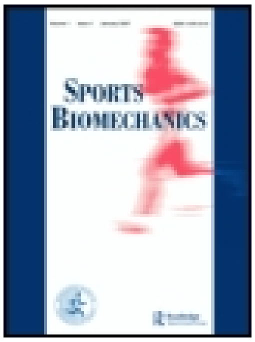

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Fatigue detection in strength training using three-dimensional accelerometry and principal component analysis

Niklas Brown[a], Sebastian Bichler[b], Meike Fiedler[a] and Wilfried Alt[a]

[a]Department of Sports and Exercise Science, University of Stuttgart, Stuttgart, Germany; [b]MINT Division, Institute of Applied Sport Science, Leipzig, Germany

ABSTRACT
Detection of neuro-muscular fatigue in strength training is difficult, due to missing criterion measures and the complexity of fatigue. Thus, a variety of methods are used to determine fatigue. The aim of this study was to use a principal component analysis (PCA) on a multifactorial data-set based on kinematic measurements to determine fatigue. Twenty participants (strength training experienced, 60% male) executed 3 sets of 3 exercises with 50 (12 repetitions), 75 (12 repetitions) and 100%-12 RM (RM). Data were collected with a 3D accelerometer and analysed by a newly developed algorithm to evaluate parameters for each repetition. A PCA with six variables was carried out on the results. A fatigue factor was computed based on the loadings on the first component. One-way ANOVA with Bonferroni *post hoc* analysis was calculated to test for differences between the intensity levels. All six input variables had high loadings on the first component. The ANOVA showed a significant difference between intensities ($p < 0.001$). *Post-hoc* analysis revealed a difference between 100% and the lower intensities ($p < 0.05$) and no difference between 50 and 75%-12RM. Based on these results, it is possible to distinguish between fatigued and non-fatigued sets of strength training.

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KEYWORDS
PCA; fatigue; resistance training; accelerometers

Introduction

In competitive sports as well as in scientific research on athletes, it is important to be able to determine the actual state of fatigue. Muscle fatigue has to be seen as a combination of exercise related changes in the muscle and neuromuscular activation (Enoka et al., 2011) resulting in a decline in muscle force generating capacity (Gandevia, 2001; Place, Yamada, Bruton, & Westerblad, 2010; Sánchez-Medina & González-Badillo, 2011) thus producing less force, velocity or power (Sánchez-Medina & González-Badillo, 2011). In a sports environment, knowledge of fatigue enables the coach to adapt the training schedule and directly improve the stress-recovery balance. Researchers need to know about fatigue to be able to interpret results of interventions and to gain knowledge about cause–effect relationships of training concepts.

CONTACT Niklas Brown niklas.brown@inspo.uni-stuttgart.de

At present, there is no method to get immediate objective information about acute fatigue of an athlete during strength training, measured directly on the athlete and being applicable in various training situations. Thus, several methods have been developed to get an estimate of acute fatigue in resistance training, i.e. using the rating of perceived exertion (Gearhart, Lagally, Riechman, Andrews, & Robertson, 2009; McGuigan & Foster, 2004; Singh, Foster, Tod, & McGuigan, 2007; Sweet, Foster, McGuigan, & Brice, 2004). As objective parameters, physiological measures of fatigue are applied to quantify fatigue using surface electromyography (sEMG) in isometric (Dimitrova & Dimitrov, 2003; González-Izal, Malanda, Gorostiaga, & Izquierdo, 2012) or dynamic muscle contractions (Dimitrov et al., 2006; Rogers & MacIsaac, 2013). Additionally, Shi, Zheng, Chen and Huang (Shi, Zheng, Chen, & Huang, 2007) examined muscle swelling in ultrasound imaging while Giannesini (2003) used accumulation of inorganic phosphate measured by magnetic resonance spectroscopy to determine fatigue objectively. A further method of determining peripheral and central fatigue is through electrical and magnetic stimulation of peripheral nerves or the brain (Millet et al., 2012; Place et al., 2010). However, most of these methods are limited to a laboratory setting and not suited for daily use in training.

In a strength training set, as well as in a multi-set exercise session, the loss of movement velocity can be seen as a clear indicator of muscular fatigue (Sánchez-Medina & González-Badillo, 2011). In a study by Sánchez-Medina and González-Badillo (2011), high correlations ($r > 0.9$) were found for loss of velocity throughout a set with blood lactate, as well as ammonia levels. Therefore, the loss of movement velocity should be taken into account, when quantifying muscle fatigue in strength training. Currently there is no method to directly quantify movement kinematics in strength training in various surroundings. Some producers of training machines implement measurement-utilities in their equipment, but limiting athletes to the use of machines and also a special manufacturer. Free-weight strength training exercises with barbells can be quantified with linear position transducers, but being limited to specially equipped training facilities. Exercises using body weight cannot readily be quantified in detail. To account for this problem, we proposed a method using three-dimensional accelerometry, quantifying numerous parameters of a strength training set (Brown, Bichler, & Alt, 2015). With this method a detailed description of the training set is possible. However, concerning the method proposed by Sánchez-Medina and González-Badillo (2011), movement velocity is not directly measurable using accelerometry, producing larger errors when differentiating acceleration signals. Additionally, range of motion (ROM) could also be affected by a decrease in muscular power, especially when training with free weights or body weight and should be taken into account, when measuring fatigue. Although many factors can be measured with the new measurement system, it is unclear, which factor or combination of factors describes fatigue in a training set. Therefore, the use of multifactorial statistics could improve knowledge in this area. Witte et al. (39) used a principal component analysis (PCA) to determine changes in movement kinematics caused by fatigue of a table-tennis player. They calculated principal components (PC) for different time windows, to compare 'eigenvalues' of the PC. PCA in combination with neural networks and sEMG data is also used for fatigue detection (Rogers & MacIsaac, 2011). PCA is further used to analyse and describe kinematic changes in walking (Federolf, Tecante, & Nigg, 2012) or classify running experience (Kobsar, Osis, Hettinga, & Ferber, 2014), and generally to find movement patterns in multivariate data-sets (Daffertshofer, Lamoth, Meijer, & Beek, 2004).

Pyne and Martin (2011) stated, that 'a systems-based approach that integrates well-chosen diagnostic tests, with smart sensor technology and a real-time database and data-management system is the future for fatigue management in elite sport'. Thus, the purpose of this study was to combine a newly developed measurement system (Brown et al., 2015) with PCA, identifying a set of variables relevant for fatigue detection in a training set. Based on this, we hypothesised that the system would be able to differentiate between fatiguing and non-fatiguing sets in various training situations and configurations.

Methods

A total of 20 participants (60% male, 25.1 ± 1.5 years, 73.9 ± 14.5 kg, 167.5 ± 40.2 cm, 6.7 ± 5.4 years of strength training experience) were recruited for this study. All participants gave informed written consent. Participants reported twice to the laboratory. On the first day, the participants were pre-tested for their 12-repetition maximum (RM) with a standardised procedure in all exercises. They had to choose a weight, which could maximally be lifted 10 times. This weight was lifted until muscular failure. Repetition number was protocolled and the 1-RM was calculated with the formula of Brzycki (1993). Then, 72% of 1-RM was chosen for the approximation of the 12-RM based on the relation of RM and per cent of 1-RM given by Baechle and Earle (2008). Then 50 and 75% of the 12-RM were calculated. This method was used to shorten the process of determining 1-RM, as only one set per exercise has to be executed. However, the method of 1-RM determination is only valid if the repetition maximum is less than 10 repetitions in the test set (Brzycki, 1993).

After two days of rest, participants returned to the laboratory for the main test. Three exercises (biceps curl, bench press, leg extension) were executed in pre- and main-test. Participants had to complete three sets of each exercise with 3 min of rest between the sets and exercises. The first set was executed with 50% of 12-RM with 12 repetitions. In the second set, the weight was raised to 75% with 12 repetitions and in the third set, participants exercised to their RM with the pre-calculated 12-RM. Acceleration data were collected with MT Manager Software (XSens, Enschede, The Netherlands) and an XSens MTw (50 Hz) acceleration sensor positioned on the participants right wrist in the biceps curl and bench press and on the left ankle in the leg extension exercise (Figure 1). Additionally, a linear potentiometer (1,000 Hz, 1 mm resolution, Chronojump Boscosystem, Barcelona, Spain) was attached to the weights as a reference system and to determine movement velocities for each repetition. After measurement and data procession as described in Brown et al. (2015), data were transferred to Matlab (Matlab 2013b for Mac, Mathworks Inc., Massachusetts, USA). Repetition number, time features of each repetition, impulses and ROM were calculated with the described algorithm (Brown et al., 2015). As a result, time points, durations, impulses and ROM for each repetition and TUT in the different contraction modes were given for each set. Linear potentiometer data were also transferred to Matlab. Time points for each repetition, further referred to as markers, were then set by two experienced investigators. Mean marker positions (of the two investigators) were then calculated and used for further analysis. For the biceps curl exercises, sEMG was recorded using standard EMG electrodes (Kendall H34SG, Covidien, Ireland, 2.5 cm inter electrode distance) firmly attached to the shaved, abraded and cleaned skin over the muscle belly of the right m. biceps brachii. EMG data was sampled with 3,000 Hz with Noraxon Software (Noraxon USA Inc, Scottsdale, California, USA) and the fatigue index presented by Dimitrov et al. (2006) was

Figure 1. Positioning of the acceleration sensor (XSens Mtw) on the participants wrist (left picture) and ankle (right picture).

calculated for each repetition. The difference of the first and last repetition of each set was used for further analysis.

Principal component analysis

For the exploratory PCA, the extracted features from the acceleration data were further processed to get scalar values for durations and ROM. Therefore, linear regression was carried out on each set, resulting in slope values for the regression function of repetition duration, ROM and impulse, with positive slope values indicating an increase in repetition duration throughout the set, negative slopes for the ROM-data indicating a decrease in ROM and also a decrease in impulses for each repetition. Also, standard deviations of duration and ROM were calculated for each set.

PCA was carried out with SPSS (Version 21 for Mac). A test for Kaiser-Mayer-Olkin criterion was carried out ($KMO = 0.79$), also the Bartlett-Test for sphericity showed the eligibility of the data for PCA ($p < 0.001$). In a primary PCA, a set of 14 variables (Table 1) was analysed, showing low loadings (<0.4, Stevens (2009)) for some of the variables. These variables were excluded for the final PCA. This was carried out with six variables (see. Table 1). All variables were centred (value-mean) and normalised by the standard deviation.

All six variables had high loadings on the first principal component (PC1, see Table 2). This component had an eigenvalue of 3.40 and explained 57% of total variance in the data.

Table 1. Included variables in the primary (top) and final (bottom part) PCA with descriptions.

Variable	Description
reps	Number of repetitions
TUT	Time under tension in concentric, isometric and eccentric contraction
TUT con	Time under tension in concentric contraction
TUT iso	Time under tension in isometric contraction
TUT ecc	Time under tension in eccentric contraction
break	Break between repetitions
Inc. Dur	Increase between first and last repetition duration
dec ROM	Decrease in ROM between first and last repetition
var Dur	Standard deviation of the durations of each repetition
var ROM	Standard deviation of the ROM of each repetition
slope Dur	Slope of the regression function of repetition durations
slope ROM	Slope of the regression function of ROM for each repetition
slope_IMPcon	Slope of the regression function of impulses in the concentric phase calculated by Acc*t of each repetition
slope_IMPecc	Slope of the regression function of impulses in the eccentric phase calculated by Acc*t of each repetition

Table 2. Loading matrix of input variables on PC one and load-dependant variables of the PCA (mean ± SD). Further PCs were excluded due to inspection of the Scree-Plot of eigenvalues. Variables see Table 1. (All data presented with * are presented as 10^{-4}.)

Variable	PC1			
variance explained	57%	Load dependant data		
eigenvalue	3.40	50% 12-RM	75% 12-RM	12-RM
var Dur	0.85	0.28 ± 0.12	0.24 ± 0.08	0.77 ± 0.40
var ROM	0.58	0.22 ± 0.19	0.17 ± 0.12	0.36 ± 0.30
slope Dur	0.73	−0.01 ± 0.04	0.00 ± 0.03	0.13 ± 0.15
slope ROM	0.81	−0.02 ± 0.04	−0.02 ± 0.03	0.05 ± 0.07
slope_IMPcon	−0.70	7.7* ± 1.2*	4.1*± 0.9*	−13.3* ± 15.6*
slope_IMPecc	−0.83	4.4* ± 0.9*	−1.7* ± 0.9*	−19.1* ± 16.7*

After inspection of the scree-plot of eigenvalues, only the first PC was included in the analysis. In a linear combination of loadings (L) and parameters (P) (see. Table 2) for each variable, a fatigue-score (F-Sc) was calculated for each set.

$$\text{Fatigue Score} = \sum_{i=1}^{6} P_i * L_i$$

Receiver Operator Characteristics Curves (ROC-Curves) for this F-Sc were checked for specificity and sensitivity to differentiate between fatigued (100% - 12-RM), partly fatigued (75%) and non-fatigued (50% - 12-RM) training sets. Additionally, two one-way analysis of variances (ANOVA) with Bonferroni *post hoc* analysis were calculated to identify differences in F-Sc between the different loading conditions and different exercises. Pearson correlations were calculated for F-Sc and change (%) in mean propulsive velocity (MPV) for first and last repetition as described by Sánchez-Medina and González-Badillo (2011). The difference in EMG fatigue index for the different intensities was analysed with Friedman-Test and Wilcoxon *post hoc* analysis. Alpha level for statistical significance was set to $p < 0.05$.

Results

A total of 173 sets could be included in the analysis. One participant could not execute the leg-extension exercise, due to injury. Two data-sets could not be analysed, due to data-loss. Participants in total executed 2099 repetitions based on the linear encoder data, with the acceleration algorithm calculating 2076 repetitions (error-rate: 1.1%).

The one-way ANOVA showed a significant difference between the different intensities (F (2, 169) = 78.9, $p < 0.001$) regarding F-Sc. *Post-hoc* analysis revealed a difference between the fatigued and the non-fatigued conditions ($p < 0.001$), but no difference between 50 and 75% of 12-RM ($p > 0.05$). Therefore, 50 and 75% 12-RM were summarised as non-fatiguing conditions. A difference between the exercises in F-Sc could not be found ($p = 0.06$) with *post hoc* test revealing no difference between bench press and leg extension as well as biceps curl and showing a difference tending to significance between biceps curl and leg extension ($p = 0.07$). A significant difference was found between all intensities regarding EMG based fatigue index ($p < 0.05$). While the 50% 12-RM loads produced a decrease in EMG fatigue index (mean ± SD = 66.2 ± 85.6), the 75% 12-RM loads had a smaller difference between first and last repetition (mean ± SD = 21.6 ± 35.4). The 12-RM sets produced an increase in EMG fatigue index (mean ± SD = −35.1 ± 24.1).

Fatiguing exercises were characterised by a higher mean variation in duration of repetitions (reps) (0.77 ± 0.41 s vs. 0.25 ± 0.10 s) and ROM (0.36 ± 0.30 m vs. 0.19 ± 0.61 m). Also the slopes of the regression analysis of reps duration (0.13 ± 0.15 vs. 0.00 ± .04) and ROM (0.04 ± 0.07 vs. -0.02 ± 0.03) were higher for the fatiguing conditions. The slopes for the impulses calculated from acceleration data showed negative slopes for the fatiguing conditions in both contraction forms (-1.3×10^{-4} for CON and -1.9×10^{-4} for ECC) and very low positive slopes for non-fatiguing exercises (5.5×10^{-5} and 1.4×10^{-5}, respectively).

The score plot for PC1 indicated a clustering of scores for the fatigued and non-fatigued conditions, with fatigued exercise scores mostly loading positive on the first component.

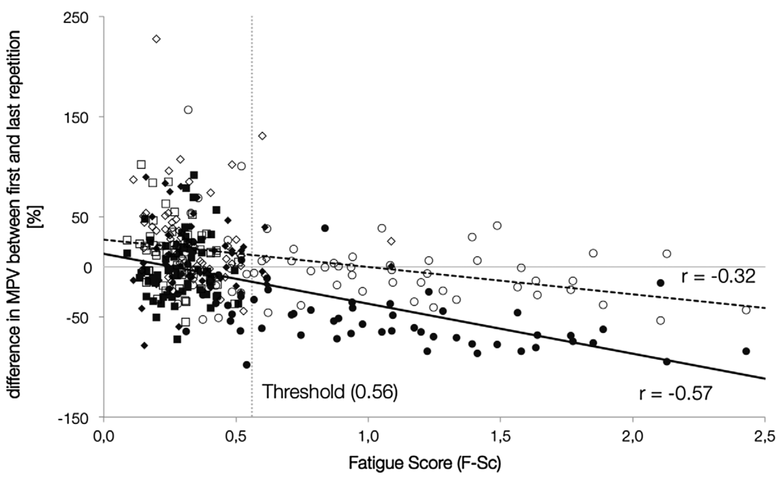

Figure 2. Relationships between loss of mean propulsive velocity (MPV) between the first and last repetition of each set for concentric (filled markers) and eccentric phases (empty markers) and fatigue score. The different shapes represent the three different intensities (diamonds: 50% 12-RM, squares: 75% 12-RM, dots: 100% 12-RM).

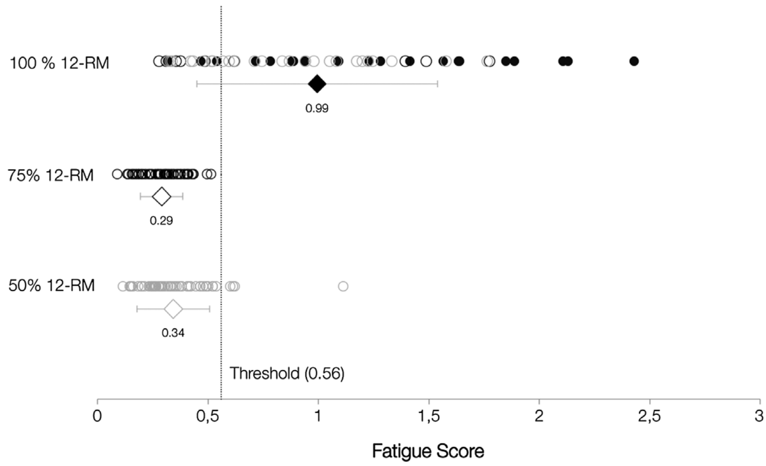

Figure 3. Fatigue Scores (F-Sc) of three different loading conditions. Diamonds indicate mean values of the different conditions. Threshold (0.56) was determined by ROC-curves. Filled dots in the 100% 12-RM condition show training sets where 12-RM could not be reached due to fatigue. Empty grey dots (100% 12-RM) represent the sets with more than 12 repetitions and empty black dots (100%-12RM) represent the sets with exactly 12 repetitions.
Note. *Indicating significance ($p < .05$).

A difference between 50 and 75% of 12-RM exercises could also not be seen in the score plots (Figure 3).

Pearson correlation coefficients indicated a medium negative relationship between F-Sc and MPV-loss of $r = -0.57$ for concentric phases (CON) and a low negative correlation of $r = -0.32$ for the eccentric phases (ECC, Figure 2). Also, a medium negative correlation ($r = -0.59$) was found for the F-Sc and the EMG based index (Dimitrov et al., 2006).

Based on the ROC-curves, a threshold of 0.56 was determined to extract differences between fatigued and non-fatigued exercises. 70% of the 100%-12-RM exercises (41 / 58) were found to be over this threshold, with only 5% of the non-fatigued data (4 / 115) resulting in higher F-Sc-values than .56 (Figure 3). The overall correct classification of fatigued and non-fatigued sets was 87.9%.

Discussion and implications

Methods and results

Using the presented method, it is possible to distinguish between fatigued and non-fatigued sets of strength training based on acceleration data with a single parameter. This parameter is calculated by a linear combination of set-specific features, such as duration and ROM of each repetition. Additionally, mean impulses for concentric and eccentric phases are integrated. Variability and changes towards the end of the set, where fatigue will most likely appear, are considered for duration and ROM. With the presented method, 87.9% of training sets could accurately be classified as fatiguing or non-fatiguing sets.

To our knowledge, no study exists, regarding variability in movement patterns in strength training due to fatigue. In gait, higher, as well as lower movement variability was found after a fatiguing exercise depending on the extracted variable (Cortes, Onate, & Morrison, 2014). In our data, higher movement variability was seen regarding repetition duration and ROM in fatiguing sets. Additionally, variability in durations as well as in ROM had high loadings on the first PC in the PCA. Also the single input variables of the PCA did not show a linear trend for load increases (see Table 2) especially between 50 and 75% 12-RM. Therefore, it can be postulated that the classification is independent of the actual load, but more specific a result of fatigue. Fatiguing sets in the presented data were further characterised by an increase in repetition duration and nearly no detectable change in ROM.

The F-Sc showed similar correlations with loss in movement velocity, as EMG-related fatigue factors (González-Izal et al., 2012) at least for the concentric phases. There was a lower correlation of the F-Sc with the eccentric phase. This is due to a higher capability of the muscle to produce force in the eccentric contraction phase (Hollander et al., 2010). Therefore, fatigue will be mostly visible in the concentric phase, but not in eccentric contractions. Consequently, due to fatigue, there could be an increase in eccentric movement speed since the muscle cannot resist the gravitational force in lowering the load. However, this was not seen in all the presented eccentric data (Figure 2). As in other studies, PCA was used to determine fatigue characteristics in movement (Rogers & MacIsaac, 2011; Witte, Heller, Baca, & Kornfeind, 2011). Although a different interpretation of PCs was used as in Witte et al. (2011), the use of PCs for the multifactorial detection of fatigue seems beneficial. Also, in the presented method, the number of relevant variables could be reduced and a single fatigue score could be calculated for each set, based on a linear combination of input variables, reconstructing the first PC. Further, the presented formula takes more fatigue-related variables into account. In comparison to the methods used by Novatchkov and Baca (2012) and McBride et al. (2009), the presented method is applicable in a wide spectrum of exercises, being pertinent for machine-based training, training with free weights and training with body-weight, thus enabling an objective training protocol and also integrating a measurement of fatigue. However, the presented concept can only be used in the specific measurement set-up, since PCA was based on values from the specific algorithm. As further confirmation of induced fatigue in the 12-RM sets, the EMG-based fatigue factor (Dimitrov et al., 2006) showed a systematic increase in the 12-RM sets. This increase also showed a medium correlation with the F-Sc, indicating a linear relation of the developed fatigue score and actual muscular fatigue. Unfortunately, EMG data and EMG-based fatigue index could only be collected for the biceps curl exercises due to anatomical reasons. Therefore, it is unclear, if the presented results are also valid for other muscle groups.

As a limitation, the presented method solely relies on kinematic data that could be manipulated by the athlete e.g. by voluntarily slowing down movement at the end of the set. Further, when training with special training equipment, e.g. kettlebells or in some olympic weight lifting exercises, the accelerometer readings could be biased by the contact with the training device. Also, results were not validated with metabolic measurements of fatigue. Therefore, actual fatigue can only be approximated by the loadings based on the 12-RM test and the loss in maximal propulsive velocity measured with the linear encoder and the EMG data for the biceps curl. Both, 50 and 75% of 12 RM exercises did not show signs of fatigue in the kinematic data, thus the training protocol in a future study for a clearer differentiation between fatiguing and non-fatiguing exercise sets should include more steps of different loadings, comparable to the study of Sánchez-Medina and González-Badillo (2011). Some of the 100% 12-RM sets were executed with more or less than the specified and calculated 12-RM. Therefore, the method of determining 12-RM seems to be inappropriate for the tested participants. Potentially, a lack of training experience to muscular fatigue was present in the population therefore producing too low estimates of the 12-RM. However, all participants executed to their subjective repetition maximum, with the fatigue score showing a higher value if the desired 12-RM could not be reached (Figure 3) indicating a higher amount of muscle fatigue.

Additionally, only one type of strength training was used in the presented study. Therefore, it is unclear, if fatigue in training for maximum strength, muscular endurance or muscular power can be detected by the presented algorithm and threshold. Since different types of strength training show differences in metabolic and hormonal reaction (Crewther, Cronin, & Keogh, 2006; Crewther, Keogh, Cronin, & Cook, 2006), also different mechanisms of fatigue are assumed (Walker, Davis, Avela, & Häkkinen, 2012). However, regardless of the central or peripheral mechanisms behind acute muscle fatigue, the given F-Sc and the underlying algorithm only quantify the effect of fatigue, expressed as a variation in movement characteristics and slowing of contraction, therefore being quantifiable with the presented algorithm. Since the algorithm is based on acceleration data, measured directly on the participant, a higher possibility of bias in the data exists, due to e.g. uncertain movements and integration errors when transferring acceleration data to velocity and position values. Therefore, the multifactorial approach seems beneficial and is also recommended by Rogers and MacIsaac (2011).

Interpretation and implications

Objectively quantifying fatigue with the developed method is valuable for both athletic training and rehabilitation. Although training to muscular failure is common in hypertrophic training schemes, recent research implicates, that training to muscular failure may not be necessary to improve strength gains (Drinkwater, Galna, McKenna, Hunt, & Pyne, 2007; Folland, Irish, Roberts, Tarr, & Jones, 2002; Izquierdo et al., 2006). With the presented method, training could be controlled towards an optimal repetition number, inducing a certain amount of fatigue, but keeping the athlete from muscular failure to minimise injury risks, similar to a proposed threshold of velocity-loss given by Sánchez-Medina and González-Badillo (2011) but with a higher amount of possible exercises in different training situations. Not only is the same concept of limiting muscular fatigue important for training of muscular power (Cormie, McGuigan, & Newton, 2011), but could also be used in a rehabilitation context or training with the elderly, where low-intensity protocols produce equal training effects as high intensity protocols without the risk of injury (Van Roie, Delecluse, Coudyzer, Boonen, & Bautmans, 2013). Further, the presented method could give an objective measure of fatigue, adding to subjective fatigue quantification and therefore providing a better estimate of the athletes' actual psychological and physiological strain.

Conclusion

If the presented quantification method can be implemented into training practice, a direct feedback on each single set could be given automatically, while additionally providing a detailed automated training protocol without the need for user input. For amateur athletes without direct coach-support and athletes training with e.g. free weights or cables, this could also provide the possibility of an automated feedback and adaptation in everyday training, thus conceivably enhancing training effects. For the high performance athlete, a combination of the method presented previously (Brown et al., 2015) and the fatigue detection presented in this article would provide an automated and highly detailed protocol of training parameters and therefore be the basis for the discovery of unused training potentials.

Further research should validate the presented fatigue score with metabolic measures, such as blood lactate or ammonia and also test the algorithms in different training schemes, such as training for muscular power.

Disclosure statement

No potential conflict of interest was reported by the authors.

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