Classification of playing position in elite junior Australian football using technical skill indicators

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Abstract

In team sport, classifying playing position based on a players' expressed skill sets can provide a guide to talent identification by enabling the recognition of performance attributes relative to playing position. Here, elite junior Australian football (AF) players were *a priori* classified as one of four common playing positions; forward, midfield, defence, and ruck. Three analysis approaches were used to assess the extent to which 12 in-game skill performance indicators could classify playing position. These were a linear discriminant analysis (LDA), random forest, and a PART decision list. The LDA produced classification accuracy of 56.8%, with class errors ranging from 19.6% (midfielders) to 75.0% (ruck). The random forest model performed at a slightly worse level (51.62%), with class errors ranging from 27.8% (midfielders) to 100% (ruck). The decision list revealed six rules capable of classifying playing position at accuracy of 70.1%, with class errors ranging from 14.4% (midfielders) to 100% (ruck). Although the PART decision list produced the greatest relative classification accuracy, the technical skill indicators reported were generally unable to accurately classify players according to their position using the three analysis approaches. This homogeneity of player type may complicate recruitment by constraining talent recruiter's ability to objectively recognise distinctive positional attributes.

Keywords: Performance analysis; machine learning; discriminant analysis; random forest; rule induction

Introduction

Talent identification is an increasingly prominent area of research within the sport sciences (Robertson, Woods, & Gastin, 2015; Rowat, Fenner, & Unnithan, in-press). This emergence may owe to the influence effective talent identification (and subsequent development) programs have toward the attainment of sporting excellence (Vaeyens, Lenoir, Williams, & Philippaerts, 2008). Specifically, the on-field success of professional sporting teams could be linked to their ability to identify, and then recruit, the best available talent, all while working within the various confines imposed by their governing sporting body (e.g. salary caps and draft restrictions). Given these various confines, professional sporting organisations are increasingly turning toward machine learning to assist with the identification of players who possess unique attributes that may offer a competitive advantage (Pion, Hohmann, Liu, Lenoir, & Segers, in-press). These non-linear analysis approaches are often used to predict a junior's future prospects based on a set of defined explanatory variables collected at specific time points during their development (Pion et al., in-press). To assist with this identification process, it may be beneficial to understand whether a players' skill profile generated during game-play enables their successful classification into playing positions; especially in team sports where players often perform mixed or multiple roles. This could facilitate the recognition of performance relative to playing position, which would be of assistance to teams who explicitly require a certain type of player (i.e., defender or forward) to fill a structural weakness on their current playing roster.

Australian football (AF) is a dynamic team invasion sport that requires players to possess a unique combination of multidimensional performance qualities (Woods, Raynor, Bruce, McDonald, & Robertson, 2016). Its rules do not constrain players to field zones, nor do they enforce an off-side ruling, which consequently allows players to roam across the full playing area. Nonetheless, players are generally classified as four player types; defence, forward, midfield, or ruck, with this partition being further pronounced at the elite senior level (i.e., within the Australian Football League; AFL). Generally however, players often perform idiosyncratic task sets in each of these positions during game-play. For instance, midfielders usually follow the ball around the field in a somewhat nomadic manner, competing against opposition players to obtain ball possession during stoppages in play (i.e., during 'ball ups' or 'throw ins'). Their more important technical skills are oriented around obtaining ball possession and providing linkage between the defensive and forward zones. Comparatively, key position players (defenders or forwards) are typically required to 'mark' or 'spoil' the ball in order to score or defend a goal, respectively. Despite players requiring a minimum level of technical skill (e.g. kicking and handballing) (Woods, Raynor, Bruce, & McDonald, 2015), these unique positional requirements may enable the classification of distinctive player types. However, it is currently unknown whether technical skill involvements acquired during game-play can be used to categorise a player's subsequent playing position in elite junior AF. The practical benefits of objectively elucidating player types are vast, with the more prominent likely to implicate talent recruitment practices, training specificity (i.e., tailoring practice conditions that target position specific task sets), and/or the recognition of players who can play mixed or multiple positions based on their expressed skill sets.

In an attempt to equalise competitive advantages, the AFL annually implements a national draft. This generates a competitive environment whereby AFL talent recruiters attempt to identify juniors who possess uniquely distinguishable performance attributes. To help facilitate this identification process, the AFL, in conjunction with state-based leagues, has established an elite Under 18 years (U18) competition, referred to as the AFL national U18 championships. This four to six week tournament provides talent recruiters with an opportunity to subjectively evaluate potential draftees. In addition to this subjective process, commercial statistical providers; namely Champion Data© (Champion Data©, Melbourne, Australia), provide talent recruiters with objective reports surrounding a players technical skill involvements. These notations often orient around discrete indicators such as the total count of skill involvements (total possessions), inside 50's (attacking passages of play), tackles, and contested possessions.

Partially explaining the subjective recruitment process, Woods, Joyce and Robertson (2016) compared the technical skill involvements of players within this tournament relative to their draft status (drafted or non-drafted). Results indicated distinctive differences in the technical skill involvements of these players, with drafted players accruing a greater count of contested possessions and inside 50's relative to their non-drafted counterparts (Woods, Joyce, & Robertson, 2016a). However, this study did not delineate the use of technical skill indicators to classify players of differing field positions. This is an important oversight, as it is likely that AFL talent recruiters base their draft choices on structural weaknesses at their club (Woods, Veale, Collier, & Robertson, in-press). For example, an AFL team explicitly requiring a defender may use the national U18 championships to identify a suitable draft candidate. However, this process of objectively identifying (and then ultimately recruiting) talent is based on the assumption that the playing conditions within the national U18 championships, coupled with the technical skill performance indicators provided to talent recruiters, enables the recognition of positional-specific player attributes. Rather contrarily, it is hypothesised that a high level of homogeneity will be present between players of differing field positions given the discrete and broad nature of the technical skill indicators provided to talent recruiters. If demonstrated, this may lead AFL clubs to develop and integrate their own positional-specific performance indicators to assist with the objective recognition of prospective draftees within the AFL national U18 championships.

This study aimed to determine whether elite junior AF players could be accurately classified according to their designated playing positions using commonly reported technical skill indicators generated during game-play. To achieve this aim, this study compared the performance of three linear and non-linear classification techniques. The subsequent results of this work are likely to implicate both performance analyses and player recruitment processes implemented within the AFL national U18 championships.

Methods

Data

Technical skill data were acquired from Champion Data© (Champion Data©, Melbourne, Australia). Ethics approval was granted by the relevant Human Research Ethics Committee. The technical indicators reported by this provider are reliable to 99% when analysing the match activities of players within the AFL (O'Shaughnessy, 2006). The dataset contained counts for 12 technical indicators, each of which are described in Table 1.

******INSERT TABLE ONE ABOUT HERE******

All players (n = 244; 17.6 ± 0.6 *y*) included in this study competed within the same national U18 championships. Players represented teams from each of the eight State Academies. The data were collected from all 16 championship games; resulting in a total of 680 player observations. Although game time durations may have different slightly between players given in-game rotations, each player completed no less than 70% of the total game time in each match. All players were *a priori* classified into one of four positions: midfield (n = 300 observations), defence (n = 168 observations), forward (n = 171 observations), or ruck (n = 41 observations). The definition of each playing position used here was in accordance with previous research in AF (Veale & Pearce, 2009; Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004); with a brief description of each position being presented in Table 2. Player position classifications were provided by each State Academy high performance manager prior to the beginning of each game, being matched to the official AFL records provided to talent recruiters. As such, within game positional changes implemented in response to team tactics or other external factors (e.g. injury) were somewhat uncontrollable. The uneven spread in observations stemmed from the nature of positional allocations in AF (i.e., fewer key position players and ruckman are selected in a typical team compared to midfielders).

******INSERT TABLE TWO ABOUT HERE******

Statistical Analysis

All analyses were undertaken using *R* version 3.2.2 (R Core Team, 2015). Descriptive statistics (mean and standard deviation; SD) for each indicator were calculated for each playing position. These indicators were visualised using a basic scatterplot overlaid within a violin plot to show the underlying distribution of the data. The violin plot functions by showing the probability density distributions of the data. In doing so, it provides an in-depth visualisation of the data with respect to properties such as skewness and modality when compared to other forms of visualisations (Spitzer, Wilderhain, Rappsilber, & Tyers, 2014).

Prior to classification analyses being performed, the mean of repeated observations were calculated, with the final dataset containing observations from 211 players: 52 defenders, 50 forwards, 97 midfielders, and 12 ruckmen. The first classification technique used was a linear discriminant analysis (LDA), classifying players in the dataset using the *lda* function in the 'MASS' package (Venables & Ripley, 2002). An LDA can be used to classify a target sample of predictors against *a priori* classes by minimising the probability of *a posteriori* misclassification. The technical skill indicators were coded as the explanatory variables, while *a priori* playing position was coded as the categorical response variable (class label). Results of this analysis were reported in the form of overall classification accuracy, as well as a confusion matrix.

Secondly, the random forest algorithm was used to classify the players in the dataset using the 'randomForest' package (Liaw & Wiener, 2002). The random forest algorithm is a non-linear machine learning technique used for classification and regression. It functions by growing a collection of decision trees, and using a random sample generated from a larger training sample, calculates the mode of the classes of the individual trees and ranking of all classifiers. From the output of the random forest model, dissimilarities of the data were plotted using classic multidimensional scaling using the *cmdscale* function in the 'stats' package (R Core Team, 2015). The distance matrix used in this analysis was derived from the proximity values of the random forest analysis. The dissimilarities for each player were calculated as one minus the proximity values (Liaw & Wiener, 2002). These data were visualised using 'ggplot2' (Wickham, 2009). Additionally, the mean decrease in accuracy of each indicator was calculated and plotted. This measure is one way to estimate the importance of each indicator for the classification. The mean decrease in accuracy is determined during the out of bag (OOB) error calculation phase, which is a method to measure the classification error of the random forest algorithm. In this case, the more the accuracy of the random forest decreases due to the exclusion of a single indicator, the more important that indicator is for the classification. It follows that indicators with larger decreases in mean accuracy are more important than other indicators in the set which have lower scores.

Lastly, a PART decision list (Frank & Witten, 1998) was used to generate a set of rules that best classified the four player positions. To prune the model, a minimum of 10 instances were required for each rule, with five-fold cross validation also undertaken in order to prevent overfitting. Results were reported in the form of overall classification accuracy, as well as a confusion matrix, with corresponding rules describing the dataset also presented.

Results

Players recorded a mean of 61.84 ± 27.53 technical skill involvements during game-play. The midfield players had the highest mean values in 11 of the 12 technical skill indicators (Table 3; Figure 1). Midfield players also had the highest variance in ten of the 12 indicators (Table 3).

******INSERT TABLE 3 ABOUT HERE******

******INSERT FIGURE 1 ABOUT HERE******

As shown in the Table 4, the LDA classified most players as midfielders, less than in the *a priori* case. The classification accuracy for the LDA was 56.8%, with the class error rate being lowest for the midfield players (19.6%), and highest for the ruckmen (75.0%). The class error was similar for both forwards (40.0%) and defenders (46.1%).

******INSERT TABLE 4 ABOUT HERE******

Comparatively, the OOB error rate for the random forest model was 52.61%. The class error rate was lowest for the midfield players (27.8%), and highest for the ruckmen (100%; Table 4). The class error rates for defenders and forwards were similar (69.2% and 72%, respectively). No ruckmen were classified according to their *a priori* classification; with three being classified as defenders, five as forwards, and four as midfielders.

The variable importance plot shows three groups of indicators that had similar effects on the mean accuracy of the model (Figure 2). The first group represents the most important indicators classifying the players into a field position; uncontested possessions, clearances, disposals, kicks, and inside 50's (midfield task set). The second group included contested marks, effective disposals, contested possessions, and tackles (defender task set). The third group included uncontested marks, marks, handballs and the State Academy that a player represented. The classic multidimensional scaling of the proximity values shows the strong clustering of defender and forward players, and the high variance within the midfield set (Figure 3). This plot shows the same data (from the random forest model) but the left panel shows the *a priori* classification and the right shows the random forest classification.

******INSERT FIGURE 2 ABOUT HERE******

******INSERT FIGURE 3 ABOUT HERE******

Results from the PART decision list revealed six rules capable of classifying playing position at accuracy of 70.1% (148 of 211 players). The rules were as presented below, with the values in the parentheses representing the true and false positive frequencies respectively for each rule as noted in the database:

- Rule 1: Disposals > 14.4 AND contested mark ≤ 0.4 THEN: **Midfielder (53.0 / 3.0)**
- Rule 2: Uncontested possession ≤ 10 AND inside 50 ≤ 1.2 AND contested mark ≤ 0.4 AND uncontested mark ≤ 2.4 AND uncontested possession > 4.3 THEN: **Defender (20.0 / 6.0)**
- Rule 3: Uncontested possession ≤ 10 AND kick > 5.3 AND inside 50 > 1 AND effective disposals ≤ 10 AND contested mark > 0.2 THEN: **Forward (33.0 / 15.0)**
- Rule 4: Kick > 5.3 AND inside 50 > 1: **Midfielder (53.0 / 3.0)**
- Rule 5: Kick ≤ 5.4: **Forward (31.0 / 14.0)**
- Rule 6: ELSE: **Defender (25.0 / 9.0)**

As shown in Table 4, the class error rates for each playing position ranged from 14.4% (midfielders) to 100% (ruck). Cross-validation results revealed a decrease in overall classification accuracy of 11.3% to 58.8%, indicating a slightly overfit model.

Discussion

The aim of this study was to investigate whether talent identified junior AF players could be accurately classified into their designated playing positions based upon technical skill indicators acquired from the AFL national U18 championships. Despite the idiosyncratic requirements of each playing position, a high level of player homogeneity was hypothesised given the discrete and broad nature of the technical skill indicators. Results partially supported this hypothesis, with the LDA (56.8%) and random forest model (52.61%) reflecting poor *a priori* classification accuracy when compared to the PART decision list (70.1%). Thus, relative to the LDA and random forest, sport scientists may wish to consider using rule induction (PART decision list) when classifying player types in other team sports, as it may offer a more granular insight into positional characteristics relative to other linear and/or non-linear approaches. From the identified classes for each model, the midfielders demonstrated the smallest classification error, being followed by defenders and forwards. Generally however, these results demonstrate an inability to accurately classify playing position when using the technical skill indicators provided to talent recruiters following the AFL national U18 championships. Subsequently, AFL talent recruiters may consider the use of tailored technical indicators specific to positional requirements. This may increase the likelihood of recognising unique player attributes relative to playing position when coupled with results stemming from supplementary talent identification practices (i.e., combine testing) (Robertson et al., 2015).

The homogeneity across playing positions suggests that AFL talent recruiters may encounter difficulties when using the technical skill indicators described here to objectively identify juniors capable of playing a specialised field position. More directly, an AFL talent recruiter looking to draft a defender who possesses unique attributes relative to their player type may not be able to rely upon the objective data stemming from the commercial performance analyses. Thus, they may have to rely upon subjective evaluations and/or measurements recorded external to game-play (i.e., combine testing results). This may be problematic, particularly for less experienced talent recruiters, as reliance upon subjectivity for talent identification could lead to unsubstantiated choices, resulting in misinformed economic investments (Meylan, Cronin, Oliver, & Hughes, 2010). It is recommended that AFL clubs conduct their own performance analyses during the national U18 championships using tailored technical skill indicators specific to player and positional types. Conversely, commercial statistical providers may look to increase the depth of indicators they report upon within this elite junior tournament. For example, counts surrounding goal ‘conversion percentage’, ‘chop-out marks’, ‘spoils’, or ‘tackles inside 50’ may increase the distinction between player types / positions.

Beyond the addition of tailored technical skill indicators, these results yield implications for coaching strategies used with the AFL national U18 championships. In its current state, this elite junior tournament may not facilitate an optimal environment to enable key position defenders and forwards to exhibit position specific attributes. In light of this, it is suggested that a greater emphasis should be directed toward showcasing a key defenders and forwards positional skill sets through the design of coaching strategies that enable the aforementioned to occur. Further, ‘flooding’ (i.e., players being instructed to crowd an oppositions forward zone to limit space) should be avoided in this elite junior competition, as such a team strategy may exacerbate the already apparent homogeneity evident across playing positions; further complicating the objective identification process facing AFL talent recruiters.

These results (somewhat) complement those presented by Veale and Pearce (2009) who profiled the physical characteristics of U18 AF players according to their playing positions. In their study, midfield players were characterised by a greater total distance run during game-play when compared to key position forwards and defenders. However, key position forwards and defenders generated similar physical activity profiles, demonstrating a clear difference in running requirements between midfielders and key position forwards and defenders (Veale & Pearce, 2009). When coupled with the current findings, it can be postulated that the physical and technical skill activity profiles of key position forward and defenders are difficult to differentiate; likely due to the fact that the defenders’ movement patterns and skill involvements would be partly controlled by the forward they are attempting to defend. However, differing to the physical results presented by Veale and Pearce (2009), the present work found that a subset of players classified *a priori* as defenders and forwards were respectively classified as midfielders (by each classification model). Thus, although potentially possessing slightly different running characteristics, certain midfielders and defenders and forwards may possess similar technical skill characteristics manifested via the indictors reported in this study.

Despite the practical utility of this work, it is not without limitations that require acknowledgement. It is not uncommon for AF coaches to rotate players through the midfield from forward or defensive positions. Acknowledging this, it is possible that players within the misclassified subsets were included within regular midfield rotations. Given that we were unable to control for this in-game rotation, it is possible that the misclassified subset of forwards and defenders were positioned in the midfield at some stage during game-play; diluting their technical skill profiles. To account for in-game rotations or unique team strategies, future work may wish to consider classifying player positions at the beginning of each quarter to enable 'real-time' classification. Further, given the primary focus of this elite junior tournament is to showcase prospective talent, it is possible that coaches actively placed players in different positions to showcase their potential versatility to AFL talent recruiters. This versatility strategy could have therefore diluted the idiosyncratic positional characteristics, as players may have reverted back to the task sets they are more suited regardless of playing position, incurring the high levels of misclassification observed here. Thus, future work is encouraged to extend these observations by investigating the classification of playing positions in the AFL, where such versatility strategies may not be as apparent given the speculated need for position specificity. Lastly, future work may look to extend the skill indicators described in this study to include 'goal conversion percentage', 'chop-out marks', 'spoils' and/or 'tackles inside 50' (non-exhaustive suggestions) in addition to quantifying the physical movement patterns of players in differing positions. This may offer a more granular insight into the positional idiosyncrasies with regards to player skill and physical profiles.

Conclusion

This study shows a high level of homogeneity across playing positions when using technical skill indicators acquired within the AFL national U18 championships, delineated using three linear and non-linear statistical techniques. Given this, AFL talent recruiters may encounter difficulties when solely relying upon the technical skill indicators described in this study to objectively recognise juniors with distinctive positional attributes. These results present clear practical implications for AFL talent recruiters and performance analysts, which are discussed below.

Practical Implications

Firstly, coaches may wish promote strategies that enable players in the AFL national U18 championship to showcase position-specific attributes, while avoiding strategies that exacerbate player homogeneity (e.g. 'flooding'). Secondly, commercial data providers and/or AFL clubs should look to increase the specificity of technical skill indicators to optimise the objective recognition of position-specific attributes. By addressing these two points, AFL talent recruiters may be provided with more insightful data of use for the identification, and subsequent drafting, of juniors capable of adding competitive value to their current playing roster.

Acknowledgements

The authors would like to thank the Australian Football League Talent Pathway for assistance during data collection. No financial support was required or provided for this study.

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Figure 1. Technical **s**kill indicators across the four player classification types (positions)

Note: The points represent observations of players. The points are horizontally ‘jittered’ to show the reader where most points are distributed. The solid line represents a violin plot of the same data. A violin plot represents the probability density of the data within each position class: defender (D), forward (F), midfield (M), and ruck (R). “Un. mark” uncontested marks; “Con. possession” contested possessions; “Eff. disposal” effective disposal; “Un. marks” uncontested marks; “Un. possession” uncontested possession.

Figure 2. Type I variable importance plot showing the mean decrease in accuracy for each predictor (technical skill indicator) when it is excluded from the model

Note: “Un. mark” uncontested marks; “Cont. possession” contested possessions; “Eff. disposal” effective disposal; “Un. marks” uncontested marks; “Un. possession” uncontested possession.

Figure 3. Multidimensional scaling plot (MDS) of the proximity matrix produced by the random forests model

Note. The left panel shows the result of the random forest model with each player labelled with their *a priori* position classification. The right panel shows result of the random forest model with each player labelled with their classification derived from the model. “D” defender; “F” forward; “M: midfielder; “R” ruck.

Table 1. The technical skill indicators and corresponding description as used within this study

Technical skill indicator	**Description**
Kick	Disposing of the ball with any part of the leg below the knee including kicks off the ground
Handball	Disposing of the ball by striking it with a fist while it rests on the opposing hand
Disposals	Summation of kicks and handballs
Effective disposals	Disposals resulting in a positive outcome for the team in possession (i.e. correctly passed to a teammate)
Contested possessions	Possessions obtained while in congested, and physically pressured situations (i.e. obtaining possessions of the ball while in dispute)
Uncontested possessions	Possessions obtained while a player is under no immediate physical pressure from the opposition
Mark	When a player cleanly catches (deemed by the umpire) a kicked ball that has travelled more than 15 metres without anyone else touching it or the ball hitting the ground
Contested mark	A mark recorded while engaging in a congested, physically pressured situation
Uncontested mark	A mark recorded while under no physical pressure
Inside 50	An action of moving the ball from the midfield into the forward 50 m zone
Tackle	Using physical contact to prevent an opposition in possession of the ball from getting an effective disposal
Clearance	Disposing of the ball from a congested stoppage in play

Table 2. Description of each playing position used within this study

Position	**Description**
Defender	Player's primary allocated to the defensive 50 m arc responsible for preventing opposition forwards from obtaining ball possession and scoring a goal. These players also provide immediate linkage from the defensive zone to the midfield zone.
Forward	Player's primary allocated to the forward 50 m arc responsible for applying scoring pressure on the opposition. In doing so, these players typically provide ball disposal options for teammates carrying the ball through the midfield into the forward line.
Midfielder	Nomadic players who compete for ball possession during stoppages in play around the ground. These players provide a critical link between the defence and forward line zones.
Ruckman	Players involved in the passage of play immediately following a stoppage, being responsible for 'tapping' the ball to their midfield teammates.

Table 3. Descriptive statistics (mean ± SD, variance) for each *a priori* position classification and technical skill indicator

Technical skill indicator	Position	Mean (± SD)	Variance
Kicks	Defender	6.31 ± 3.45	11.87
	Forward	5.90 ± 3.26	10.63
	Midfield	9.53 ± 4.35	18.96
	Ruck	5.33 ± 2.72	7.42
Marks	Defender	2.77 ± 1.95	3.80
	Forward	2.86 ± 2.22	4.93
	Midfield	3.43 ± 2.12	4.51
	Ruck	3.28 ± 2.21	4.87
Handballs	Defender	4.91 ± 2.80	7.86
	Forward	4.42 ± 2.85	8.14
	Midfield	6.77 ± 3.85	14.82
	Ruck	5.00 ± 2.91	8.48
Tackles	Defender	2.23 ± 1.69	2.87
	Forward	2.33 ± 1.89	3.58
	Midfield	3.12 ± 2.13	4.56
	Ruck	2.12 ± 1.45	2.11
Clearances	Defender	0.60 ± 0.83	0.69
	Forward	0.82 ± 1.35	1.83
	Midfield	2.09 ± 2.17	4.69
	Ruck	1.35 ± 1.23	1.52
Uncontested marks	Defender	0.40 ± 0.68	0.47
	Forward	0.50 ± 0.73	0.53
	Midfield	0.25 ± 0.58	0.33
	Ruck	0.79 ± 1.01	1.03
Contested possessions	Defender	4.30 ± 2.49	6.19
	Forward	4.53 ± 2.72	7.40
	Midfield	6.46 ± 3.37	11.33
	Ruck	5.05 ± 2.58	6.66
Disposals	Defender	11.22 ± 5.02	25.16
	Forward	10.32 ± 4.58	21.02
	Midfield	16.31 ± 6.32	39.90
	Ruck	10.33 ± 4.77	22.75
Effective disposal	Defender	8.09 ± 4.16	17.28
	Forward	6.84 ± 3.54	12.53
	Midfield	11.22 ± 4.92	24.18
	Ruck	7.67 ± 4.42	19.51
Inside 50 m	Defender	1.19 ± 1.37	1.87
	Forward	1.58 ± 1.62	2.63

	Midfield	2.65 ± 1.93	3.71
	Ruck	1.47 ± 1.28	1.64
Uncontested marks	Defender	2.37 ± 1.70	2.90
	Forward	2.35 ± 1.92	3.70
	Midfield	3.18 ± 2.03	4.13
	Ruck	2.49 ± 2.00	4.02
Uncontested possession	Defender	6.78 ± 3.78	14.28
	Forward	5.67 ± 3.30	10.91
	Midfield	9.76 ± 4.54	20.58
	Ruck	5.09 ± 2.99	8.94

Table 4. Confusion matrices for the LDA, random forest (RF) and PART decision list classifying players using technical skill indicators

	Defender			**Forward**			**Midfielder**			**Ruck**			**Total (211)**	**Class error**		
	LDA	**RF**	**PART**	**LDA**	**RF**	**PART**	**LDA**	**RF**	**PART**	**LDA**	**RF**	**PART**		**LDA**	**RF**	**PART**
Defender	28	16	30	17	15	9	7	21	13	0	0	0	52	0.461	0.692	0.423*
Forward	15	12	11	30	14	35	5	24	4	0	0	0	50	0.400	0.720	0.300*
Midfielder	10	15	4	8	12	10	78	70	83	1	0	0	97	0.196	0.278	0.144*
Ruck	1	3	0	8	5	10	0	4	2	3	0	0	12	0.750*	1.000	1.000

Note. The rows represent the *a priori* classification accuracy. * denotes the smallest classification error relative to the three analysis techniques