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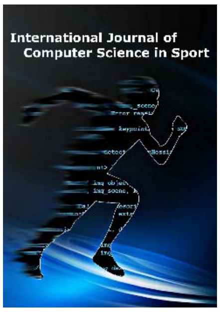

Predicting ratings of perceived exertion in Australian football players: methods for live estimation

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Abstract

The ability of machine learning techniques to predict athlete ratings of perceived exertion (RPE) was investigated in professional Australian football players. RPE is commonly used to quantifying internal training loads and manage injury risk in team sports. Data from global positioning systems, heart-rate monitors, accelerometers and wellness questionnaires were recorded for each training session (n=3398) from 45 professional Australian football players across a full season. A variety of modelling approaches were considered to investigate the ability of objective data to predict RPE. Models were compared using nested cross validation and root mean square error (RMSE) on RPE predictions. A random forest model using player normalised running and heart rate variables provided the most accurate predictions (RMSE ± SD = 0.96 ± 0.08 au). A simplification of the model using only total distance, distance covered at speeds between 18-24 km·h^{-1}, and the product of total distance and mean speed provided similarly accurate predictions (RMSE ± SD = 1.09 ± 0.05 au), suggesting that running distances and speeds are the strongest predictors of RPE in Australian football players. The ability of non-linear machine learning models to accurately predict athlete RPE has applications in live player monitoring and training load planning.

KEYWORDS: GPS, RPE, MACHINE LEARNING, TRAINING LOAD

Introduction

A rating of perceived exertion (RPE) is a subjective numerical value reported by an athlete following physical activity (Foster et al., 2001). The rating represents the perceived amount of effort experienced by the athlete, from rest to maximal exertion. In team sport environments, it is common practice to quantify internal training load using a global RPE value reported post training multiplied by the session duration (session-RPE) (Clarke, Farthing, Norris, Arnold, & Lanovaz, 2013; Impellizzeri, Rampinini, Coutts, Sassi, & Marcora, 2004; Ritchie, Hopkins, Buchheit, Cordy, & Bartlett, 2015). Session-RPE training load data is useful in monitoring athlete injury risk (Gabbett, 2010; Gabbett & Jenkins, 2011; Rogalski, Dawson, Heasman, & Gabbett, 2013), perceived fatigue and performance (Saw, Main, & Gastin, 2016). In light of these multiple applications, it can be desirable for physical preparation staff to have a level of control over the amount of RPE-based load that athletes experience.

As RPE data is collected from athletes post-training, it is difficult to confidently integrate into future planning protocols. A predictive model may enable RPE-based training load planning to be based on more controllable external training load parameters such as duration, distance, and speed. With the growing adoption of athlete monitoring technology and live data capture within professional team sport (Cummins, Orr, O'Connor, & West, 2013) live estimates of RPE may be possible, enabling training sessions to be extended, restricted or modified in order to elicit a desired RPE response. For example, if training load limits are prescribed using session-RPE, the data stream from athlete monitors will enable a live on-going RPE forecast as the session progresses, thus reducing the chances of exceeding thresholds and placing the athletes at higher risk of injury (Gabbett, 2010; Rogalski et al., 2013). Similarly, if coaching staff are attempting to structure training at a specific exertion level, a live estimate of internal training loads could provide immediate feedback on how close the session is tracking to target. An accurate predictive model may also serve a more pragmatic purpose by allowing missing data values to be imputed on the rare occasions when circumstances prevent the collection of RPE.

Moderate to strong relationships between athlete RPE and heart rate have been reported in previous studies (Borresen & Lambert, 2008; Clarke et al., 2013; Impellizzeri et al., 2004; Kelly, Strudwick, Atkinson, Drust, & Gregson, 2016; Lovell, Sirotic, Impellizzeri, & Coutts, 2013; Nicolò, Marcora, & Sacchetti, 2015). Respiratory frequency (Nicolò et al., 2015), running distance and speed (Bartlett, O'Connor, Pitchford, Torres-Ronda, & Robertson, 2016; T. Gallo, Cormack, Gabbett, Williams, & Lorenzen, 2015; Gaudino et al., 2015; Lovell et al., 2013), accelerations and collisions (T. Gallo et al., 2015; Gaudino et al., 2015; Lovell et al., 2013), wellness ratings (T. F. Gallo, Cormack, Gabbett, & Lorenzen, 2016), playing position, and experience (T. Gallo et al., 2015) have also shown associations with RPE. Accounting for different individual responses to external training stimulus has been shown to improve the accuracy of RPE predictions (Bartlett et al., 2016). These results suggest that a predictive modelling approach incorporating multiple training variables and a consideration of individualised responses may enable accurate RPE predictions.

The purpose of this study was to investigate the accuracy of predictive models for RPE in Australian football players using data typically collected during training sessions. It extended previous research by Bartlett et al. (Bartlett et al., 2016) by considering a larger set of predictor variables, alternate modelling approaches and different ways of accounting for individualised responses to training stimulus. Out of sample error estimates were used to evaluate predictive models to prevent overfitting and optimistic error estimates from resubstitution (Hawkins, 2004). Thus providing a robust assessment of the ability of these techniques to generalise to a live prediction environment.

Methods

RPE and training load data were collected in all field-based training sessions from a team of professional Australian football players over a single season. These sessions represented occasions when live data capture was used. Multiple predictor variables and modelling approaches were considered and evaluated on their ability to predict RPE data.

Subjects

Data were collected from 45 male Australian football players (mean ± SD: 23.8 ± 4.3 yr, 188.1 ± 6.6 cm, 85.7 ± 8.2 kg) comprising the entire senior list at a professional club. Consent was received from the club for the analysis of de-identified training data. The La Trobe University Faculty of Health Sciences Human Ethics Committee (FHEC14/233) approved the project.

Data Collection

RPE were collected from the cohort over a period of one competitive season (2015) using the Borg CR10 scale modified by Foster et al. (Foster et al., 2001). This scale has previously been employed in studies examining training loads and injury risk in team sport athletes (Gabbett, 2010; Rogalski et al., 2013). All players were experienced in using the scale and ratings were recorded within 30 minutes of the completion of training. Each player reported a single exertion rating after each field training session. Field training sessions included skill, conditioning, and match simulation sessions. No data from competitive matches or resistance training were included in the analyses.

Player physical movements and physiological responses were recorded from commercially available 10 Hz GPS devices that incorporated 100 Hz tri-axial accelerometers (Catapult® Optimeye S5) and heart rate monitors (Polar® T31) throughout each training session. Each player wore the same device throughout the season and the club performance analyst collected all data. The technology used had been validated as an athlete monitoring tool in Australian football (Boyd, Ball, & Aughey, 2011; Rampinini et al., 2015; Varley, Fairweather, & Aughey1, 2012). Additionally, players reported wellness ratings using a customised questionnaire in the morning prior to each training session. The questions asked players about their levels of fatigue, motivation and soreness. These values were included in the analyses as there is evidence suggesting that athlete wellness levels can influence subsequent RPE data (T. F. Gallo et al., 2016). A description of the variables collected is presented in Table 1.

Modelling Approach

In this study the task of predicting athlete RPE was treated as a supervised machine learning problem (James, Witten, Hastie, & Tibshirani, 2013). For each unique player training session (i) a set of predictor variables ($\boldsymbol{x}_i$) was observed (Table 1) and an outcome label (y_i) was recorded, the athlete RPE. A supervised machine learning approach seeks to find a relationship between the predictor variables and outcome labels, enabling prediction of unknown outcomes given new data. In this context, new data may be coming in the form of live sensor data from players during training sessions. Two predictive modelling approaches were considered, regression and classification.

Table 1. Predictor variables

Category	Variable	Description
Running	Duration	Session time (min)
	Distance	Total distance (m) above 3 km·h^{-1}
	Vel. zones 1-7	Distance covered (m) in velocity zones: 3-7, 7-12, 12-18, 18-24, 24-27, 27-29 & 29-40 km·h^{-1}
Heart rate	HR zones 1-7	Time (min) spent in heart rate zones: 50-60, 60-70, 70-80, 80-85, 85-90, 90-95 & 95-105% of max heart rate
Acceleration	Accelerations (High/Med/Low)	Number of accelerations in zones: 1.5-3, 3-4 & 4-8 m·s^{-2}
	Explosive efforts	Sum of high intensity accelerations, decelerations and changes of direction
	Effort zones 1-3	Number of times entering into velocity zones 5-7
Player load	Player load	Magnitude of rate of change of acceleration (Boyd et al., 2011)
Wellness	Fatigue	1-10 rating
	Stress	1-10 rating
	Motivation	1-10 rating
	General soreness	Mean rating of body part soreness (hamstrings, quadriceps, groins, calves, lower back)
Derived metrics	Mean speed	Distance / duration (m·min^{-1})
	Vel. zone 4%	Vel. zone 4 / distance
	Vel. zone 5-6%	Vel. zone 5-6 / distance
	Player load per minute	Player load / duration
	Vel. zones 1-7 per minute	Distance in each velocity zone / duration
	Explosive efforts per minute	Explosive efforts / duration
	Explosive efforts per metre	Explosive efforts / distance
	Distance-load	Distance × mean speed
	TRIMP per metre	Edwards TRIMP (Edwards, 1993) / distance
	Player load per TRIMP	Player load / TRIMP
	Total accelerations	Sum of all accelerations, decelerations and changes of direction

Regression models

The regression approach treated the RPE response (y_i) as a continuous real-valued number. This approach reflected that players were not restricted to integer responses when reporting their RPE. Models were built using R (R Core Team, 2014) and the CARET package (Kuhn, 2008), the regression models considered were:

- Linear regression
- Multivariate Adaptive Regression Splines (MARS) (Milborrow, 2012)
- Random forests (Liaw & Wiener, 2002)
- Support vector regression (SVM) with Gaussian kernel (Karatzoglou, Smola, Hornik, & Zeileis, 2004)
- Neural networks (single hidden layer feedforward with sigmoid activation function) (Venables & Ripley, 2002)

Linear regression provided a baseline test for predictive accuracy and has been employed by other studies on RPE and training data (Lovell et al., 2013). MARS, random forest, SVM and neural network models were chosen to compare with a linear model as they are able to account for non-linear relationships (Kuhn & Johnson, 2013). Neural networks were trained using backpropagation and the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm to optimise weights (Venables & Ripley, 2002). Support vector regression with linear and polynomial kernels was also considered but not included in final model comparisons. The linear kernel method gave accuracy similar to ordinary linear regression and a polynomial kernel improved accuracy but was outperformed by a Gaussian kernel.

For each model three different data pre-processing protocols (R1, R2, R3) were considered.

- R1: Scale each predictor variable by subtracting the mean and dividing the standard deviation (calculated from pooled player data).
- R2: Scale each predictor variable *for each player* using means and standard deviations calculated from each player's individual data. This approach prevented the use of wellness features as some players exhibited zero variance in these variables.
- R3: Scale RPE outcomes as well as predictors for each player. Predictions were then transformed back to the original scale before evaluating results. Similar to protocol R2 this approach prevented the use of wellness variables as features.

For all scaling protocols, means and standard deviations were calculated from the training data set and applied to the testing data before calculating error metrics. Scaling the data by each player's specific mean and standard deviation (protocol R2 and R3) was performed in order to try and account for the individual effects of age, experience, and fitness on RPE values (Bartlett et al., 2016; T. Gallo et al., 2015).

Classification models

The classification approach treated the RPE response as a discrete categorical variable. Although players were not restricted in what they could report, an examination of the data showed that the majority of outcome labels given were integer or half-integer values. The classification models considered were;

- Random forests (Liaw & Wiener, 2002)
- Support vector machines (Gaussian kernel) (Karatzoglou et al., 2004)
- Naive Bayes (Weihs, Ligges, Luebke, & Raabe, 2005)
- C5.0 decision rules (Kuhn, Weston, Coulter, Culp, & Quinlan, 2014)
- Neural networks (single hidden layer feedforward with sigmoid activation function) (Venables & Ripley, 2002)
- Ordered logistic regression (Venables & Ripley, 2002)

For each model three different data preparation protocols (C1, C2, C3) were considered.

- C1: Scale predictor variables by substracting the mean and dividing by the standard deviation calculated from each player's individual data and restrict RPE to {1, 2, …, 10} (10 classes). This restriction caused a loss of training data when the outcome label was non-integer, however due to the relative rarity of these events model performance was not significantly negatively impacted.
- C2: Scale predictor variables using the pooled mean and standard deviation and allow RPE in {1, …, 10} or {4.5, 5.5, 6.5, 7.5, 8.5} (15 classes) to incorporate the most commonly reported non-integer values.
- C3: Scale predictor variables using the pooled mean and standard deviation and allow RPE in {1, 2, …, 10} (10 classes). Non-integer predictions were then generated by examining the model probabilities for each of the 10 classes and employing the rule; if the largest predicted class probability ≤ 0.5 then return the mean of the two most probable classes (e.g. if a training session was predicted to have an RPE of 6 with probability 0.45 and RPE of 7 with probability 0.4 then return an RPE of 6.5), otherwise return the most probable class.

Feature sets

To investigate which training variables best predicted RPE values, seven combinations of predictor variables were tested for each modelling and data pre-processing approach (Table 2). The selected predictors were chosen to reflect findings from previous studies that heart rate, running distances and speeds, accelerations and wellness ratings impact athlete RPE (Bartlett et al., 2016; Borresen & Lambert, 2008; Clarke et al., 2013; T. Gallo et al., 2015; T. F. Gallo et al., 2016; Gaudino et al., 2015; Impellizzeri et al., 2004; Lovell et al., 2013; Nicolò et al., 2015). The combinations were chosen to investigate the relative predictive ability of different variable categories when used alone and together.

Table 2. Feature sets for predictive models

Feature set	Categories
1	Running + Player Load
2	Accelerations
3	Derived metrics
4	Heart rate
5	Running + Derived metrics + Player Load
6	Running + Derived metrics + Heart rate + Player Load
7	All variables

Model evaluation

Nested cross validation was used to evaluate the accuracy of each predictive model (10-fold outer cross validation) and to tune model parameters (5-fold inner cross validation) (Varma & Simon, 2006). The sampling for the inner and outer folds was not stratified by player identity. This approach was taken to ensure that models were being evaluated on out-of-sample predictions, giving a realistic estimation how well they will generalise to new data (Hawkins, 2004; Varma & Simon, 2006). Predictive accuracy of each model was assessed using the root mean square error (Equation 1).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \qquad (1)$$

Where $\hat{y}_i$ is the predicted RPE, y_i is the observed RPE, and n is the number of observations. RMSE measures the mean difference between predicted values and actual values, giving an indication of how reliable the model will be when deployed. Smaller RMSE values indicate better predictive accuracy.

Model parameters were tuned during the inner cross validation loop using a grid search implemented by the CARET package in R (Kuhn, 2008). The values considered for each model were;

- Neural networks: number hidden nodes = {1, 3, 5, 7, 9, 11, 13, 15} and weight decay = {0, 0.0001, 0.1}.
- SVM: regularisation parameter = {0.25, 0.5, 1.0} and inverse kernel width automically chosen using the kernlab R package (Karatzoglou et al., 2004).
- Random forests: number of trees = 500 and number of randomly selected variables at each node = {2, 6, 10}.

- MARS: maximum number of model terms = {2, 8, 10} and maximum degree of interaction = 1.
- C5.0 rules: number of boosting iterations = {1, 10, 20}.

Results

There were 3398 observations of athlete RPE which were recorded from 45 players during the season considered from on-field football training sessions. The median number of records per player was 76 (range 28-100). The variation in player record numbers reflected the different levels of training interruption caused by player injuries. The median RPE reported was 6 (range 0.5-10) suggesting that training plans incorporated a range of intensity levels throughout the season.

Regression models

Figure 1 shows the mean and standard deviation of RMSE for each tested regression model. The best performing regression model (RMSE ± SD = 0.96 ± 0.08 au) was a random forest using player normalised running, heart rate and derived metrics as predictors (set 6) and player normalised RPE as the outcome label (protocol R3).

Data pre-processing protocols R1 and R3 gave similar performance outcomes, and both showed consistently better predictions than those using protocol R2. This suggests that if predictive features are to be scaled by each individual player identity, it is important to also scale the RPE outcomes. This makes intuitive sense since RPE is a subjective value that is likely to have some dependence on player identity.

Models trained using only acceleration data (feature set 2) or heart rate data (set 4) gave significantly poorer predictions than other methods. Improved accuracy was observed with the inclusion of more information to the models (feature sets 5-7). This result indicates that running distances and speeds are the strongest predictors of athlete RPE in Australian football players. It also highlights that metrics derived from distances and speeds cannot fully explain the variance in RPE and that predictions can be improved by including heart rate and wellness variables.

For each pre-processing protocol and feature set pair, some common trends were seen in the performance of each machine learning algorithm. Random forests consistently gave the best RMSE values, followed by support vector machines (SVM) and neural networks in most cases, whilst linear regression was generally the worst performing method. This result suggests that there is complexity within the relationship between objective training measurements and athlete RPE that is better captured by more powerful machine learning models than ordinary linear regression.

Figure 2 shows the relative importance of each predictor variable in the best performing model. The three variables identified as most important in predicting RPE were; (i) distance covered in velocity zone 4 (18-24 $km \cdot h^{-1}$), (ii) total distance above 3 $km \cdot h^{-1}$ and (iii) distance-load (a derived metric calculated as the product of total session distance and mean speed). High speed velocity zones 5-7 were afforded little importance in the random forest model. This unexpected result may indicate that intermittent bouts of high intensity running influence RPE less than sustained moderate intensity running in Australian football players.

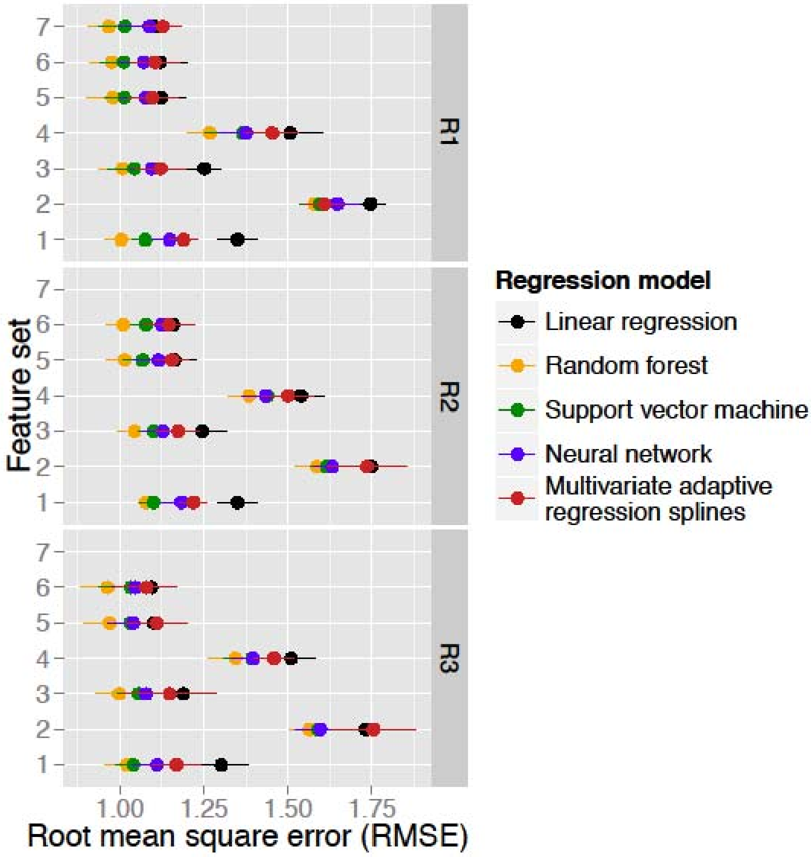

Figure 1. Mean and standard deviation of RPE prediction error for regression models under data pre-processing protocols R1 (scaled predictors), R2 (individualised scaled predictors) and R3 (individualised scaled predictors and outcomes) and feature sets 1 (Running & Player Load), 2 (Accelerations), 3 (Derived metrics), 4 (Heart rate), 5 (Running, derived metrics & Player Load), 6 (Running, derived metrics, heart rate & Player Load) and 7 (All variables). Smaller RMSE values indicate better performance. Feature set 7 was excluded from protocols R2 and R3 due to players exhibiting zero variance in wellness variables.

Given the small number of predictors identified as highly important, another random forest prediction model was built and tested using only 3 predictor variables and protocol R1. Protocol R1 was chosen as it is a simpler, and possibly more practical, data pre-processing protocol than R3. The model performed with RMSE ± SD = 1.09 ± 0.05 au which is only a minor decline in accuracy from the best performing regression model. This reduction in performance may be worthwhile given the significant reduction in model complexity by reducing the number of features from 33 to 3. A predictive model using only 3 sessional distance and speed variables may be possible to practically integrate with training plans.

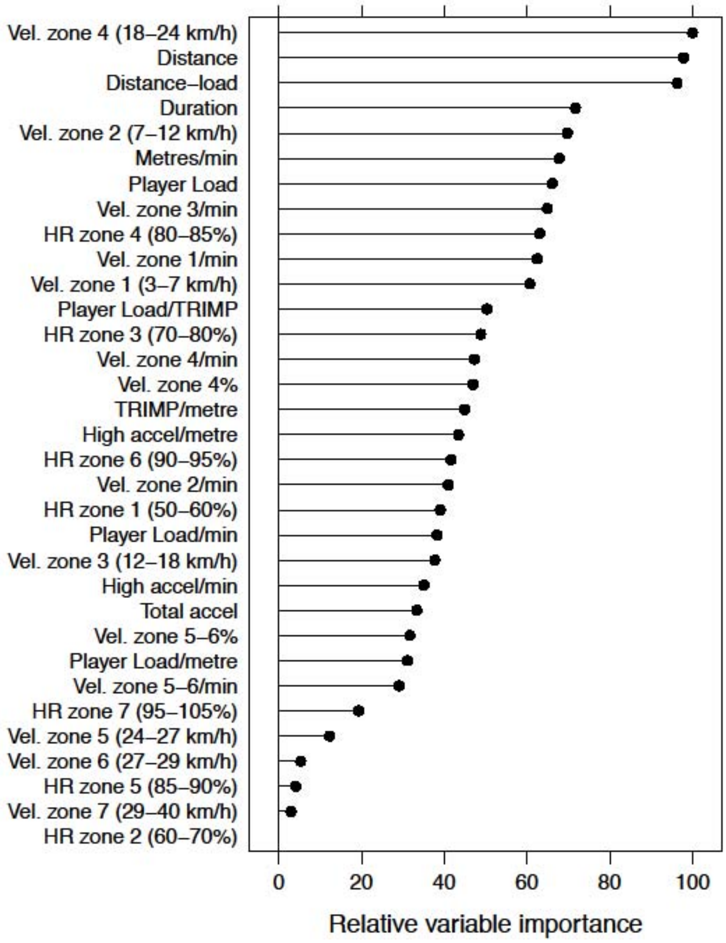

Figure 2. Relative importance of each predictor variable in the best performing random forest regression model.

Classification models

Figure 3 shows the RPE prediction results using classification models. The best performing model (RMSE ± SD = 1.04 ± 0.09 au) was a random forest using normalised running and derived variables (set 6) with 10 allowed classes and predictions based off class probabilities (protocol C3).

Data processing protocol C1, which modelled RPE as a discrete 10-category variable displayed poorest performance, suggesting this restriction prevented models from reflecting the true nature of athlete reported RPE. Protocol C2 allowed the responses to take a selected set of common half-integer values and lead to improved predictions. The best performance was observed in C3 by allowing for non-integer values based off predicted class probabilities.

Similar to the results observed with regression models, feature sets containing running variables provided the most accurate predictions. The inclusion of heart rate and derived metrics provided only marginal improvements in model predictive ability.

Random forest classification models gave the most accurate RPE predictions in nearly all cases. Similar performance was observed for neural networks, C5.0 decision trees, support vector machines, and ordered logistic regression models. A naive Bayes approach general gave the least accurate predictions. Similar to the results from regression modelling, the more powerful machine learning techniques were able to better capture the relationships between training variables and athlete reported RPE.

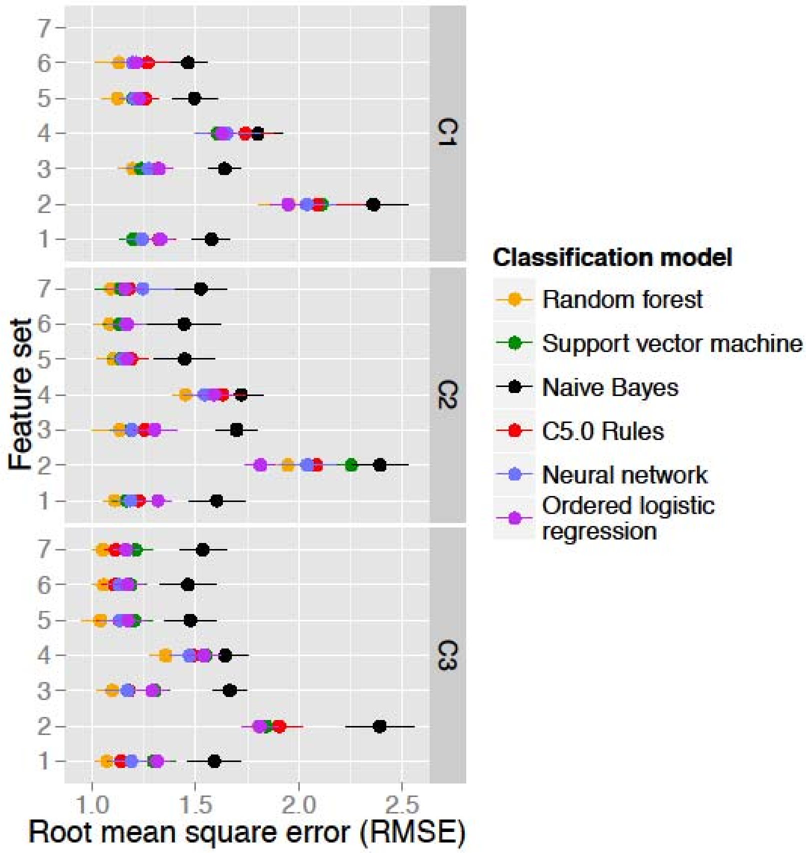

Figure 3. Mean and standard deviation of RPE prediction error for classification models under data pre-processing protocols C1 (10 classes), C2 (15 classes) and C3 (10 classes with mixing based on class probabilities) and feature sets 1 (Running & Player Load), 2 (Accelerations), 3 (Derived metrics), 4 (Heart rate), 5 (Running, derived metrics & Player Load), 6 (Running, derived metrics, heart rate & Player Load) and 7 (All variables). Smaller RMSE values indicate better performance. Feature set 7 was excluded from protocol C1 due to players exhibiting zero variance in wellness variables.

Discussion

This study aimed to develop and assess the accuracy of predictive models in predicting RPE in Australian football players from data typically collected during training sessions. Collectively, the results demonstrated that RPE could be predicted from a non-linear regression model using total distance above 3 $km \cdot h^{-1}$, distance covered between 18-24 $km \cdot h^{-1}$ and the product of distance and mean speed as predictor variables. Including additional predictors such as wellness ratings, heart rate and accelerations lead to only marginal improvements in predictive accuracy.

Modelling approaches

Training data was modelled to identify which interaction between measures could best predict RPE data. Both the regression and classification approaches provided similar predictive ability for RPE, with the two methods achieving a best case RMSE of approximately 1. The models that could account for non-linearity in the relationship between training variables and RPE showed a clear tendency to give better predictions, similar to previous studies (Bartlett et al., 2016). Suggesting that linear approaches were less able to capture the complexity of interactions between training variables and exertion ratings.

The accuracy of classification models was dependent on the number of allowed classes. Protocol C3 displayed the best performance by allowing for non-integer predictions. This potentially replicates the thought process of an athlete who cannot decide whether to give a session a 5 or 6 RPE so chooses 5.5. Regression models gave marginally better predictions and were simpler to implement as they naturally allowed non-integer RPE predictions. Collectively, this demonstrated that a regression approach may be more appropriate for practical implementation in the prediction of RPE values using training monitoring data.

The different methods of data pre-processing showed only slight influence on model performance. Normalising predictor variables and RPE responses by player identity improved the accuracy of the models when compared to predictor scaling without consideration of player identity (Figure 1). However the improvements were only marginal and this pre-processing procedure may be potentially compromised by the introduction of new players to a team, or at the start of a new competitive season when it is not possible to scale predictors from past data. For these reasons, a normalisation procedure that is not player identity dependent could be more readily implemented in a practical setting with minimal impact on prediction accuracy. As such, a global prediction model could assist in training planning using RPE data without the need to consider individual athlete characteristics.

Predictor variables

The training variables identified as most important when predicting athlete RPE were related to external training load measures; distance covered at speeds between 18-24 $km \cdot h^{-1}$, total distance above 3 $km \cdot h^{-1}$, and the product of total distance and mean speed. Such measures encompassed information related to both training session volume and intensity, identifying both aspects as important contributors to perceived exertion in team sport training, in agreement with previous studies (Bartlett et al., 2016; T. Gallo et al., 2015; Gaudino et al., 2015; Lovell et al., 2013).

The most accurate RPE predictions were from models that incorporated multiple running and heart rate variables (RMSE ± SD = 0.96 ± 0.08 au), supporting the suggestion that RPE is related to the imposed external demands and resultant physiological responses (Lovell et al., 2013; Scott, Lockie, Knight, Clark, & Janse de Jonge, 2013). However, a considerably simpler model using only three variables gave comparable prediction accuracy (RMSE ± SD = 1.09 ± 0.05 au) and compared favourably to previous modelling studies using multiple neural networks (RMSE = 1.24 ± 0.41 au)(Bartlett et al., 2016). It should be highlighted that the choice of predictor variables in a practical setting may largely depend on the required task. Using a smaller subset of variables may be more appropriate for planning purposes when manual manipulation is required. When high accuracy is the most important objective, results suggest that using a larger combination of variables from multiple sources may lead to better performance.

Limitations and extensions

The study was limited to a single season worth of data due to changes in data collection processes between competitive seasons. The accuracy of predictive models for previously unseen players was not evaluated. As such, the ability of models to generalise to a new player joining the team was not investigated. A larger data set would enable a better assessment of the accuracy of the modelling approach taken.

The data used is from a cohort of professional Australian football players. It is likely that their training history and physiological characteristics have been shaped by the demands of their sport and the models produced would not likely generalise well to other athletes. However, it is proposed that a similar approach would provide accurate results for other sports that use similar training monitoring and planning practices.

The limitations of GPS devices for accurately recording movement patterns in team sports have been previously highlighted (Jennings, Cormack, Coutts, Boyd, & Aughey, 2010; Rampinini et al., 2015). However results suggested that the current level of accuracy was sufficient to predict athlete RPE in Australian football. Improvements in player tracking technology may lead to improvements in the accuracy of predictive models.

Applications

Predictive models using live sensor data from GPS and heart rate devices allows for live RPE forecasting during training sessions. Decision making regarding training drill intensity and duration to elicit desired exertion levels in athletes may be performed with increased accuracy and confidence. It may also allow physical preparation staff to better match actual training outcomes with plans. An RPE estimation method also enables RPE-based planning of athlete training loads. This has potential benefits for training practitioners given the level of evidence regarding injury risk and RPE-based training load measures (Gabbett, 2010; Gabbett & Jenkins, 2011; Rogalski et al., 2013).

A comparison between predicted RPE values and actual observations may prove useful for player monitoring and retrospective analysis. Athletes reporting exertion ratings considerably different to those predicted may indicate an altered physical state, and may provide a useful trigger for intervention.

Conclusion

Athlete RPE can be predicted in professional Australian football players using a machine learning approach. Objective data recorded using GPS devices, accelerometers and heart rate monitors can accurately predict RPE from field-based training sessions. Regression modelling using non-linear machine learning algorithms outperformed classification approaches and linear approaches. The results could potentially enable athlete training practitioners to monitor an estimated RPE live during training sessions and to plan future training to obtain desired session-RPE levels.

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