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Preferred Running Head: Microsensors and rugby scrums

Title: Validity of a microsensor-based algorithm for detecting scrum events in rugby union

Submission Type: Original Investigation

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Purpose: Commercially-available microtechnology devices containing accelerometers, gyroscopes, magnetometers, and global positioning technology have been widely used to quantify the demands of rugby union. This study investigated whether data derived from wearable microsensors could be used to develop an algorithm that automatically detects scrum events in rugby union training and match-play.

Methods: Data were collected from 30 elite rugby players wearing a Catapult S5 Optimeye microtechnology device during a series of competitive matches (n=46) and training sessions (n=51). A total of 97 files were required to "train" an algorithm to automatically detect scrum events using random forest machine learning. A further 310 files from training (n=167) and match-play (n=143) sessions were used to validate the algorithm's performance.

Results: Across all positions (front row, second row and back row) the algorithm demonstrated good sensitivity (91%) and specificity (91%) for training and match-play events when confidence level of the random forest was set to 50%. Generally, the algorithm had better accuracy for match-play (93.6%) events than training events (87.6%).

Conclusions: The scrum algorithm was able to accurately detect scrum events for front row, second row and back row positions. However, for optimal results practitioners are advised to use the recommended confidence level for each position to limit false positives. Scrum algorithm detection was better with scrums involving five players or more, and is therefore unlikely to be suitable for scrums involving 3 players (e.g. Rugby Sevens). Additional contact and collision detection algorithms are required to fully quantify rugby union demands.

Keywords: algorithm; microtechnology; team sport; scrum

Commercially-available microtechnology devices containing global positioning systems (GPS) and microsensors (accelerometers, gyroscopes and magnetometers) are commonly used to quantify the physical demands of Rugby Union.[1] During match-play and training, players are divided into subgroups of forwards and backs and are required to perform repeated bouts of high-intensity locomotor activity (sprinting, running, accelerations) separated by low-intensity activity (standing, walking, jogging).[1-6] In addition to the locomotor demands of match-play, players are frequently involved in high-intensity physical contacts and collisions such as mauls, tackles and rucks, with forwards also required to compete in scrums.[1-8] Scrums are used to restart play after a minor infringement and involve all eight forwards from each team, forming three interconnected rows of players. While facing each other, the players forming the front row for each team lock heads and shoulders with the opposition forwards and attempt to produce a greater force than their opponents to gain possession of the ball. [9]

Despite researchers accurately quantifying the locomotor demands of elite rugby union, contact events such as scrums, rucks, mauls and tackles are usually combined and defined as 'impacts' when using microtechnology.[1,4,7] Similarly, research evaluating contact events via video-based time-motion analysis has typically categorised these incidents as 'high-intensity efforts'[3] or 'static exertions'. [5,6,8] Success in rugby union frequently depends on the players' ability to tolerate contact events.[10] However, research summarising the physical contribution of contact events (scrums, tackles, rucks and mauls) during match-play, either provide a count of the total number of contact events, a rating of the force involved[1], or the total time attributable to collisions.[8] To date, no research has differentiated between scrums, rucks, mauls and tackles, which inadvertently implies that each form of contact poses an equal physiological stress to the players.[11] Classification of each contact would contribute to an improved understanding of the unique stresses associated with each of these collision types. In turn, this would potentially assist to improve player preparation and help to reduce the risk of injury and/or re-injury during training and competition.

Microsensors have been used to quantify the demands of sport-specific movements in team sports, snow sports, individual sports and water sports.[11] Validated algorithms have been applied to microsensor data to automate the collection of sport-specific movements, such as cricket fast bowling, [12] baseball pitching,[13] and rugby league tackling. [11,14,15] To date, researchers have only used microsensors to quantify the tackle in rugby union,[16] whilst scrums, rucks and mauls have been neglected.[11] Researchers have highlighted the injury risk associated with scrums,[17] predominantly in match-play.[18] Currently there is no other valid method of quantifying scrum workload during training or match-play apart from using video-based time motion analysis, which is a labour-intensive process.[11] Many researchers have highlighted the need to further investigate contact movements in rugby union, as they generally require the body to endure very high forces that are imparted over a relatively short time period. However, despite the relatively short duration of each contact event, the repeated collisions involved in a typical training or match-play scenario make a significant contribution to the players' total workload. Of the contact movements performed during regular match-play, scrum events occur around 25 times per game, while depending on playing position, each player will complete approximately 30 rucks and tackles per match.[5,11,19-21]

Given the need for more time-efficient and accurate methods of evaluating the incidence and physical demands of contact events in Rugby Union, this research sought to establish the validity of a microsensor-based algorithm for the automatic detection of scrum events during training and match-play. Based on the demonstrated capabilities of inertial devices to quantify other aspects of sports performance,[11,22] it was hypothesised that scrum events could be accurately detected using wearable microsensors.

Methods

Subjects

Thirty elite forwards (mean ± SD age; 28.3 ± 4.0 yrs), including players from all positions of the scrum (Front Row, n=16; Second Row, n=8; Back Row, n=6) were recruited to develop and validate the scrum-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 consent prior to their involvement. The Institution's Human Research Ethics Committee approved all experimental procedures (Approval #2014-135Q).

Design

Phase 1 – Algorithm Development

To facilitate the initial development and training of the scrum detection algorithm, data were collected for the 30 participants using a Catapult S5 Optimeye device (Melbourne, Victoria, Australia) positioned between the players' shoulder blades in a purpose-built vest. Each device contained an array of inertial sensors (i.e. tri-axial accelerometer, gyroscope, magnetometer), which captured data at 100 Hz during a series of competitive matches (n=46) and training sessions (n=51). A total of 97 data files (Front Row, n=49 files; Second Row, n=25 files; Back Row, n=23 files) that captured 1057 scrum events were required to develop and optimize the final scrum-detecting algorithm. Timestamps of the scrum instances were manually identified using video data, which were coded alongside Opta Sports events when available (i.e. during match-play).

The development of an algorithm to detect scrum events involved two separate, but inter-related processes. Firstly, given the unique posture adopted by players while performing scrums, orientation of the device was estimated using a proprietary sensor fusion algorithm that included accelerometer and gyroscope data (Catapult; Melbourne, Victoria, Australia) within a match-play or training session. According to previous research, accelerations and the orientations determined from microsensor data using fusion-based methods have excellent reliability and concurrent validity.[23-25] While the wearable sensors provided an array of measures, the following criteria were shown to have the ability to identify all scrum instances in the training set and, hence, were the two orientation measures consistently used in the scrum detection algorithm:

i. The orientation of the device was below 25 degrees compared to the horizontal plane for at least 4 s. When this criterion was met, the algorithm established this time period as a potential event window.

ii. The event was recorded only if the orientation of the device went below the horizontal plane during the event window.

For data to be considered to potentially represent a true scrum event during training or match-play, both of these orientation criteria were required to be met. This was typically met by participants in preparation for the scrum so that even if a scrum collapsed it would enter the second step of the algorithm. These two initial criteria were intended to remove other non-relevant contact instances. All possible scrum instances within the time-series data were then classified as true and false scrum instances based on video analysis conducted by Opta Sports (http://www.optasports.com) statistics. The window of the classified events were then created for the inertial data and window mid-points were then extracted to become the event timestamp. This first step of the algorithm development aimed to efficiently transform the data from a time series into a classification problem using the orientation criteria. The second step extracted features of the accelerometer and gyroscope signals from each event. These calculations included summary statistics using different time windows around the event timestamp and formed the variables 33for the machine-learning process. Variable selection was then performed using the R statistical software package's Variable Selection Using Random Forests (VSURF)[26] function. Based on a 10-fold cross-validation mean classification accuracy, 11 signal features were eventually selected from the accelerometers and gyroscopes and included in the final version of the random forest classifier.[27] R statistical software package (http://www.r-project.org/) was used throughout the development of the algorithm.

A scrum confidence scoring was attached to the algorithm based upon the number of trees in the random forest agreeing that a scrum event had taken place. If only the minimum orientation measures were met then the algorithm would return a confidence of 0%. In contrast, when a larger number of trees in the random forest reported detecting a scrum event based on the 11 signal features (Table 1), the algorithm returned a higher confidence rating (maximum 100%).

Table 1. List of scrum algorithm signal features

Signal Feature	Feature Name	Feature Description
1	Horizontal Position 5	To detect how long the estimated orientation of the device is below 5 degrees (i.e. forward flexion)
2	Horizontal Position 15	To detect how long the estimated orientation of the device is below 15 degrees (i.e. forward flexion)
3	Horizontal Position 25	To detect how long the estimated orientation of the device is below 25 degrees (i.e. forward flexion), which corresponds with scrum activity
4	Raw Player Load Q75	75th percentile of raw player load during the scrum activity

5	Rotation Median	Median of smoothed total rotation during the scrum activity
6	Smooth Player Load 75	75th percentile of smoothed player load during the scrum activity
7	Raw Player Load Q90	90th percentile of raw player load during the scrum activity
8	Raw Player Load Median	Median of raw player load during scrum activity
9	Inertial Side Q10	To detect how long the estimated orientation of the device is below 5 degrees (i.e. forward flexion)
10	Raw Player Load Pre 30	To detect how long the estimated orientation of the device is below 15 degrees (i.e. forward flexion)
11	Raw Rotation Player Load Pre 30	To detect how long the estimated orientation of the device is below 25 degrees (i.e. forward flexion), which corresponds with scrum activity

Phase 2 – Algorithm Validation

To validate the random-forest classifier-based algorithm, a testing set of 21 participants (Front Row, n=9; Second Row, n=5; Back Row, n=7) from the same cohort were monitored using Optimeye S5 devices across 11 international matches (143 full match files) and 9 training sessions (167 full training files). Training session scrums included events against opposition (8v8) or against a scrum machine (front 3 against machine, front 5 against machine and 8 against machine). A total of 261 scrum instances (international matches, n=169; training, n=92) were manually coded using video data and the timing of each scrum instance was noted according to video, time of day and time on the Catapult raw file. Video coded instances were compared to those detected by the algorithm. Scrum algorithm confidence scoring was set to the lowest possible setting, 0%, therefore incorporating all 4833 instances. Each instance was then matched with the relevant time stamp and false positives were thoroughly checked against video coded scrum events.

Statistical Analysis

True positive and negative results and false positive and negative results (Table 2) were determined to calculate algorithm accuracy, precision, specificity and sensitivity. Receiver Operating Characteristic (ROC) analyses were conducted to determine the sensitivity and specificity of the algorithm's confidence in predicting scrum events. The predictive confidence value that yielded the best sensitivity and specificity was selected as the optimal cut-off score and represented the point that simultaneously maximised both on the ROC curve. All statistical analyses were conducted in the Statistical Package for the Social Sciences (SPSS v24).

Table 2. Criteria of algorithm results.

	True	False
Positive	Scrum event and scrum correctly detected	No scrum event, scrum event incorrectly detected
Negative	No scrum event and no scrum event detected	Scrum event and no scrum event detected

Results

To evaluate the performance of the scrum detection algorithm when only the two initial orientation criteria were applied without considering the results of the machine-learning model (i.e. the non-optimised algorithm), the sensitivities and specificities associated with an algorithm confidence of 0% were examined. When data for all positions (i.e. front row, second row, back row) and all sessions (i.e. training, competitive matches) were considered, the non-optimised algorithm identified 3904 possible scrum instances. Of these instances, only 25 true negatives were recorded, yielding a sensitivity of 99.5%, a specificity of 31.5% and a precision of 47% (Table 2). Overall, algorithm performance was slightly better for match-play (sensitivity 99.8%, specificity 35.0%) than training (sensitivity 98.9%, specificity 28.1%).

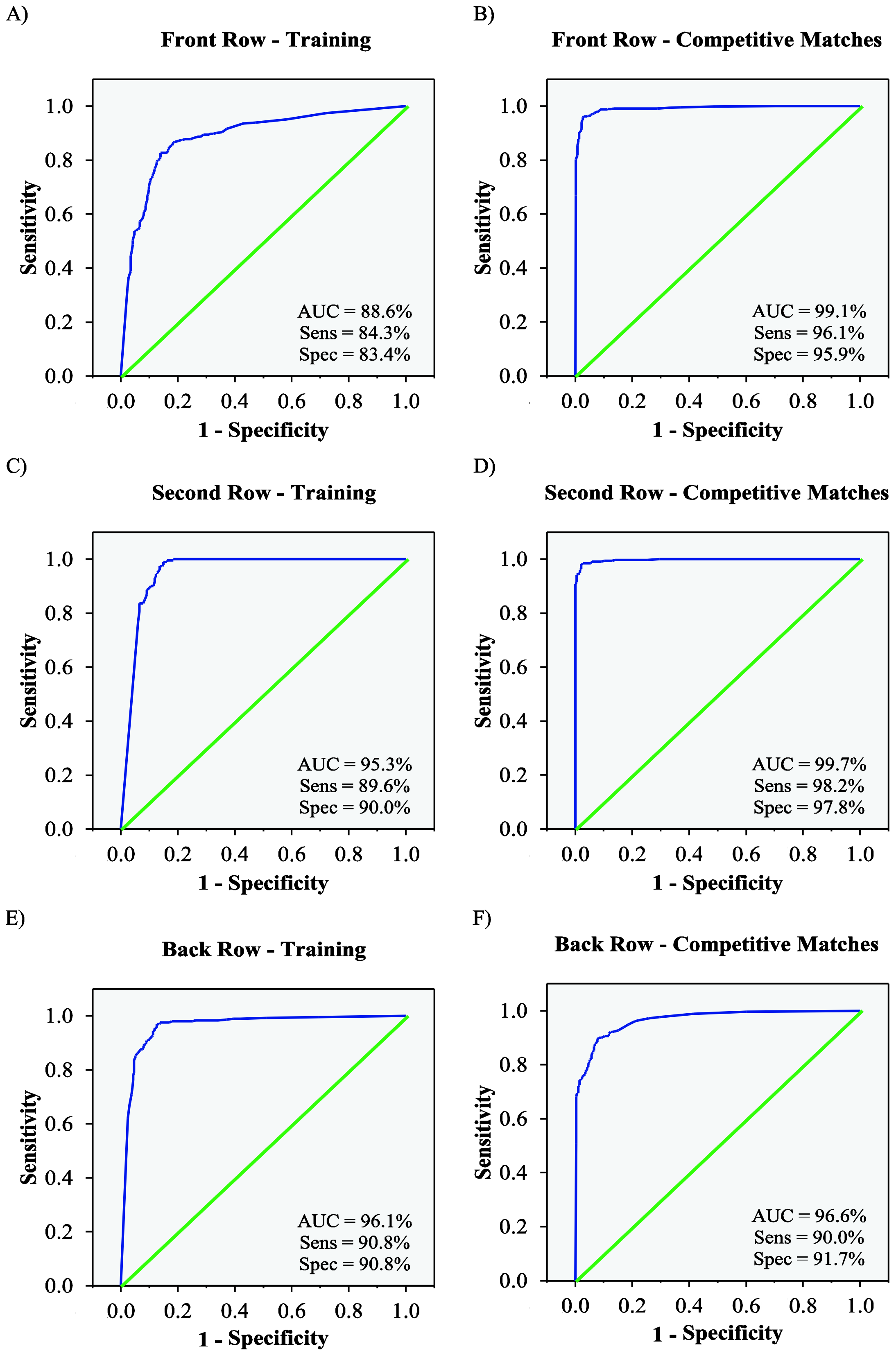
Using the 11 signal features identified during the model learning process, the algorithm's predictive capacity was improved and this was reflected in the higher predictive confidence values (i.e. the optimised algorithm). Table 3 demonstrates the algorithm confidence cut-offs that returned the best results for the entire dataset and for the three positional groups during the training and match-play sessions based upon receiver operating characteristic analysis (Figure 1). On the basis of these results, the predictive confidence threshold that yielded the best combination of sensitivities and specificities for the entire cohort was 50%, while the optimal cut-off for matches (37%) was somewhat lower than determined for the training data (54%) (Table 2). When the study cohort was subdivided into positional groups, it was shown that the optimal cut-off for front row players was 27% for training and 51% for match-play, compared with 91% and 49% for the second row. In contrast the predictive confidence values that provided the best sensitivities and specificities for back row players during training and match-play were 63% and 21%, respectively.

Various training scenarios were observed during data collection, involving three, five and eight players against a scrum machine and opposed "eight verses eight" scrums. Importantly, the first two scenarios were only included in the validation phase. Scrums involving the front row only had the lowest sensitivity (50%) and specificity (97%); this improved when including both the front row and second row (i.e. for five player scrums), with both positions attaining sensitivity and specificity of 100%. Eight man scrums against a scrum machine had the highest sensitivity and specificity for all positions: respective sensitivity and specificity values; front row, 98% and 99%; second row, 100% and 100%; and back row, 100% and 100%. Opposed scrums in training involving 16 players (8v8) also demonstrated high sensitivity and specificity for all 3 positions (front row, sensitivity 98% and specificity 99%; second row, sensitivity 100% and specificity 100%; back row, sensitivity 99.5% and specificity 99.7%).

	Accuracy (%)	AUC (%)	Optimal Cut-Off	Sensitivity	Specificity
Scrum Identification					
Probability For All Data	91.0	95.8	50%	0.91	0.91
Data Source					
Probability For Training Data Only	87.6	92.9	54%	0.89	0.87
Probability For Match Data Only	93.6	98.2	37%	0.94	0.94
Position					
Probability For Front Row Only	90.4	95.1	41%	0.91	0.90
Probability For Second Row Only	94.4	97.1	83%	0.94	0.93
Probability For Back Row Only	89.8	95.8	36%	0.91	0.91
Position By Data Source					
Probability For Front Row in Training	83.8	88.6	27%	0.84	0.83
Probability For Second Row in Training	91.4	95.3	91%	0.90	0.90
Probability For Back Row in Training	90.6	96.1	63%	0.91	0.91
Probability For Front Row in Matches	95.9	99.1	51%	0.96	0.96
Probability For Second Row in Matches	98.1	99.7	49%	0.98	0.98
Probability For Back Row in Matches	89.6	96.6	21%	0.90	0.92
Position By Data Source (Limited)					
Probability For Front Row in Training	85.2	90.5	39%	0.86	0.86
Probability For Second Row in Training	91.3	95.3	91%	0.90	0.90
Probability For Back Row in Training	90.8	96.2	63%	0.91	0.91

Table 3 – Accuracy, Area Under the Curve (AUC), Optimal algorithm cut-off, sensitivity and specificity for each position during each scenario

Figure1 –Receiver Operating Characteristic (ROC) analyses for Front Row (A, B), Second Row (C, D) and Back Row (E, F) players during the training and competitive match scenarios, respectively.



Discussion

This is the first study to investigate the use of microtechnology and associated algorithms to automatically detect scrum events in elite rugby union. Our results demonstrate that scrum events were best detected with high sensitivity and specificity when algorithm confidence level was at 50%, although algorithm performance was better during match-play than training. In training, scrums that involved a minimum of 8 players (8 against a machine or contested scrums involving 16 players) returned higher accuracy than those scenarios that involved 3 or 5 players. This finding can be explained by the lack of the latter scenarios in the training phase of the algorithm. Accuracy was best for the front row, with detection of scrum events poorest in the back row. These findings provide a practical and valid method of quantifying scrum events in professional rugby union match-play and training sessions.

False negatives during training were only recorded during 3-man scrums performed against a machine. This may have been due to the activity duration being insufficient to satisfy the algorithm's minimum requirements, thus affecting the overall sensitivity and specificity for the front row players during training sessions. Other false negatives in training occurred when scrums collapsed (front row falls to floor) or were reset (incorrect positioning) affecting both the front row and back row. During match-play, all false negatives were attributable to players in the back row who did not maintain a horizontal position for an adequate period of time to satisfy the algorithm's least common denominators before a scrum collapse. As shown in the results for these players, the tendency for back row players to change their trunk orientation prior to a scrum collapse significantly affected the algorithm's sensitivities and specificities for this positional group. Although the results for the back row players were negatively affected by this phenomenon, they do suggest that the physical exertion exhibited by these individuals during a particular scrum event may be quite different to that of front and second row players, even if a scrum is completed or collapses.

The comparisons of video-based notational analysis and the scrum algorithm demonstrated the best results with a 50% threshold cut off. The overall outcome of the algorithm was better for match-play than training. Fewer scrum variations occur in match-play (i.e. each scrum is always contested by 16 players), whereas training activities may involve contested '8 v 8' scrums, eight players against a scrum machine, or the front five (involving front row and second row) and front row positions only, which may account for the differences in algorithm performance in different scenarios. Further analysis of the different types of scrum-based technical drills utilized during training indicated that the algorithm performed worse for drills involving only three or five players. Although these results suggest that the algorithm's performance may be improved by including such drills in the "learning" phase of the algorithm, it could be argued that scrums involving 5 or fewer players are aimed more at developing technique, rather than specifically preparing the athletes for the demands of match-play. As such, the specific differences between these training-based drills and actual scrum events may contribute to these incidents not being identified as a scrum using the specified algorithm criteria.

We found that algorithm performance differed among positions during match-play and training. Optimal sensitivity and specificity for all positions occurred when the algorithm confidence rating was set at 37% for match-play and 54% for training (Table

2). Due to the differences in algorithm performance among positions, setting confidence thresholds of 51%, 49% and 21% during match-play and 27%, 91%, and 63% during training for the front row, second row, and back row, will likely produce optimum results, although caution must be taken when extrapolating these results to other independent data sets. False positive events (threshold set to 50%) totaled 168 and 1668 true negative events (predominantly scoring below 5% confidence) across the validation data set. Most events were off camera, although events scoring the highest confidence rating were from rare static maul events where players were not moving and positioned in a similar posture to that observed during a scrum

The results of the scrum algorithm are in agreement with a recent systematic review that evaluated the use of microsensors for the detection of sport-specific movements.[11] This technology has been applied in cricket to count balls bowled[12] and bowling intensity,[28] baseball throwing,[13] tennis serves,[29] and several individual,[11,30-32] snow,[11,33-38] and water-based[11,39-41] sports. Microsensors and associated algorithms have been used to detect tackles in rugby league[14] with accuracy improving with greater impact forces and longer duration of events.[15] However, this technology has previously been shown to be less useful for detecting tackle events in rugby union[21] and Australian football[42] match-play. A possible explanation for the poor performance of the algorithm in Australian football and rugby union match-play is that the tackle algorithm was trained on rugby league players, to identify rugby league tackles. The differences in tackles between rugby league and that of Australian football and rugby union may explain the differences in accuracy and show the importance of the representativeness of the training data set for developing movement specific algorithms. Given the differences in findings among rugby league, rugby union, and Australian football, and the present findings that 3- and 5-man scrums were less accurate than 8-man scrums, we would recommend only using the scrum algorithm for detecting scrum events involving 15-a-side rugby union.

Although this algorithm advances the ability of sport scientists to automatically detect scrum events in elite rugby union, there are some potential limitations to the research. The algorithm was designed using two elite level teams and tailored primarily for front row players due to their role within scrum events. This may account for the slight, but incremental decrease in algorithm performance for the second row and back row positions, respectively. Elite male players were used to train the algorithm; consequently, the algorithm may be less applicable for younger and smaller junior rugby union participants, or female players, due to possible difference in microsensor signals. Finally, at present, the scrum algorithm only detects the number of scrum events and does not account for the forces applied during these events. Despite these limitations, this study demonstrates the potential for microsensor technology in the detection of rugby union-specific collision events provided an adequate (i.e. specific and representative) training data set. While the demonstrated success of the presented algorithm suggests that practitioners will be better able to detect scrum events in training and match-play to monitor players' total training loads, it is important to acknowledge that the scrum is one of many contact types experienced in rugby union. Hence, despite the algorithm success, a complete understanding of a player's match demands and total training load would require the development of alternate, but complementary methods to identify rucks, tackles and mauls using microtechnology.

PRACTICAL APPLICATIONS

The majority of rugby union GPS analyses have focussed on the locomotor demands (i.e. low-speed activities, high-speed running, and sprinting) of the game.[1-6] However, disregarding the physically demanding collision events that may result in very little locomotor activity, may severely underestimate the physical demands of match-play. The development and validation of a scrum algorithm to automatically detect scrum events during training and match-play improves the understanding of an important component of rugby union. Previously, this type of analysis would require time consuming video-based notational analysis. The automated detection of scrum events using data provided by the GPS units worn by players allows practitioners to more easily quantify the occurrence of scrum events during regular training and match-play situations. By improving the efficiency of this process, it becomes far more viable for sports scientists to determine the physical load associated with these contact events, which should ultimately improve player preparation and reduce the risk of injury. Further research investigating the use of this technology to quantify the ruck, tackle and maul is warranted.

CONCLUSION

In conclusion, we investigated the use of microtechnology and associated algorithms to automatically detect scrum events in elite rugby union. Receiver Operating Characteristic analyses provided optimal random forest algorithm confidence thresholds to generate best sensitivity and specificity (typically >90%). Algorithm performance was better during match-play than training for front row and second row, although conversely, results revealed better performance for the back row during training than match-play. In training, scrums that involved a minimum of eight players were readily detected, while scrums involving three players were less accurate. Scrums involving five players or more attained markedly better results. Detection was best for the second row, with decreased detection in the front row, with back row positions performing comparatively lower. These findings provide a practical and valid method of quantifying scrum events in professional rugby union match-play and training.

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