rate and movement that occurs during these phases. Fida (2015) achieved success when including a transition category, however this study only examined transitions from sitting, standing, and walking through a defined circuit, where the change in the signal magnitude vector will be most prominent. Within our study, including the transition state caused a reduction of overall accuracy for all algorithms with SVMcubic providing the highest accuracy (74%, $K = 0.62$). This comprised of an accuracy reduction for stand (1%), walk and run (4%), and jump (5%) classes when compared to WC2 (Table 4). Detecting the athlete transitioning from one movement to another was successful with 69% of transition windows classified correctly. It is suggested the distribution of false discoveries for the transition windows is reflective of the amount that each class is performed during the game (Table 1). To get a greater understanding of transition classification further analysis of the direction of transition, i.e. stand to run, run to stand, would be beneficial. This would be particularly useful to the physical conditioning staff by providing the frequency and accumulative time of high energy loading movements as the athlete rapidly decelerates or accelerates.

Accelerometer v Gyroscope Data Set

Both accelerometer and gyroscope features were found to significantly contribute to the model, however maximum accuracy was achieved when feature sets from both sensors were included (Table 5). Our research showed when the model was built exclusively with accelerometer derived predictors, accuracy decreased from the combined set by 2% when using the SVMquad algorithm (92% to 90%, $K = 0.88$ to 0.85), and exclusively on gyroscope predictors model accuracy decreased by 7% (92% to 85%, $K = 0.88$ to 0.78). This is consistent with other HAR studies that have achieved higher classification accuracy when increasing the available features for model building, including specific tests where gyroscope data is included in a model built with accelerometer data (Barshan & Murat, 2014; Chen, Jafari, & Kehtarnavaz, 2015; Shoaib, Bosch, Incel, Scholten, & Havinga, 2014; Ustev et al., 2013; Wundersitz et al., 2015). Shoib (2014) showed that both gyroscope and accelerometer are capable of taking the lead roles in the activity recognition process depending on the type of activity being recognised, body position, classification method, and feature set being used. However, Chen (2015) suggests that the choice of sensors should not be task specific, but combining multiple sensor features will maximise classification accuracy.

The greatest reduction in class classification accuracy from the combined data set occurred when modelling with the gyroscope features (shuffling: 88% to 74%). This compares to the accelerometer features showing a 6% decrease in accuracy for shuffle classification (88% to 82%). We suggest the accuracy reduction in shuffle classification is greater for the gyroscope due to the range of movement the subject may undertake during this specific form of locomotion. With additional yaw as the athlete's rotates to sight the opponent or ball through the movement will cause a greater range of energy over the frequency spectrum. This movement will have limited effect on the accelerometer due to their inability to record rotation around the vertical axis. A similar decrease in classification accuracy was also seen in standing classification (gyroscope: 80%, accelerometer: 89%, combined: 91%). With standing having the lowest signal energy, any yaw of the athlete's torso will have minimal effect on the accelerometer readings compared to the gyroscope. It is believed the increase of recorded energy has caused the model to classify the window to the next highest energy category of walking.

The findings from our research suggest that the highest accuracy will be achieved by using the combined data set of each sensor. However if gyroscope data is unavailable, or minimum

computational cost is desired, the use of an accelerometer may achieve sufficient classification accuracy. Alternatively, if a finer resolution of the relationship between upper torso, hip, or limb movement of the subject is desired additional sensors may provide beneficial.

Time v Frequency Domain Feature Set

Previous studies have shown HAR models achieve the highest predictive accuracy when built using a combined feature set of data projected on the time and frequency domain (Anguita, Ghio, Oneta, Parra Perez, & Reyes Ortiz, 2013; Chen et al., 2015; Ermes et al., 2008; Karantonis et al., 2006; Preece et al., 2009; Wundersitz et al., 2015). Due to the biomechanics of human gait different locomotion modes have been found to produce distinct peak frequencies (Figure 4). These characteristic frequency curves have been found to provide a good mechanism for separating acceleration data into its locomotion type (Neville, Wixted, Rowlands, & James, 2010). This study tested this relationship by comparing two models, the first built on features mapped to the time domain ($n = 450$), the second mapped to the frequency domain ($n = 734$). Model accuracy for time and frequency domain data sets were found to be identical using the SVMcub (Time Domain: 91%, Freq Domain: 91%, $K = 0.86/0.87$) and a negligible increase when both features were combined (92%, $K = 0.88$) (Table 6). All locomotion categories were classified with equal accuracy (stand 90%, walk 92%, shuffle 86%, run 91%) indicating that each method was equally able to separate all ambulatory modes within the data set. In the only other published study known to the authors on investigating the predictive abilities between modelling on the time and frequency domain in HAR, Erdas (2016) found a similar 3% increase in classification accuracy when modelling on the time domain than the frequency domain. Conversely, Erdas did report a 1% higher overall accuracy when using the time domain data set (87%) than the combined data set (86%). This study however used accelerometer data logging at a low frequency (5Hz) for low energy activities such as standing, working at a computer, and walking.

Our research showed the model developed on the frequency domain resulted in a decreased ability to classify jumps. It is suggested that the time domain model provided a greater separation of this class as it could directly compare the peak accelerations occurring during take-off and landing to the lower values experienced when undergoing the lower energy locomotion modes. However, when modelling on the frequency domain, the algorithm could not define a clear difference between jumping and the other classes. The reason for the misclassification may also be compounded by the relatively large variation of jump types including heights, velocity pre and post jump, the number of legs used on take-off and landing, or the likelihood of rotation through the event. These may have resulted in a greater range of frequency for the class reducing the dissimilarity between jumps to the other locomotion categories.

This study has demonstrated a process that is far more efficient than traditional video analysis by substantially reducing the time spent classifying locomotion in team sport. If we consider the trade-off in time, manual classification of one player for one game takes approximately 40 hours vs the algorithm's 30 seconds. Although we may consider the relatively small amount of data as a limitation, the algorithms used to build the model are substantial in size (over 5000 readings) despite being restricted to the data generated from six athletes.

Figure 4. Spectral density of walk, shuffle and run calculated from the z axis of the accelerometer with a Savitzky-Golay and 0.5Hz high-pass filter.

Limitations of this study include the relatively small sample size. To improve model performance additional manually notated data on the existing team may increase classification accuracy, particularly for the jump category (as this is a fairly infrequent activity in netball). Additionally, increasing the number of test subjects may provide a better representation of different gaits and movement characteristics that may be encountered within an elite netball team. Future work may also evaluate the generality of the model by assessing its performance when used on state and junior level netballers, and athletes participating in other sports. Another limitations of this study was the manual classification of the start and stop time of each movement. With players frequently changing from one mode to another manual classification was challenging to identify when they switch from each of the defined movement classes. To minimise the effect this has on model accuracy further examination of the transition category is required. This may include the transition class being broken down into its transitional direction e.g. stand to walk, walk to run. Alternatively, rather than a supervised classification model being developed, an unsupervised model may give a truly unbiased analysis of the movement. This method would define locomotion based on clustering of the IMU data rather than the human interpretation of the movement.

Practical Application

This research constitutes the first step in using IMUs to understand the locomotion of indoor team sport athletes. This process has provided time-stamped locomotion classifications of elite athletes during a match, providing greater detail of the composition of their external work load. This enables semi-live video replay of actions when tied to performance analysis, such as a desire to enhance jumps against a set player benchmark. The use of the classification model also allows rapid classification of new game data that can then be imported into video coding software to provide a semi-automatic video editing process of all athletes' locomotion. Using this method will also allow an efficient method for building player movement profiles to assist in understanding player and team performance. This may include changes to locomotion profile occurring due match tactical changes, comparison between training and game movement profiles to evaluate player preparation for the match, or developing a model to evaluate injury on movement characteristics.

Conclusion

The results of this study show classification of athlete locomotion in elite sports matches is possible using a single tri-axial accelerometer and gyroscope. HAR on IMU data is far more efficient than traditional notational methods, with the additional advantage it can be utilised in indoor sports. While this study is specifically relevant to netball, there are multiple sports whereby player movement analysis is required.

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