Title: Automatic detection of one-on-one tackles and ruck events using microtechnology in rugby union

Submission Type: Original Investigation

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Abstract

Objective: To automate the detection of ruck and tackle events in rugby union using a specifically-designed algorithm based on microsensor data.

Design: Cross-sectional study

Methods: Elite rugby union players wore microtechnology devices (Catapult, S5) during match-play. Ruck (n=125) and tackle (n=125) event data was synchronised with video footage compiled from international rugby union match-play ruck and tackle events. A specifically-designed algorithm to detect ruck and tackle events was developed using a random forest classification model. This algorithm was then validated using 8 additional international match-play datasets and video footage, with each ruck and tackle manually coded and verified if the event was correctly identified by the algorithm.

Results: The classification algorithm's results indicated that all rucks and tackles were correctly identified during match-play when 79.4 ± 9.2% and 81.0 ± 9.3% of the random forest decision trees agreed with the video-based determination of these events. Sub-group analyses of backs and forwards yielded similar optimal confidence percentages of 79.7% and 79.1% respectively for rucks. Sub-analysis revealed backs (85.3 ± 7.2%) produced a higher algorithm cut-off for tackles than forwards (77.7 ± 12.2%).

Conclusions: The specifically-designed algorithm was able to detect rucks and tackles for all positions involved. For optimal results, it is recommended that practitioners use the recommended cut-off (80%) to limit false positives for match-play and training. Although this algorithm provides an improved insight into the number and type of collisions in which rugby players engage, this algorithm does not provide impact forces of these events.

Keywords: algorithm; microtechnology; team sport; ruck; tackle

Introduction

Commercially-available microtechnology devices containing global positioning systems (GPS) and microsensors (accelerometers, magnetometers and gyroscopes) are extensively used to quantify the activity demands of various sports, including rugby union.[1-5] Rugby union is a high-intensity sport involving demanding bouts of intense locomotor activity (running, sprinting and accelerations) and requires players to perform a range of high-intensity collisions (rucks, tackles, mauls and scrums),[3-5] interspersed with activities that have lower locomotor demands (standing, walking and jogging).[1, 5, 6] Physical demands of rugby union have frequently been reported using video-based time motion analysis and more recently with the use of microtechnology.[7, 8] Recent research using microtechnology predominantly focuses on positional match-play demands of rugby union reporting locomotor metrics, such as distance covered, high-speed running and accelerations assisting with athlete physical preparation and injury prevention.[6, 8, 9]

In combination with customised algorithms, microtechnology devices have demonstrated a capacity to detect sport-specific movements in individual sports such as snow and aqua sports,[1] as well as team sports reporting fast bowling and intensity in cricket,[10, 11] and throwing in baseball.[12] Furthermore, a small number of studies have focused on the non-running demands of contact sports.[13] Specifically, such studies have determined whether these microtechnology devices have the ability to detect tackles in rugby league,[14, 15] rugby union[13] and Australian Rules football.[16, 17] Studies have shown that tackles performed in rugby league can be reliably detected using wearable microsensors (mild collisions: $r = 0.89$; moderate collisions: $r = 0.97$; heavy collisions: $r = 0.99$)[14] with high sensitivity (97.6% ± 1.5) and specificity (87.6% ±1.2).[15] Attempts to apply the same algorithm for tackles in Australian Rules football and rugby union were unsuccessful due to obvious variations between contact events in these sports. Specifically, when applied to these sports the rugby league tackle algorithm had a tendency to over-estimate the number of tackle events, incorrectly classifying some rapid changes of direction and other contact events as tackles.[7, 16, 17]

Interestingly, recent research investigated whether existing algorithms developed for rugby league can be adapted for rugby union.[7] This study has shown that manipulation of g-force parameters within the algorithm was inadequate to provide an accurate tool for automatically recording collisions in rugby union; possibly due to the wide variety of tackle types.[7] Other encouraging results in rugby union using an accelerometer-based tackle detection algorithm developed applying a limited training set of ‘contacts’.[13] However, researchers concluded that the algorithm’s performance might be improved if accelerometer data were complemented with magnetometer and gyroscope data.[1, 13]

Of the various types of contact events experienced during rugby match-play, rucks and tackles are reported to be the most frequent.[4, 9, 18] On average, tackles and rucks are performed 116 times by each team during a competitive match, with front on one-on-one tackling the most frequently occurring tackle type.[8, 19, 20] Competition success usually dependent on a team’s ability to endure repeated collision events that characterise the sport.[8, 13, 21]

A rugby union tackle is similar to that of other collision-based sports when a defender successfully brings an opposing ball carrier to the ground[19, 22], other techniques include a standing a tackle when an attacker is not brought to ground and can potentially become a maul.[23] The ruck, as performed in rugby union, is a unique event that occurs when at least one player from either team competes in a physical contest for possession after a completed tackle for the ball that is on the ground.[20] Although these collision-based events may involve only a single player from each team, they often escalate involving numerous players from one or both teams.[22] Forwards predominantly perform greater tackle and ruck events during competitive matches than backs, a player's involvement in these events is not restricted and, hence, any player may be exposed to these situations during training or match-play.[24]

As there is currently no validated algorithm capable of detecting tackles in rugby union, current practice involves manually counting and subjectively classify tackle events using video footage. This process is time-consuming and labour-intensive and often prone to many inaccuracies.[1, 7] This early work can be further improved upon by seeking to develop methods that can differentiate tackles from other contact events in rugby union (e.g. rucks, scrums, mauls), as combining these events in a single category implies that each event places an equivalent physiological stress on the athletes' bodies.[1] In light of recent research shortcomings, there is an increasing requirement for automated algorithm detection to improve quantification of unique rugby union contact events, providing enhanced understanding of the physical demands.[1, 2, 7]

To address this, the study purpose is to use data derived from player-worn microtechnology to develop and validate an algorithm capable of identifying tackle and ruck events in rugby union match-play scenarios. It was hypothesised that using the accelerometer, magnetometer and gyroscope data provided, an algorithm could be developed to automate detection of tackles and rucks in rugby union.

Methods

Twelve elite male rugby union players (mean ± SD age; 26.6 ± 3.3 yrs; forwards n=7, backs n=5) were recruited to develop and validate a tackle and ruck detection algorithm. At the time of testing, all participants were free of injury and had no known medical conditions that would compromise their participation or influence the recorded outcomes. All participants received a clear explanation of the study's requirements and provided written informed consent prior to their involvement. The study's experimental procedures were reviewed and approved by the Institution's Human Research Ethics Committee (Approval #2014-135Q).

Participants were required to wear a single Catapult S5 Optimeye device (Melbourne, Victoria, Australia) positioned between the shoulder blades in a purpose-built vest to assist initial algorithm development. Devices contained tri-axial accelerometers, gyroscopes and magnetometers that captured data at 100 Hz. A total of 40 (n=19 Forwards; n=21 Backs) data files were captured across a series of elite international rugby union matches (n=6) using the aforementioned cohort. Using television broadcast footage of each match, ruck and tackle events were also manually identified by a single assessor on two separate occasions that were separated by at least 10 weeks. Statistical comparison of the two assessments indicated excellent intra-rater reliability for the visual identification of tackles

(ICC: 0.998; 95% CI: 0.995 to 0.998) and rucks (ICC: 0.997; 95% CI: 0.995 to 0.998). Tackle criteria were set as one-on-one tackles completed by defenders, where an opposing attacking player was taken to ground as a result, using varied tackling techniques and varying points of impact. Due to one-on-one tackling being the most common tackle type, any assisting tackle events were excluded.[19] Ruck events were selected based on the criteria that a player had taken part in a ruck and was involved in a physical competition for possession with an opposing player in attack or defence. Events that did not require a competition with an opposing player were not included.

A total of 250 tackle (n=125) and ruck (n=125) events were manually identified from the video using the defined criteria, only using tackles requiring one player from either team from the selected sub-group. Microtechnology and video data were then synchronised in order to construct 20-second video clips of each identified ruck/tackle instance (10-seconds before and after the frame of impact in each selected ruck/tackle instance). The corresponding 20-seconds of data from the microtechnology device was then extracted at 100 Hz. In addition to the ruck/tackle event data gathered from match-play, a further 29 microtechnology data files were collected from training sessions completed by the aforementioned cohort. These supplementary training files did not include any ruck, tackle or contact events, but rather were used within the investigation and categorised as ‘other movements’. Each of the ‘other movement’ files were at least 1-hour long, with 20 second windows across the files randomly extracted to assist algorithm differentiation between ‘contact’ and ‘non-contact’ events. An initial two-second sliding window was designed to develop a descriptive feature set for tackle and ruck movements.[25] For individual movement identification in isolated windows (activity-specific recordings) accelerometer and gyroscope data (X, Y, and Z axes) were utilised to effectively develop a descriptive feature set for each of the required movements (tackle, ruck and ‘other movement’) over each of the 50% overlap of sliding window (S*) regions (Figure 1).[21] Features were extracted from within each of these regions for each of the relevant sensor outputs, with the feature set containing both temporal and spatial features of each contact type.

FIGURE 1 HERE

Once temporal and spatial features were identified, these signals were applied to a random forest classification model using 166 (two thirds) randomly selected files from the total 250 tackle and ruck files to train the algorithm. Resultant magnitude of accelerometer data was identified using $\sqrt{\boldsymbol{x}^2 + \boldsymbol{y}^2 + \boldsymbol{z}^2}$, where $\boldsymbol{x}, \boldsymbol{y}$, and $\boldsymbol{z}$ represent data from each of the individual accelerometer axes. These were then smoothed using a low-pass 4th order Butterworth filter with a 25 Hz cut-off frequency. Movement profiles were clustered using Gaussian Mixture Models (GMM)[26] over one-second windows and classified using Dynamic Time Warping (DTW)[27] methods. Random forest models were optimised using the original 166 files using the identified variables for detection (Figure 2). This process was repeated 10 times to achieve a 10-fold cross-validation, after which the means and standard deviations were calculated. The remaining 84 files from initial ruck and tackle events were subsequently used to validate algorithm's capability to detect both ruck and tackle events.

FIGURE 2 HERE

Following development and optimisation of the ruck and tackle classification algorithm, we sought to validate the algorithm using an additional 177 microtechnology data files with synchronised video data, collected from the same cohort during eight international matches. Video data recorded during these matches were initially manually coded by an experienced sports scientist who recorded all rucks (979 total) and tackles (781 total) completed in these matches and their timings for the video and microtechnology datasets. the 177 data files collected were processed in the R statistical software package (http://www.r-project.org/) using the developed tackle- and ruck-detecting algorithm.

To effectively process continuous match-play data to identify the incidence of rucks and tackles, the algorithm sequentially processed the time-series of the three-dimensional accelerations and orientations from the microtechnology units within consecutive 2-second windows with a 0.5 second overlap for event identification. For each 2-second window, the algorithm generated a series of decision trees from the random forest using recognised variables that collectively determined whether the data within the window represented; i) a tackle; ii) a ruck; or iii) another movement; providing a confidence score based on each outcome (sum of probabilities within each window equalled 100%). For example, within a 2-second window, the proportion of decision trees agreeing that the data represented a ruck might have been 60%, while 25% might have indicated a tackle and 15% may have indicated another movement.

The proportion of decision trees agreeing data within each 2-second window represented a tackle, a ruck, or another movement was exported to Excel, where these data were compared with visually-identified events derived from synchronised video data. This process involved determining the optimal proportion of decision trees that were required to be in agreement to maximise the likelihood of correctly identifying that a specific movement had occurred. To facilitate this, the criteria of true positives, true negatives, false positives and false negatives were determined, with the optimal cut-off considered to be the proportion of agreeing decision trees that generated the least number of false positives and false negatives.

To evaluate the performance of the ruck and tackle algorithm, results were provided as a percentage of random forest decisions that agreed with video-based determination of ruck, tackle or other movement events. In the first instance, the movement that corresponded with the highest proportion of agreeing decision trees was recorded as the event that was occurring during each 2-second window. Using this approach resulted in a high number of false positives being recorded (e.g. a tackle or a ruck being recorded when one did not exist); hence the optimal proportion of agreeing decision trees was sought to maximise the algorithm's predictive capacity of the validation data set.

Means and standard deviations were calculated for the entire cohort and each positional sub-group (forwards, backs) using all ruck and tackle results. Normative distributions of the data were also derived to gain a better understanding of any outliers and overall spread of the results. Finally, the data were also evaluated to determine whether the performance of the algorithm was frequency dependent; that is, if algorithm performance was influenced by the number of rucks or tackles performed by a specific player.

Results

For the entire cohort, the results of this process indicated that rucks were accurately predicted by the algorithm when an average of 79.4 ±9.2% of the decision trees agreed that a ruck event had occurred (Figure 3). Importantly, this value was not influenced by the players' sub-group, with the respective cut-offs for forwards and backs being 79.8±9.8% and 79.1±8.5%. With respect to the algorithm's capacity to predict tackles, it was shown that events were correctly identified when an average of 81.0±9.3% of the decision trees agreed that a tackle had taken place. Sub-analysis of the positional groups indicated that the optimal cut-off for tackles experienced by forwards (77.7±12.2%) was significantly lower than the cut-off for tackles experienced by backs (85.3±7.2%). The proportion of agreeing decision trees required to optimise the algorithm's ability to predict rucks (79.4±9.2%) and tackles (81.0±9.3%) was not influenced by the number of actual rucks and tackles performed by each of the players.

FIGURE 3 HERE

Discussion

This is the first study to investigate the use of microtechnology and associated algorithms to automatically detect ruck and tackle events in elite rugby union. Results demonstrate that ruck and tackle events can be correctly detected when applying a specifically-designed algorithm to microtechnology data during international match-play. The algorithm was developed and trained to return a number reflecting the algorithm's confidence that a time-series of data represented a ruck, tackle or ‘other’ event (e.g. a locomotor activity, such as running). To minimise the risk of over- or under-reporting the number of rucks and tackles, the optimum confidence cut-off was determined via validation of the algorithm's outcomes against traditional video coding techniques. Results showed that using an algorithm confidence cut-off of 80% for both rucks and tackles would provide practitioners with the best ability to characterise a large proportion of commonly occurring contact-related demands of rugby union training and match-play.

Overall, the results revealed similar optimal algorithm confidence cut-off for rucks involving the whole cohort and the forwards (79.7%) and backs (79.1%), separately. Furthermore, optimal cut-offs for both groups had low standard deviations, which can likely be attributed to the homogeneity of the ruck movement, regardless of playing position. In contrast, the optimal cut-off for tackles completed by the backs (85.3%) was marginally higher than reported for the forwards (77.7%). Although tackle techniques are similar, there are likely to be a number of potential variations that occur due to differences in the speeds and points of contact made between the athletes involved in one-on-one tackles. This study focused on tackles that required the ball carrier to be taken to ground; however, there are other one-on-one tackle situations that do not require the attacking player to go to ground, but still impede the ball carrier’s progress.[23] Therefore, a limitation of this study was that only one-on-one tackles resulting in the ball carrier being taken to ground were validated. In contrast, the algorithm’s predictions of ruck events were possibly more consistent due to the body position required to best compete for possession after a completed tackle.

To determine whether the predictive capability of the algorithm was influenced by the number of collision events that a specific player was involved in, the optimal algorithm cut-offs were analysed separately for players who completed few rucks/tackles and those who completed many. On the basis of this analysis, it was shown that the algorithm's predictive ability was not affected by the frequency of either collision event; returning similar optimal cut-offs for players who performed one tackle and/or ruck and those who completed many (up to 21 tackles and 31 rucks). These results demonstrated that the algorithm is capable of providing a consistent account of a player's contact events, irrespective of the number of contacts they perform during training or match-play.

Results of this study complement those of a recently published paper that describes the use of microtechnology data to quantify the number and timing of scrum events completed by rugby union players during training and match-play.[28] Furthermore, this study adds to growing literature that has highlighted the overwhelming potential of the time-series data that is available from athlete-worn microtechnology.[1] Application of these specifically-designed algorithms have already been highlighted. However, it is important to recognise that many of the algorithms developed using microtechnology data are highly specific to the sports for which they were developed, which likely influences their transferability to sports that share some similarities. For example, previously highlighted research in rugby league, demonstrates the performance decrement of an tackle detection algorithm when applied to rugby union and Australian Rules football.[7, 14, 16, 17] The reduced performance of the rugby league-specific algorithm in other codes of football is likely explained by the distinct variations that exist in the tackling techniques of the different sports.[29] Furthermore, each of these sports involves unique collision events that may elicit similar patterns in the microtechnology data, but are considered quite different to tackles in the context of the game (e.g. hip and shoulder in Australian Rules football). Collectively, these data suggest that it is important to implement collision-detecting algorithms that have been developed and validated using data derived from athletes that are intended to be examined.[1, 16, 17]

During rugby training and match-play, coaches and analysts count tackles and rucks using labour-intensive and time-consuming video notational analysis. Previous research highlights microtechnology's limitations in rugby union and inability to detect and distinguish between collisions, as previous research identifies all contacts as 'collisions' or 'static exertions'.[1] This research has found a practical method to automate collection and differentiation of such events and builds on earlier work in this area.[7, 28] Collectively, these results provide practitioners with novel and time-efficient means for discriminating between the different types of contact events in rugby union, which will ultimately facilitate better interpretation of an individual's physical load in training and match-play situations.[1]

Although results of this study suggest that the presented algorithm may provide sports scientists with an efficient and objective means of understanding the contact demands of training and match-play in rugby union, there are a number of potential limitations that should be considered. First, this algorithm was developed and validated using data collected during match-play for one International rugby union team. Although it could be argued that tackles and rucks would not differ considerably between other elite level squads, at lower levels of competition subtle differences may exist, where techniques may vary. As such, future research is needed to determine the suitability of the presented algorithm for use in different rugby union populations. Second, although this algorithm has been shown to accurately detect ruck and tackle events, it is not capable of providing insight into the nature of the forces experienced by the players during such events. As such, the presented algorithm is limited by the assumption that all tackles and rucks involve equal force; emphasising future developments that are capable of providing insight into the specific physical demands of each collision to further quantify total training and match loads. As previously stated, the algorithm was trained using one-on-one tackles, thereby disregarding the contact load required during tackle assists. Despite the advancements in detecting contact demands in rugby union there is still a possibility that there is an underestimation of a player's contact demands.

Conclusion

Current research has focused on the running demands of rugby union and more recently scrum demands. This study provides sport scientists with a valid method of quantifying the contact and collision demands of rugby union by counting ruck and tackle events. This research enhances the ability to improve preparation and injury prevention of rugby union players. Automated detection of ruck and tackle events provides a time-efficient alternative to traditional time-consuming and labour-intensive methods requiring video-based analyses. Furthermore, it complements previous research that has described microtechnology-based algorithms to quantify the running demands and scrum incidence in rugby union athletes. Further research investigating forces within these contact movements is advocated.

Practical Applications

- Results demonstrate the competencies of microtechnology, demonstrating the ability to detect ruck and tackle events in rugby union when applying a specifically designed algorithm. In collaboration with recent research, providing sport scientists the capability to detect and quantify the most frequent collisions in rugby union using microtechnology devices.
- This current study provides practitioners with a time efficient and validated method to detect and monitor rucks and tackles events during match-play and training to assist with player preparation and injury prevention. Providing more objective results than previous labour-intensive methods that are potentially error prone.
- This research will provide sport scientists with a more in-depth understanding of a player's demands by allowing different contact types, in this instance rucks and tackles, to be independently classified.

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Figure Captions

Figure 1. Schematic overview of methodology

Figure 2. Decrease in accuracy due to exclusion of a single predictor variable. Variables with a larger mean decrease in accuracy are of greater importance for event classification.

Figure 3. Study outcomes showing the; A) distribution of rucks completed by players and lowest returned average algorithm percentage; B) distribution of tackles completed by players and lowest returned average algorithm percentage; C) variation amongst the cohort, with respect to the number of rucks completed during match play (x-axis) and the corresponding optimal algorithm cut-off (y-axis); and D) variation amongst the cohort, with respect to the number of tackles completed during match play (x-axis) and the corresponding optimal algorithm cut-off (y-axis). Note: The optimal cut-off refers to the percentage of decisions trees within the random forest classification algorithm that produced the greatest level of agreement between the algorithm's predictions and the vide-based appraisal of the collision events.

Figures

Figure 1.

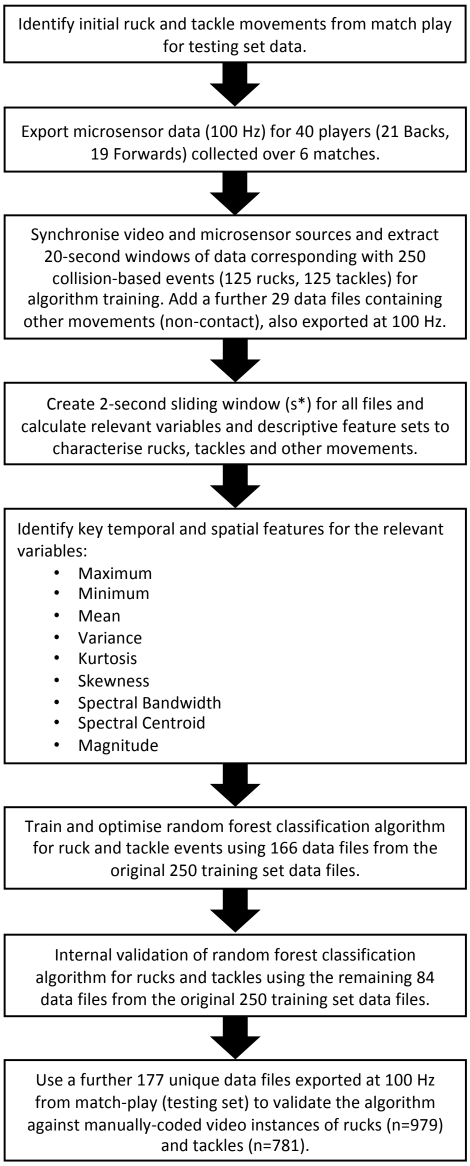
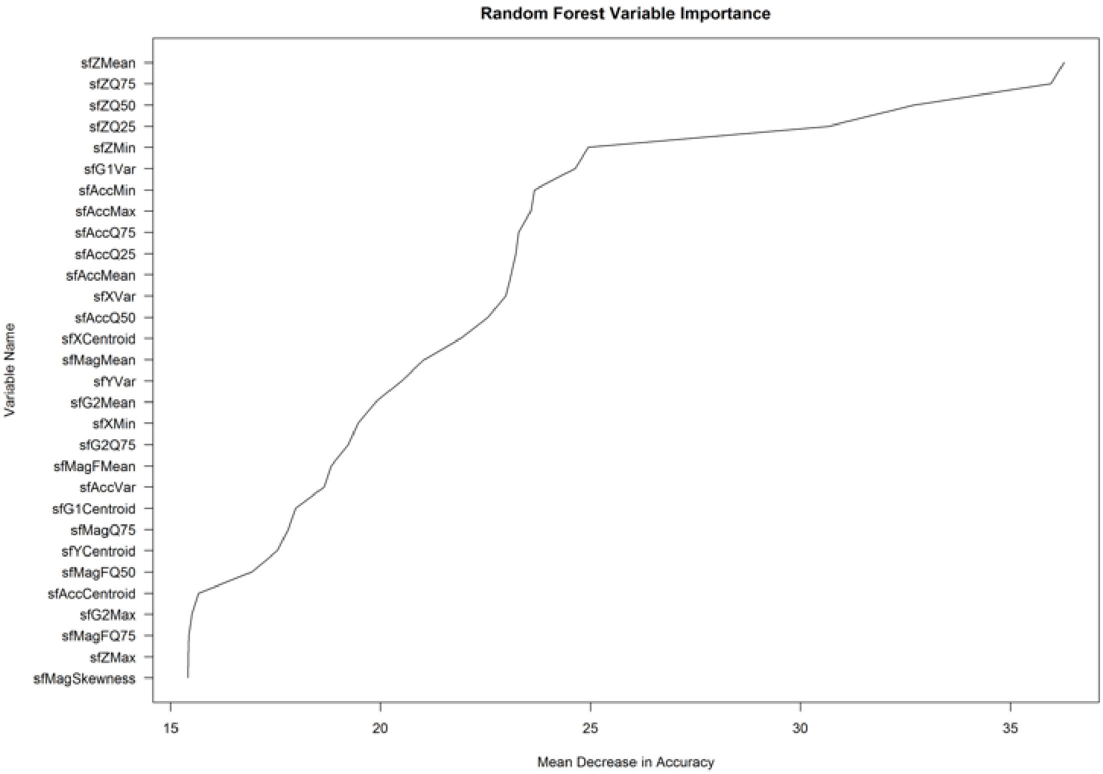
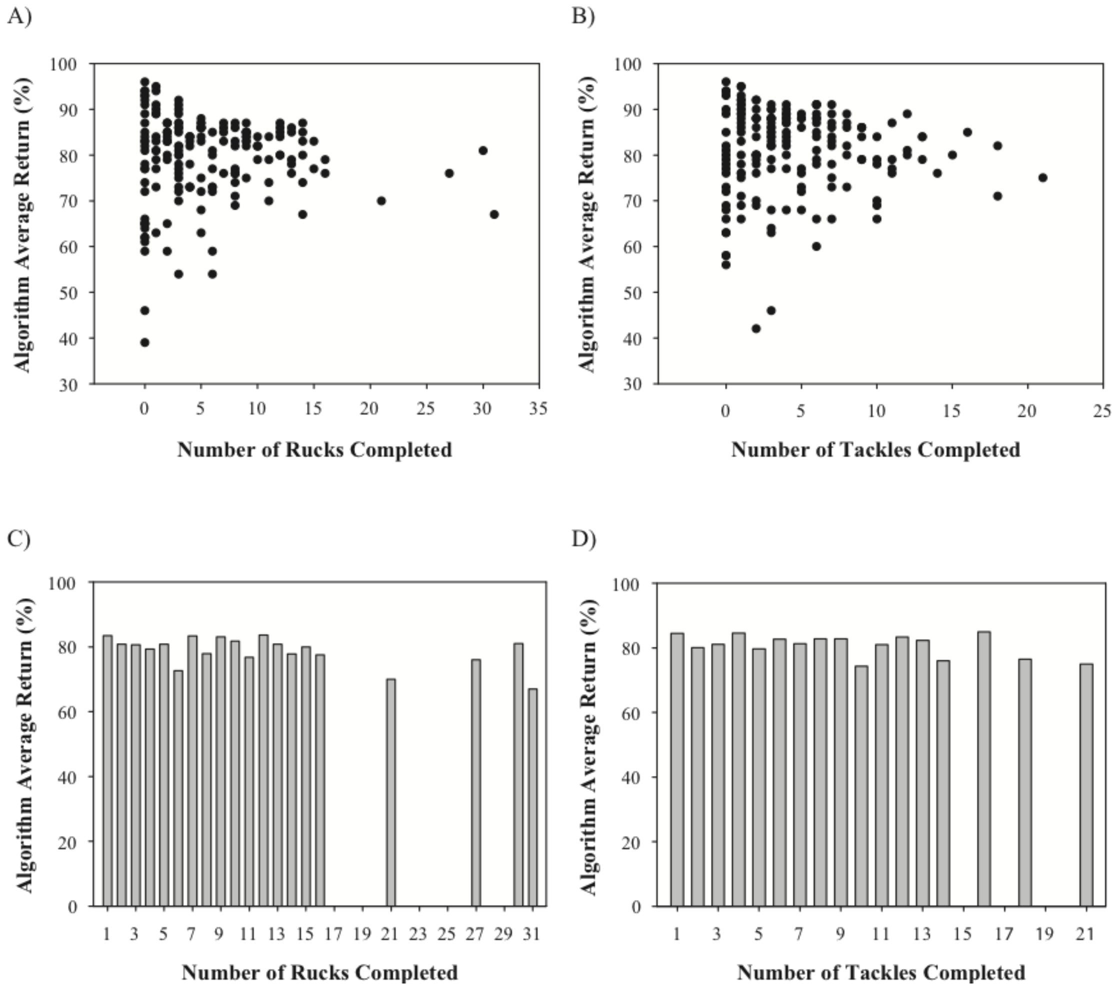


Figure 2.



Random Forest Variable Importance
sfZMean
sfZQ75
sfZQ50
sfZQ25
sfZMin
sfG1Var
sfAccMin
sfAccMax
sfAccQ75
sfAccQ25
sfAccMean
sfXVar
sfAccQ50
sfXCentroid
sfMagMean
sfYVar
sfG2Mean
sfXMin
sfG2Q75
sfMagFMean
sfAccVar
sfG1Centroid
sfMagQ75
sfYCentroid
sfMagFQ50
sfAccCentroid
sfG2Max
sfMagFQ75
sfZMax
sfMagSkewness
Variable Name
15
20
25
30
35
Mean Decrease in Accuracy

Figure 3.


A)
B)
C)
D)
Algorithm Average Return (%)
Number of Rucks Completed
Number of Tackles Completed