Enabling Training Personalization by Predicting the Session Rate of Perceived Exertion (sRPE)

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Abstract. In order to achieve optimal gains from training while reducing the risk of negative effects, athletes must perceive an ideal Internal Training Load. This load is invoked by the training content and individual characteristics. Training sessions are often team-based, although each athlete has his/her own characteristics, making it hard for coaching staff to optimize the training load for each athlete individually. In this paper, we propose a methodology for a decision support system that predicts three different sRPE scores: an average group score and an individualized score prior to and after training. This system can be used to personalize training sessions and to follow-up the training in a real-time fashion. We report results on a dataset collected from association football (soccer) players of a Belgian club. The reported results are better than current state-of-the-art from literature in the Australian football domain, with a smaller dataset and less invasive features.

Keywords: predictive modeling, training personalization, training follow-up

1 Introduction

Sport training consists of systematically performed exercises, in order to improve physical abilities and acquire skills connected to a specific sport. It has been shown that when an athlete achieves the optimal training load, the performance can improve while minimizing the risk of negative training effects such as injury [7,15]. The total load can be described by an External Training Load (ETL) which is defined by the content of the training, designed by the coaching staff. This ETL, combined with individual characteristics such as oxygen uptake, invokes an internal physiological stress, called an Internal Training Load (ITL) [14].

While the ETL can be quantified using different statistics that describe the content of the training, such as the duration, it is not straight-forward to quantify the ITL. Foster et al. [9] showed that this ITL can somewhat be assessed through quantification of the training sessions' duration and intensity. The former can be quantified in time, while the latter can be quantified using different methods such as heart rate (HR) monitoring or the Rate of Perceived Exertion (RPE) [5, 14]. The disadvantages of HR monitoring is that on the one hand it requires physiological expertise in order to interpret the longitudinal data produced by the sensors [1]. On the other hand, it tends to underestimate the intensity during intermittent activities, which can place a greater demand on the cardiovascular system than steady state exercise [15, 16]. Therefore, RPE could serve as an interesting alternative or addition, as it requires minimal effort from the athlete. This RPE is expressed as a score on a validated scale and is a simple, practical tool that represents the athletes' own perception of training stress [13]. When the RPE is assessed from a complete training, it is called the session Rate of Perceived Exertion (sRPE).

The athlete's individual characteristics can have a impact on the perceived ITL [14]. Thus, individuals within the same team may perceive an equal ETL differently. As an example, when an athlete has a high maximal oxygen uptake (VO_2max), the athlete may perceive a training stimulus to be lower than an athlete with a lower VO_2max [4]. Therefore, the coach should take the athletes' individual characteristics into account when prescribing the ETL. As there are often quite a lot of different athletes with varying characteristics to consider, it can be very complex to personalize trainings. Furthermore, coaches tend to underestimate the athlete's sRPE [6]. Therefore, a decision support system that helps the coaches in assessing both the ETL of their prescribed training sessions as the ITL of each of the athletes individually, through the form of an sRPE score, can be very useful. A schematic overview of such a system is depicted in Figure 1. This system is composed of two large components. First, there is an application that allows the coach to design the next training in an intuitive and user-friendly manner. Second, a machine learning module is present that deploys three different predictive models:

- A model that predicts **the group sRPE**, given statistics concerning the content of a training, such as the duration and an estimated distance that the athletes will need to traverse. With this model, the coach can get a general idea of the training load of his/her prescribed training before it occurs.
- A model that predicts the **sRPE of each of the athletes individually prior to training**, given their individual characteristics and the content of the training, allowing for coaching staff to tailor their training sessions on an individual level to the characteristics of each player.
- A model that predicts the **sRPE of each athlete individually after or during training**, given their individual training statistics (such as the actual distance the athlete traversed, how long the athlete participated to the training, etc.) and their individual personal characteristics (such as their age or oxygen uptake). This model allows to follow-up the training of each athlete in a real-time fashion and could serve as some form of anomaly detection. When we assume that the model is quite accurate in predicting the individual sRPE scores of athletes, a high positive deviation between the reported sRPE and predicted sRPE score could give an indication of injury.

The main flow of this system is the following. First, the coach plans his training using an application with a user-friendly interface. Based on this plan, different estimates of statistics are calculated, such as the expected duration and the distance that the athletes will need to run. These estimates are combined with weather forecasts and fed to the machine learning module in order to generate a prediction of the *group sRPE*, which gives a general overview of the training load. The coach can then adapt his planned training until he or she gets the expected training load, allowing for the coaching staff to better control the intensity factor of the ITL. Moreover, individual characteristics of each athlete, such as their VO_2max and deviation from group sRPE in the past, can be fed to another predictive model in order to generate *individual sRPE predictions*, enabling better personalization of training sessions. Finally, after training, personal training statistics, such as the effective distance traversed and the amount of time an athlete participated to the training can be fed to a final predictive model to generate a better individual sRPE prediction. This prediction can be compared to the score reported by the athlete. When the absolute difference between the two scores exceeds a certain threshold, an alert can be generated for the coach to enable some form of anomaly detection. Moreover, this fine-grained individual sRPE prediction can also be generated during the training, allowing for the coaching staff to follow up the different athletes in a real-time fashion.

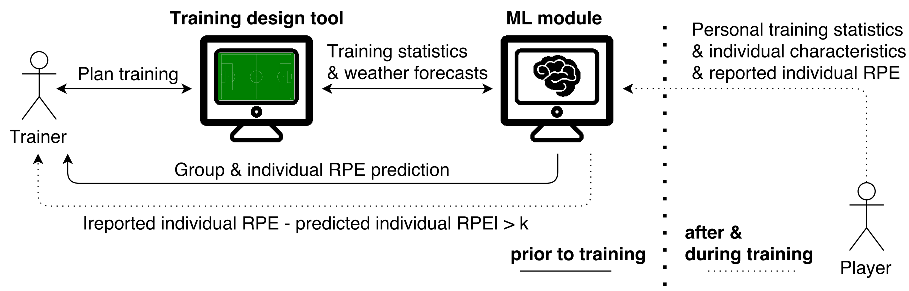

Fig. 1. A schematic overview of a decision support system for a coach to assess both the ETL of prescribed training sessions as well as the ITLs of each athlete individually, through the form of sRPE scores

The focus of this paper is on the machine learning module of the proposed system. The training planner application is considered out of scope. Our contribution is two-fold: on the one hand we propose a system that can support the coaching staff in designing their training sessions and increase the efficiency of these sessions for athletes individually; on the other hand we present, to the extent of our knowledge, results that are better than current state-of-the-art on predicting the individual sRPE scores, from a different sport domain but with a smaller dataset and less invasive features. The outline of the remainder of the paper is as follows. In Section 2, related work concerning the prediction of sRPE scores in sports, along with corresponding results is given. In Section 3, a methodology and preliminary results for the three discussed predictive models are discussed. Finally, we conclude our paper and give future research directions in Section 4.

2 Related work

While quite some studies have already investigated the factors impacting the RPE-score in different sport domains [10–12], only a limited amount of studies have already attempted to predict the sRPE-scores for athletes. These studies are solely situated in the Australian football sport domain, while our study concerns association football data. In Bartlett et al. [3] a labeled dataset was constructed consisting of 2711 training observations corresponding to 41 AFL[3] players. The data consisted of six features derived from GPS sensor measurements: the training duration, session distance, high-speed running (HSR), ratio of HSR and distance, duration divided by session distance and PlayerLoad™ [2]. The labels are the sRPE-scores on Borg's CR-10 scale, indicated by the athletes themselves [5]. Both Generalised Estimating Equations (GEE) and Artificial Neural Networks (ANN) were evaluated to predict sRPE values in combination with two methodologies: constructing one global model, trained on all collected samples, and constructing a model for each player individually. For the GEE, a Root Mean Squared Error (RMSE) of 1.85 ± 0.49 and 1.58 ± 0.41 were reported for the global and individual models respectively. For the ANN, a RMSE of 1.42 ± 0.44 and 1.24 ± 0.41 were reported. Unfortunately, our study was performed on retrospective data, and does not include all the variables used in the study of Bartlett et al., such as PlayerLoad™. This makes it impossible to create a baseline with the same variables on our association football dataset.

In Carey et al. [8] a lot of different regression and classification models were evaluated on a dataset of 3398 records, corresponding to 45 professional AFL players. The labels were scores on the session RPE scale, which adapts the descriptions of the Borg CR-10 scale [5,9]. A lot of different features have been used derived from global positioning systems, heart-rate monitors, accelerometers and different questionnaires, increasing the effort required from athletes. The most accurate model was a Regression Random Forest with a reported RMSE of 0.96 ± 0.08.

3 Methodology & Results

3.1 Data Collection & Pre-processing

In order to collect labeled data, 61 different training sessions from one of the top football teams in the Belgian Jupiler Pro League[4] were attended from the 21st of June 2015 until the 4th of May 2017. During each training, players were wearing

[3] `http://www.afl.com.au/`

[4] `http://www.sport.be/nl/jupilerproleague/`

Team Pro Polar sensors[5], which measures a multitude of different variables, such as speed and heart rate. Within thirty minutes after training, the sRPE (using a slightly adapted scale from Borg, introduced by Foster et al. [9]) was asked to each of the athletes individually, each time presenting the scale. In total, 913 records were collected from 45 different field players. A distribution of the different sRPE-values can be found in Figure 2. In order to generate a dataset for the group sRPE prediction model, means were taken for each training, resulting in a dataset of 61 records. The different variables used in the three predictive models can be found in Table 1. We also experimented with extracting two kinds of features from the heart rate and speed time series, generated by the Polar Team Pro sensors. The first kind of features were just generic features, such as the number of peaks or the maximum value, extracted from the time series using the TSFRESH[6] package in Python. The second kind of features we extracted from (a subset of) the timeseries were shapelets, which identifies subseries that posses a lot of discriminative power for a specific class [18]. Unfortunately, the predictive performance of the model that predicts the individual sRPE scores after training did not improve with the incorporation of both feature categories. This could be due to the fact that we did not have the time series for all samples, resulting in a smaller dataset.

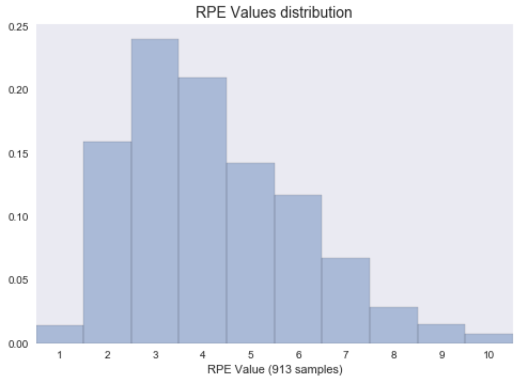

Fig. 2. The sRPE values follow a normal distribution with a 'long' tail to the right

3.2 Group Training sRPE Prediction

As depicted in Table 1, the data for the predictive model that predicts the sRPE score for a training was generated by grouping the original dataset by training and taking the mean of the different variables and sRPE values. As only 61 training sessions in total have been attended, the dataset used for this predictive model was rather small. We evaluated different machine learning techniques,

[5] `https://www.polar.com/en/b2b_products/team_sports/team_pro`
[6] `https://github.com/blue-yonder/tsfresh`

Category	Feature name	Model	Description
weather	Temperature	group	the temperature at the start of the training
	Humidity	group	measured at start of training
	Windspeed	group	measured at start of training
	Visibility	group	measured at start of training
training stats	Distance	group	Calculated by taking the mean of distances from a training
	Duration	group	Calculated by taking the mean
	Number of sprints	group	Calculated by taking the mean
	Training sRPE prediction	prior indiv	generated by the training group sRPE model
individual characteristics	Position	prior indiv	5-dim vector summing to four: {central def, wing def/mid, central mid, central atk, wing atk}
	Player name	prior indiv	one-hot encoded
	Age	prior indiv	
	sRPE deviation stats	prior indiv	the mean, std, max and min of deviations from reported sRPE values from the player and the mean sRPE of that training (the training of the current sample is not included)
	Clustered location	prior indiv	the continent of the player (one-hot encoded)
	VO_2max	prior indiv	
	Speed aerobic threshold	prior indiv	
	Speed anaerobic threshold	prior indiv	
	Time on 5m sprint	prior indiv	measured at start of season
	Time on 10m sprint	prior indiv	measured at start of season
	Time on 5x10m shuttle run	prior indiv	measured at start of season
	Height countermovement jump	prior indiv	measured at start of season
	Muscle fiber type	prior indiv	
individual training stats	Duration deviation	post indiv	the difference between the mean duration of each player participating to the training and the player itself
	# sprints deviation	post indiv	diff. overall mean and own value
	Distance deviation	post indiv	diff. overall mean and own value
	Average speed	post indiv	
	Time in different HR zones	post indiv	divided in five equally spaced zones (HR50-60 until HR90-100+) where HR50-60 represents the time the athlete had a heart rate between 50 and 60 percent of his/her maximal heart rate, normalized
	Dist. different speed zones	post indiv	divided in four equally spaced zones (3-7 km/h until 19+ km/h), normalized
	# pos. and neg. accelerations	post indiv	divided in different zones and normalized

Table 1. The different features used in the three predictive models. prior indiv = predictive model that predicts the individual sRPE score prior to training; post indiv = predictive model that predicts individual sRPE score after training. All features from the prior indiv sRPE model are also included in the post indiv sRPE model.

using a leave-one-out cross-validation strategy: Random Forest Regression (RF), Decision Tree Regression (CART), Multivariate Adaptive Regression Splines (MARS), Linear Regression (LR), Generalized Additive Models (GAM) and Support Vector Regression (SVR). Results for each of these techniques can be found in Figure 3. While the Support Vector Regression model performs the best overall with a Mean Absolute Deviation (MAD) score of 0.89, the performance of the models on each of the samples individually fluctuates a lot. Therefore, a stacking strategy was applied. In other words, the predictions from each of the models were fed as features to a second-level model, a Random Forest. This increased the predictive performance significantly (MAD and RMSE score of respectively 0.66 and 0.81), as can be seen in Figure 3. The prediction from this second-level model was then fed as an extra feature to the two other models that predict the sRPE scores individually.

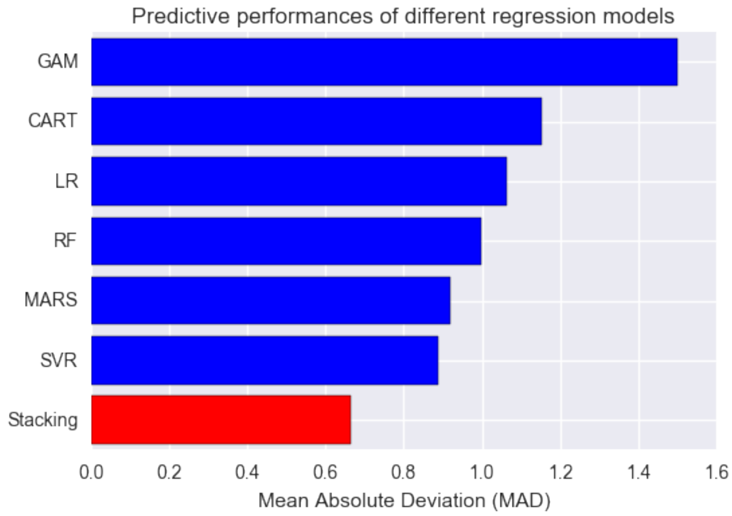

Fig. 3. The Support Vector Regression achieves the lowest error rate in predicting the group RPE for the individual models while applying stacking, using the predictions from all models, results in a serious improvement.

3.3 Individual Training sRPE Prediction: prior to training

The coaching staff may not only be interested in getting a global indication of the load of their planned training, but potentially would like an individualized indication as well to allow for training personalization. One simple baseline would be to take the average difference between the mean training sRPE and the individual sRPE values of a player (indicating whether or not an athlete systematically scores higher or lower than his/her peers) and add this to the predicted sRPE value for the training:

$$R\hat{P}E_{ind} = R\hat{P}E_{group} + \mu_{dev}$$

Applying this formula to our dataset already results in a RMSE score of 1.47, which is competitive to the best performing global model of Bartlett et al. [3] with a much smaller dataset. Of course, the model can be improved even more by including more variables, which can be found in Table 1. It's straight-forward that for the model that predicts individual sRPE values prior to training, only variables can be used that are available at that time. Predictions were generated using Generalized Additive Models (GAM). We applied 5-fold cross-validation to the complete dataset, which is the same validation strategy used in the study of Carey et al. [8]. The achieved RMSE, averaged over the five folds, is 1.0176 ± 0.06. The MAD is equal to 0.7435 ± 0.06. These results are already better than the currently best reported results from Bartlett et al. [3], with a smaller dataset and without features describing the individual ETL. It is important to note that this comparison should be taken with a grain of salt, since the results stem from two different sport domains.

3.4 Individual Training sRPE Prediction: after training

A predictive model that can accurately predict an individual sRPE score after the training can enable some form of anomaly detection by calculating the absolute difference between the predicted sRPE score and the reported sRPE score of the athlete. If this difference exceeds a certain threshold, an alert can be generated for the coaching staff. Moreover, this model can also be deployed during training in order to generate sRPE scores for the players individually in a real-time fashion, allowing the staff to better follow-up athletes. The features used in this predictive models are the same features from the model that predicts the sRPE score prior to training combined with features describing the ETL of each athlete individually, such as the times in different heart rate zones. Again, we used a GAM as the predictive model and 5-fold cross-validation was the chosen validation strategy. The achieved RMSE and MAD are respectively 0.8548 ± 0.09 and 0.6086 ± 0.06, which is better than the currently best reported results in literature from a different sport domain [8]. While still requiring more thorough investigation, we believe that the alerts generated by our system could sometimes indicate injury. For three of the eight samples were the MAD was higher than 3, an injury occurred on the day itself or the next day. As an example, the sample with the highest MAD, equal to 7.58, corresponded to a player that fell sick the next day. Another example, with a MAD of 4.20 corresponded to a player who had an injury to the knee on a training later that day. These samples should be removed from the dataset, since they confuse the model, which would result in an even lower error value. The results of the three different predictive models are summarized in Table 2.

4 Conclusion and future work

In this paper, we presented the methodology for a machine learning module of a decision support system that can aid the coaching staff in personalizing the

Predictive model	RMSE	MAD
Group sRPE	0.6637 ± 0.90	0.8147 ± 0.95
Individual sRPE prior to training	1.0176 ± 0.06	0.7435 ± 0.06
Individual sRPE after training	0.8548 ± 0.09	0.6086 ± 0.06

Table 2. Summarization of the results of the three different predictive models. The high standard deviations of the group sRPE model could be due to the very small size of the dataset.

training load for each athlete individually and allows for the coaching staff to follow up the training in a real-time fashion. The machine learning module is composed of three predictive models that predict the sRPE for the complete group and for each athlete individually before and after training. For the group sRPE score model, a mean absolute deviation of 0.66 was achieved. This group sRPE prediction was, in combination with the average deviation of the sRPE score of an athlete to the mean sRPE score of the corresponding training, the two most important features for the models that predict the individual sRPE scores. The mean absolute deviation for the predictive model prior and after training is respectively 0.74 and 0.61. The root mean squared error for both models is 1.02 and 0.85. The latter error is better than the current state-of-the-art, with a smaller dataset and using variables that are less invasive. Future work includes incorporating more features and more data, such as match data, applying this methodology on data collected from athletes exercising different or individual sports, such as running or cycling. We would also like to construct a model that predicts whether an athlete is going to be injured in the nearby future, as done by Rossi et al. [17], and study the impact of the deviation between the reported and predicted RPE on the predictive performance of this model. Moreover, we would like to check whether the results also generalize to data collected from other football teams. Finally, we would like to develop the graphical user interface that allows the coaching staff to define the ETL for their training sessions, and investigate how we can extract variables describing this ETL (such as the total distance that will be traversed) while keeping the interface user-friendly and intuitive.

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