Artificial Intelligence in Sports on the Example of Weight Training

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Abstract

The overall goal of the present study was to illustrate the potential of artificial intelligence (AI) techniques in sports on the example of weight training. The research focused in particular on the implementation of pattern recognition methods for the evaluation of performed exercises on training machines. The data acquisition was carried out using way and cable force sensors attached to various weight machines, thereby enabling the measurement of essential displacement and force determinants during training. On the basis of the gathered data, it was consequently possible to deduce other significant characteristics like time periods or movement velocities. These parameters were applied for the development of intelligent methods adapted from conventional machine learning concepts, allowing an automatic assessment of the exercise technique and providing individuals with appropriate feedback. In practice, the implementation of such techniques could be crucial for the investigation of the quality of the execution, the assistance of athletes but also coaches, the training optimization and for prevention purposes. For the current study, the data was based on measurements from 15 rather inexperienced participants, performing 3-5 sets of 10-12 repetitions on a leg press machine. The initially preprocessed data was used for the extraction of significant features, on which supervised modeling methods were applied. Professional trainers were involved in the assessment and classification processes by analyzing the video recorded executions. The so far obtained modeling results showed good performance and prediction outcomes, indicating the feasibility and potency of AI techniques in assessing performances on weight training equipment automatically and providing sportsmen with prompt advice.

Key words: Artificial intelligence, machine learning, pattern recognition, weight training, feedback.

Introduction

The design and implementation of innovative systems on the basis of state-of-the-art information and communication technologies in combination with sophisticated processing methods are getting increasingly important for the instant collection, transfer, storage as well as analysis of sensor data in sports. Moreover, the integration of machine-aided intelligence into the development of modern sport information systems enables a prompt and automatic evaluation of sport-specific parameter values, thereby allowing the establishment of computer-based feedback and intervention routines (Baca et al., 2009; 2012).

In general, artificial intelligence (AI) is derived from imitating human actions and abilities such as thinking and learning. It involves the idea of designing so-called intelligent agents or machines that are similarly able to acquire, simulate and employ knowledge, analyti-

cal capabilities and professional skills for the overall purpose of problem solving (Poole et al., 1998). While AI techniques experienced a boom with the rise of expert systems in the 1980s, such methods are meanwhile mainly applied for rather specific and isolated research topics. Chess and particularly the first win of a computer against a world champion (Deep Blue vs. Garry Kasparov) in 1997 (Newborn, 1997; Campbell, 2002) is an example illustrating the high potential of AI. It has to be considered, however, that such achievements are strongly related to the constant increase of computer power – a main feature and benefit of today's information technology environment.

Weight training fundamentals and research goals

The current paper focuses on the implementation of AI routines for the automatic evaluation of exercises in weight training. Weight training is commonly described as a specific type of strength training where lifting weights causes an overload of a certain muscle or muscle group to trigger adaptive reactions of the organism (supercompensation). Also known as resistance training, weight training is nowadays among the most popular stabilizing, invigorating or even prime sport activities at professional and amateur level. Positive effects of this type of training include the overall strengthening as well as the improvement of the physical condition, fitness and performance levels. Thus, not only athletes but also non-professional sportsmen can benefit from resistance training. Other known advantages of weight training include prevention (e.g. in case of back pain or osteoporosis), maintenance of muscular functional abilities, fat loss and promotion of a healthy cardiovascular system (Winett and Carpinelli, 2001). Therefore, weight training is often recommended by specialists and professional organizations (Westcott, 2009), as it decreases the risk of injuries and serves as effective prophylaxis compared to other exercises.

Nowadays, plenty of diverse weight training machines exist, aiming at a controlled and hence less risky execution. Particularly inexperienced individuals initially prefer exercising on such equipment, due to their convenience, easier use and supporting purpose in comparison to free weights and in order to get used to the movement. However, it is still important that experts like fitness coaches assist and provide advice to beginners, inexperienced and elderly people for the purpose of adjusting and correcting the execution, preventing health and injury risks as well as adapting and improving the overall training. Today's weight training machines usually include directions on how to use the equipment, visually illustrat-

ing and describing the proper technique (for example: performing each repetition in a slow and constant manner). Also in the literature, it is reported that the flexion and extension phases should be executed smoothly and completely with preferable time durations of 2-3 seconds (e.g. Evans, 1999). Similarly, the velocity (in terms of a constant and consistent movement) plays a crucial role for a correct and low-impact execution (Rana et al., 2008).

Figure 1 represents an example of a typical beginner's mistake. It shows the measured parameters (cable force and weight displacement) on an incline bench press machine, illustrating inconstant and incorrect characteristics with noticeable force fluctuations at the turning point of a single repetition. The visible oscillation in the cable force graph was most probably caused by a sudden release of stress and a consecutive loading, which is a common error among beginners.

Based on such abnormalities, it can be concluded that determinants like force, displacement, velocity and duration are essential for the analysis of the quality of the technique. In particular, these features may be applied for the automatic evaluation of weight training exercises with the help of sophisticated modeling methods. Moreover, such routines could be integrated in an automated coaching system, allowing real-time analysis of the quality of the movement and returning prompt feedback information. The notifications for the mistake in Figure 1 might for instance alert on the occurred fluctuation point and provide directions for error correction.

In the area of weight training, only few approaches integrating computer-based evaluation routines have been presented in the literature so far. Although Ariel (1984) suggested first ideas for the design of intelligent weight training machines on the basis of AI methods already in 1984, no effective realizations have been constructed up to now. The author proposed the implementation of a feedback-based system integrating factors like

duration, displacement and force characteristics of the movement, thereby suggesting the most suitable exercise. A more recent study (Chang et al., 2007) concentrated on the recognition of various free-weight exercises by applying specific classifiers and models to measured acceleration characteristics. The purpose of the developed methods, though, was to determine which but not how the exercise was executed.

The research objectives of the present paper were to confirm and demonstrate the high capability and potential of AI and, in particular, of machine learning methods in the field of sports by the practical and still not well-investigated example of weight training. A specific aim included the assessment of measured way, force and further derived characteristics on the basis of common pattern recognition methodologies including automatic classification algorithms. First results involving rather basic data analysis provided thereby a basis for the improvement, optimization and extension of the developed machine learning routines (Novatchkov and Baca, 2012). The current research, however, focused on the implementation of more enhanced, exact and in-depth modeling techniques and outcomes by applying multi-scale feature spaces and further classification types.

Based on the analysis conducted so far, the ultimate goal is to integrate machine-aided techniques into a mobile coaching system (Baca et al., 2010), providing athletes with automated and instant evaluation and feedback notifications. This system integration would enable a real-time data transfer – for instance via an Internet enabled portable device such as a handheld or tablet PC – to a server component (see also section "Data acquisition and equipment" in the chapter "Methods"), where the measured parameters would be analyzed and assessed by the developed models. Crucial notifications could be then sent to the exercising person, giving feedback on the quality of the execution as well as providing appropriate
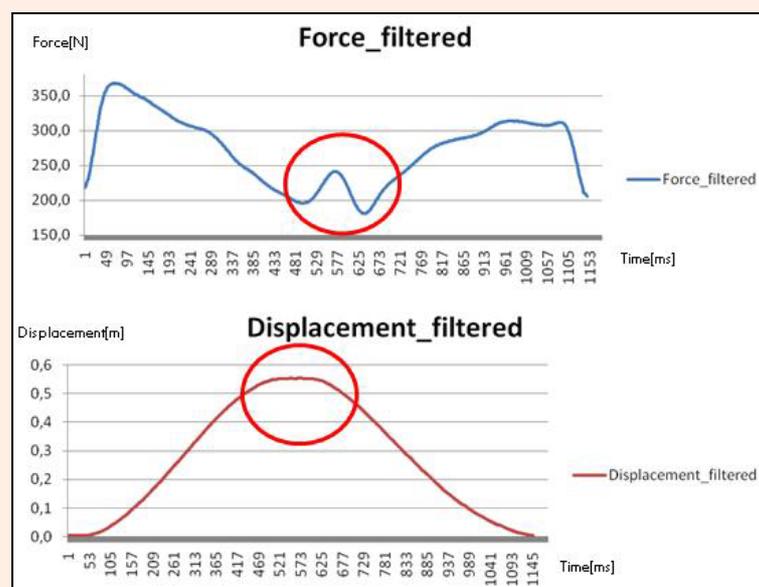

Figure 1. Filtered cable force and weight displacement data of an execution by an inexperienced individual on a sensor-equipped incline bench press machine collected at 200 Hz with a load of 30 kg. The red circles label the turning point of the repetition, indicating the discrepancy of the measured channels with appearing force fluctuations.

advices. This information could be presented to the performing individual via a mobile device, indicating occurred mistakes, suggesting corrective measures and in this way reducing the risk of injuries. In an alternative design of the mobile coaching system, the portable devices could be replaced by an in-built computer device including a screen, used for the instant transfer of the measured information to the server component and the prompt display of feedback alerts.

In the following, the overall method including relevant AI fundamentals, main application fields as well as the underlying study design and applied procedure are presented. The rest of the article includes current results, an outlook and final conclusions.

Methods

AI techniques in sports

Practical concepts for the realization of AI-based methodologies for sport science disciplines like biomechanics or kinesiology have been already discussed and reviewed earlier (e.g. Lapham and Bartlett, 1995; Bartlett 2006). A commonly used technique involves the development of methods on the basis of AI for the assessment of different sport-related data measurements or game analysis. The so-called TESSY (tennis simulation system) framework, for instance, is one of the first knowledge-based decision-making implementations, aiming at the supervision, processing and interpretation of results and tactical behavior as well as the subsequent transformation of conclusions into tennis practice (Lames et al., 1990). Other, more recent, approaches also suggest the implementation of expert systems integrating fuzzy logic procedures for diverse purposes like the evaluation of the fast bowling technique in cricket (Bartlett, 2006; Curtis, 2010) or for the identification of sport talents (Papić et al., 2009). Ratiu et al. (2010) provide an overview on the overall application of AI in sports biomechanics, giving examples of diagnostic tools for the evaluation of movements in different sports.

Specific investigations, on the other hand, focus on the design of machine learning methods for the clustering, classification, pattern recognition and prediction of sport-specific data such as movement sequences. Today, particularly performance analyses by means of self-learning algorithms like artificial neural networks (ANNs) are increasingly discussed as promising application areas in the mathematics and computer science related sports literature and fields of activities (Perl, 2004a; 2004b; McCullagh, 2010). Successful implementations include also analytical studies for different movement evaluations in sports such as golf (Ghasemzadeh et al., 2009), baseball (Ghasemzadeh et al., 2011), and soccer or basketball (Lamb et al., 2010; Bartlett and Lamb, 2011). As another example, Silva et al. (2007) present predictive solutions for the dynamic system modeling and talent identification in swimming. Furthermore, in (Baca and Kornfeind, 2012) a self organizing map is trained for the purpose of clustering stability of the aiming process of elite biathlon athletes.

But also other classifiers like the k-nearest

neighbor (k-NN) algorithm or Support Vector Machines (SVMs) are commonly applied modeling tools, providing good opportunities for the analysis and recognition of sport-specific data patterns. Acikkar et al. (2009), for instance, use SVMs in their approach in order to predict the aerobic fitness of athletes. A number of further studies are related to running, aiming either at the in-built classification of track inclination and speed parameters (Eskofier et al., 2010) or the identification of differentiation of kinematic characteristics (Fischer at al., 2011).

Design and procedure

Based on the above described methodologies, the current study was built on a typical machine learning approach including the following distinct and successive phases: data acquisition, preprocessing, feature extraction and classification. Figure 2 shows in detail the connections, purpose and significance of each step.
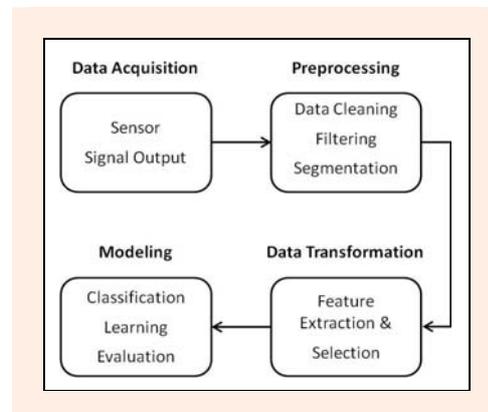

Figure 2. Applied machine learning approach.

In the following, all stages are described individually, giving an overview on used equipment, participants, applied data processing as well as analysis and modeling techniques.

Data acquisition and equipment

The data acquisition procedure was based on sensors attached to various exercise equipment, allowing the collection of crucial characteristics during the workout. For the current study, a weight leg press machine was equipped with a load cell (PW10A or PW12C3, Hottinger Baldwin) and a rotary encoder (DP18, Altmann). In this way, significant force and displacement parameters could be measured directly and thereupon used for the detection of single repetitions and extraction of further determinants such as time periods, velocity, acceleration or power. The data was acquired at a sampling of 100 Hz for each channel. In addition, a special sensor construction (NEON, Spantec) with an integrated microSD card served as collection point of the measured values. As the sensor platform supports wireless sensor transmission on the basis of the so-called ANT+ (Dynastream) protocol, one future aim is to immediately forward the gathered information to a handheld PC such as already available smartphones with in-built ANT technology or a more powerful laptop including an USB reception hardware. Figure 3 illustrates the university sport's hall with the

Figure 3. Sensor-equipped weight training machines and attached force (load cell) and way (rotary encoder) sensors to a leg press machine.

installed weight machines and embedded sensors.

Participants

The current study examined executions by 15 individuals with a rather inexperienced background in weight training, performing 3-5 sets of 10-12 repetitions on a leg press machine. Descriptive details regarding the participants are shown in Table 1.

Table 1. General biographical characteristics of the study participants.

Men (n)	8
Women (n)	7
Mean age (±SD) [years]	24.6 (2.7)
Mean height (±SD) [m]	1.73 (.10)
Mean body mass (±SD) [kg]	63.6 (13.8)

All subjects gave written informed consent for the study procedures, which were reviewed and approved by the research Ethics Committee of the Medical University of Vienna.

Table 2 gives an in-depth description of the subject's biographical characteristics, experience level and used load for each of the performed sets. The participants in this study were primarily inexperienced and slightly experienced individuals, since the overall goals were to assess the quality of the movement focusing on beginners and to identify significant characteristics regarding the performances of unskilled people. The initial intention was neither to investigate the maximum load and force potentials of the participants nor to examine the condition and improvement in performance, power and muscle gain. The actual research idea was rather to evaluate and classify the performed exercises according to crucial criteria such as duration, constancy and completeness and not to analyze the effects of different exercise methods. Therefore, commonly recommended exercise methods with a reasonable amount of sets, repetitions and loads for basic resistance training were chosen to be followed (Garber et al., 2011). The variable selection was chosen in accordance with the literature-based importance of the mentioned criteria as well as today's effective possibilities to instantly measure, derive and assess significant parameters by integrating modern sensors into the equipment. Finally, another major aspect refers to the applicability of the measured data to AI-based modeling techniques for automatic classification purposes.

Data preprocessing

Once the raw sensor output was collected, the subsequent step included the preprocessing of the acquired

Table 2. Detailed biographical characteristics of the participants, experience level and used load for each set.

Subject Number	Age	Sex	Height (m)	Mass (kg)	Experience	Load Set 1 (kg)	Load Set 2 (kg)	Load Set 3 (kg)	Load Set 4 (kg)	Load Set 5 (kg)
1	22	f	1.62	49	Yes	30	40	40	50	60
2	30	m	1.72	66	Yes	110	120	110	100	
3	22	f	1.63	46	Yes	40	50	60	70	
4	27	f	1.68	55	Yes	50	70	80	90	
5	21	m	1.80	73	Yes	120	100	90	90	
6	21	f	1.80	63	Yes	60	60	60	60	
7	23	m	1.73	80	No	40	60	60	80	
8	24	m	1.76	72	No	40	60	90	120	
9	27	m	1.78	71	No	40	60	60	70	
10	24	m	1.72	79	Yes	50	100	110	120	
11	25	m	1.90	72	No	50	70	100	120	140
12	31	f	1.62	43	No	30	30	30	30	
13	27	m	1.93	85	No	40	60	70	80	100
14	25	f	1.64	51	No	40	40	40		
15	20	f	1.62	49	No	40	40	40		

measurements. This procedure was necessary for the preparation of the data without any loss of significant information, the improvement of its quality and, consequently, the final outcome and performance of the applied machine learning method on the refined training set. In particular, this comprised the processes of cleaning and filtering the measured parameters. The cleaning routine involved procedures such as detecting, correcting and removing unreliable, incorrect and irrelevant data. Filtering, on the other hand, had the goal of smoothing the time series by the reduction of the effect of noise. A detailed survey regarding the most useful preprocessing methods is described by Kotsiantis et al. (2006). In addition, also the segmentation of the gathered data was closely connected with the preparation step, as it was essential in forming the basis for the fragmentation (particularly into single repetitions).

As it was necessary to preprocess the time series before analyzing and classifying them, after several tries, the measured displacement values were refined by a strong low-pass filter (with a passband frequency of 0.1π radians/sample, stopband frequency of 0.3π radians/sample, 10 dB of allowable passband ripple and a stopband attenuation of 20 dB) in order to simplify the process of segmenting the data. On the other hand, the force input was essential for identifying possibly occurring fluctuations (relevant for the classification of the data) and was therefore smoothed by applying an average digital low-pass Butterworth filter with normalized cutoff frequency of 0.02 radians/sample, which is equivalent to 1

Hz. Figure 4 shows the measured and subsequently filtered force and displacement data of a rather well-performed and, in comparison, a poor execution (stable/complete vs. instable/incomplete movement range and constant vs. inconstant time and force characteristics) of the same participant.

Figure 5, on the other hand, illustrates the acquired signals of an inexperienced in relation to a slightly experienced female individual, both with similar biographical data and identical load set-up (subject 1, set 4 and subject 15, set 1 from Table 2). Obviously, the execution of the complete beginner is characterized by variable properties including bigger force fluctuations and variable displacement paths, compared to the rather smooth completion of the slightly experienced participant.

The last task of the preprocessing step involved the segmentation of the data into single repetitions. This procedure was accomplished on the basis of the filtered displacement measurements by detecting peak regions. In particular, the filtered force characteristics were partitioned into individual cycles by identifying extrema and turning points within the entire data sets. Since some of the first and last repetitions appeared to be interrupted (e.g. by correcting the feet position just after the initial extension or abandoning the final flexion phase) causing, for instance, "incorrect" time intervals, these sequences were not included in the classification process. Furthermore, the time series were divided into single stages (extension, flexion and holding phases), allowing precise data analyses in the subsequent transformation procedure.
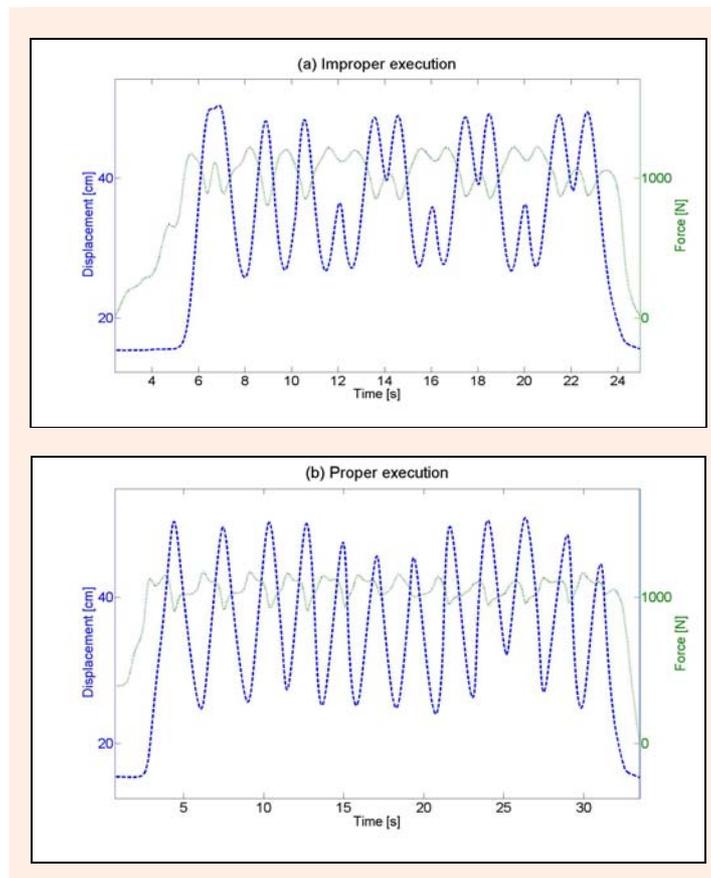

Figure 4. Comparison of the time series of improper (a) and proper (b) executions of an entire set by the same subject.
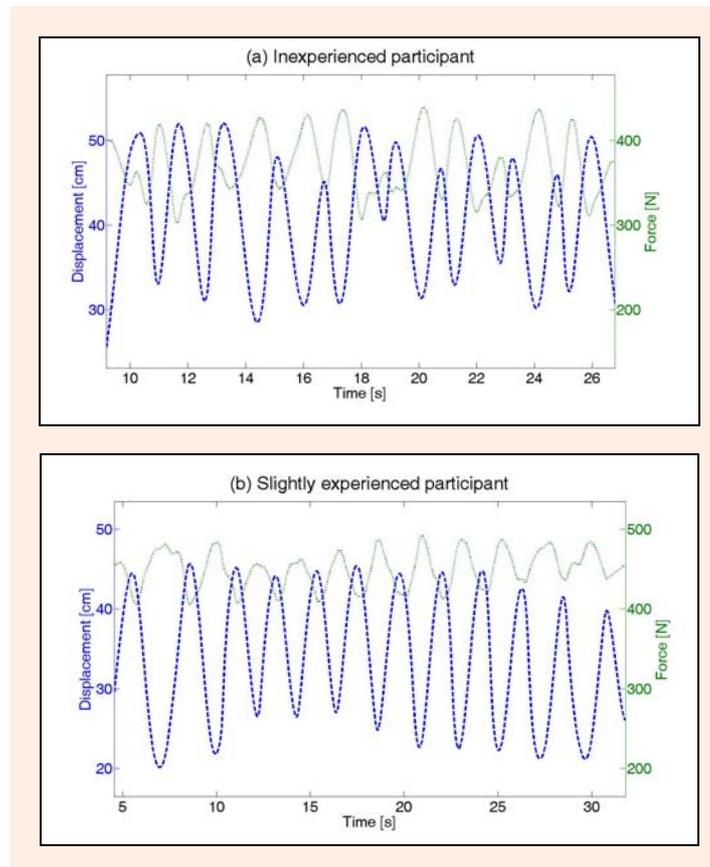
Figure 5. Comparison of the time series of an inexperienced (a) and a slightly experienced (b) female participant with similar biographical characteristics, using the same load.

Table 3. Gathered parameters, main criteria and exemplary features derived for the applied pattern recognition procedure.

Parameters	Criteria	Features
		Extension/flexion/reversal:
Displacement	Time	Durations
Cable force	Completeness	Maxima
Velocity	Constancy	Minima
Acceleration		Ranges
Power		Relations
		Fluctuations
		Amplitudes
		Inclines
		Declines

Data transformation

In the following step, the initially cleaned, filtered and segmented sensor measurements were applied to further data analyses. This mainly included the identification and deduction of relevant information, describing the gathered time series. This feature extraction procedure aimed at the data characterization by dimension reduction, detecting and deriving crucial attributes (e.g. durations, amplitudes, fluctuations or ranges) within the segmented periods. The features were transformed into a vector representing the data in feature space. A selected subset was thereby applied for the classification regarding various criteria including time, completeness and constancy (see also Table 3).

The preprocessing, data analysis and transformation stages were carried out using MATLAB® version R2010b for Windows. The programming environment includes the so-called Neural Network Toolbox™, providing functions for the design, realization, visualization and simulation of various ANNs. The practical application of the routines is described in the following sections.

Modeling and supervised classification (ANNs)

In the overall machine learning theory, the specific area of ANNs is generally divided into the so-called supervised and unsupervised learning methods depending on the labeling of the data. While supervised techniques require labeled input data, the goal of unsupervised procedures is to find significant patterns from the given examples. A typical ANN structure with input, hidden and output layers is illustrated in Figure 6.

For the current study, the use of supervised learning methods, mapping input objects to desired output values, appeared to be a suitable modeling technique, considering the inclusion of the measured time series and the experts' evaluations of the executions. These assessments in respect to pre-defined indicators and specifications were carried out on the basis of video recordings with the help of professional coaches. In particular, the chosen evaluation process was based on the available literature discussed earlier and common recommendations stating that factors like time, velocity, constancy and completeness are significant determinants for the execution and the quality of the movement.

The appraisements were furthermore used for training and classification purposes by labeling the
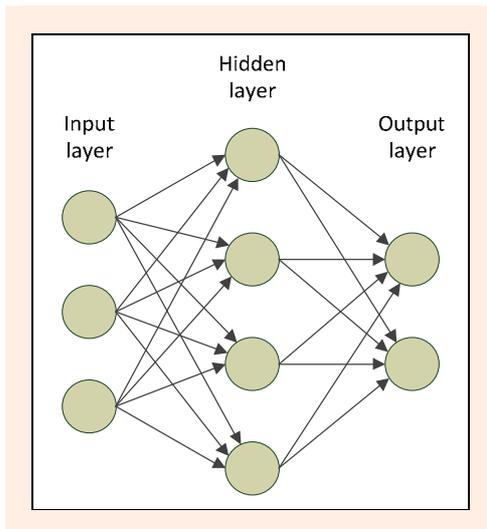
Figure 6. The typical design of an ANN with an input, hidden and output layer, respectively consisting of 3, 4 and 2 neurons.

extracted feature information in respect to the evaluated exercises. Consequently, with regard to the presented weight training approach, the application of supervised procedures aimed at the classification of the executions into rather good and bad categories in terms of the mentioned factors. In this way, particularly inexperienced individuals could benefit from the realization of automatic algorithms by optimizing their technique and hence their training.

In the present research, the modeling of the measured signals included the design and realization of conventional ANNs. More precisely, various multilayer pattern recognition networks (special type of feedforward networks) were set up for learning and classification purposes. The first step included the assignment of the extracted information to chosen labels or classes, which were thereupon applied together as training sets for the development of data models. Thereby, the extracted features were combined into input vectors characterizing each repetition and thus defining the shape of the training data and number of dimensions. The output, on the other hand, consisted of the expert assessments, also representing the number of neurons and the respective layer size. Traditionally, the mapping of the data was accomplished by the insertion of hidden layers. The used training function was based on the Levenberg-Marquardt algorithm, which is among the fastest techniques for feedforward networks due to its high efficiency in minimizing a function by applying curve-fitting methods.

In order to enhance and evaluate the learning process, the computed feature vectors were divided into 3 subsets. This fragmentation was particularly needed for identifying a model fitting the seen set, representing the actual training process. Afterwards the model was pruned based on different techniques such as the estimation of prediction error (also known as validation) and finally evaluated by unseen data (often referred to as testing stage). The division ratio was fixed to 70:15:15.

This split-up was furthermore important for improving generalization, whereas the performances of the

created models were measured on the basis of the error rate (where error rate is defined as the number of incorrectly classified instances). For these purposes, the so-called early stopping method was applied, aborting the learning process at the point of minimal validation set error, where the networks usually generalize the best. In this way, the performance was verified and controlled after each iteration and an overfitting or overtraining could be avoided. A practical example including the classification and performance outcome of the designed ANN is presented in the following section.

Results

Data segmentation and feature extraction
The implemented algorithm was able to segment all performed sets (more than 60), detecting all executed repetitions (over 750). The outcome of the segmentation procedure on the example of continuous executions is illustrated in Figure 7.

As shown, the determined peaks (visualized by asterisk markers) were used to detect two subsequent repetitions including the durations of the reversals and the concentric and eccentric actions. In addition, due to further data transformation needs and simplification purposes, the data was not only divided into single repetitions but internally also into extension and flexion phases as well as holding times in between both movements. This division was accomplished by taking into consideration the measured time series and particularly the changes of the displacement values. Moreover, when looking at the force characteristics, similar patterns can be recognized, based on which the application of supervised machine learning techniques appears to be a suitable classification method. In particular, various specifications including time, force, velocity, consistency, range and completeness factors were defined for feature extraction and selection purposes (see also Table 3).

Modeling
Figure 8 shows the classification results of the applied pattern recognition network in respect to the overall execution based on the specified constancy, time and completeness criteria, considering duration, force and velocity dependent features. The layer sizes of the networks were fixed as follows: 7 (input), 10 (hidden) and 3 (output). The selected labels are illustrated in Table 4.

Table 4. Definition of labels for classification purposes regarding the overall stability of the executions.

Label/class	Definition
1	Stable execution
2	Instable eccentric stage
3	Instable concentric stage

Sub-chart (a) reflects the classification outcome in form of a confusion matrix, indicating the correlations of the labels. Apparently, the agreement is quite high for all 3 labels, demonstrating the high potential of the applied pattern recognition method. Sub-diagram (b), on the other hand, highlights the performance development of the ANN throughout the training stage, illustrating also the
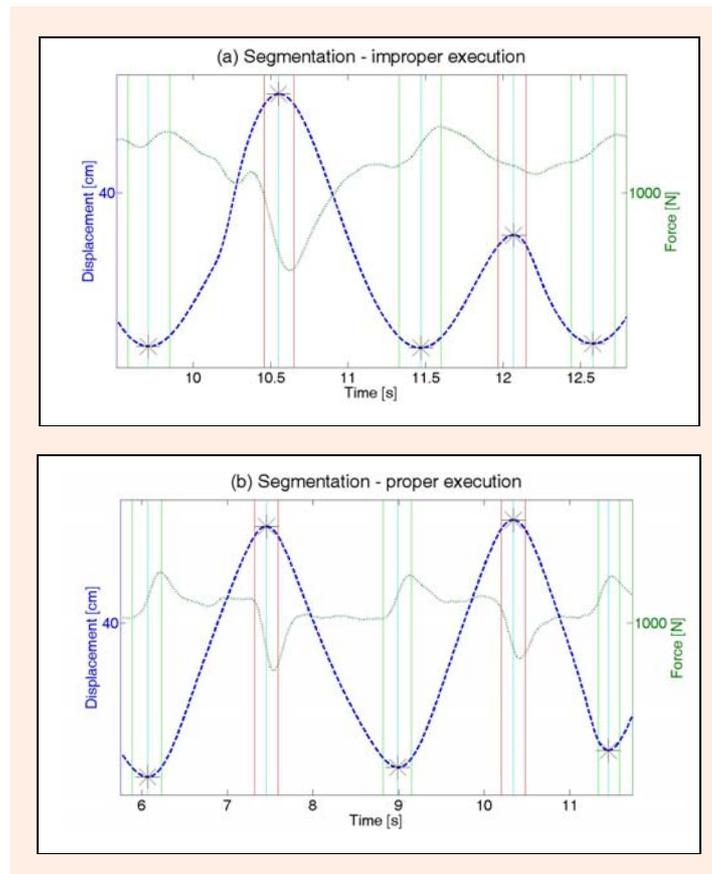
Figure 7. Illustration of the segmentation process for an improper **(a)** and proper **(b)** execution applied on the same data as in Figure 4. The displacement data was segmented into single repetitions based on peak detection techniques (marked by asterisk). The red and green lines indicate the starting and ending points in time of the holding phases after the concentric and eccentric actions.

application of the used stopping methodology. Thereby, the best performance was reached at epoch 70 (with a maximum failing rate fixed to 5). As the displayed training, validation and test curves represent quite similar characteristics with likewise and constant slopes, the performance outcome appears to be an adequate foundation for the developed techniques and further applications.

Discussion

Nowadays, due to the progress of information and communication technologies including simplified and convenient implementations of wireless sensor networks for data acquisition and mobile devices for processing purposes, the integration of intelligent methods becomes increasingly important for the automatic analysis of measured parameters and the realization of prompt intervention routines.

AI concepts appear to be particularly suitable for the design of effective evaluation and feedback frameworks in sport. After the initial boom in the 1970s and 1980s, the use of AI techniques is meanwhile limited to rather specific application fields including also sport, as their application gets essential for the assessment of sports data. Recent examples include the development of mobile monitoring systems integrating classification algorithms for the real-time analysis and feedback generation in sports like, for instance, running (Kugler et al., 2011) or

golf (Eskofier et al., 2011). Similarly, the current study investigated the application of AI methods in combination with novel measuring instruments in the field of weight training.

Today, due to the advances in measuring technologies, effective hardware implementations exist that enable the integration of modern sensors into the fitness equipment itself. For example, it is possible to attach load cells or rotary encoders directly to weight training machines, allowing the measurement of relevant force and displacement characteristics. The gathered data can thereby be used for the implementation of sophisticated routines by means of machine learning techniques, automatically analyzing the exercises. Particularly supervised ANNs appear to be promising classifiers, as they offer effective techniques for mapping input data into already labeled output information.

In light of the current popularity of fitness studios and the broader usage of weight training machines, also the accuracy and correctness of the performances and executions on the offered equipment has become crucial (particularly for inexperienced or elderly individuals). Practically, the quality of the movement plays a significant role, as it contributes to the efficiency and value of the workout. Therefore, a particular focus of the illustrated approach was to provide automatic analysis on the technique as well as appropriate interventions and suggestions. The development and integration of such models
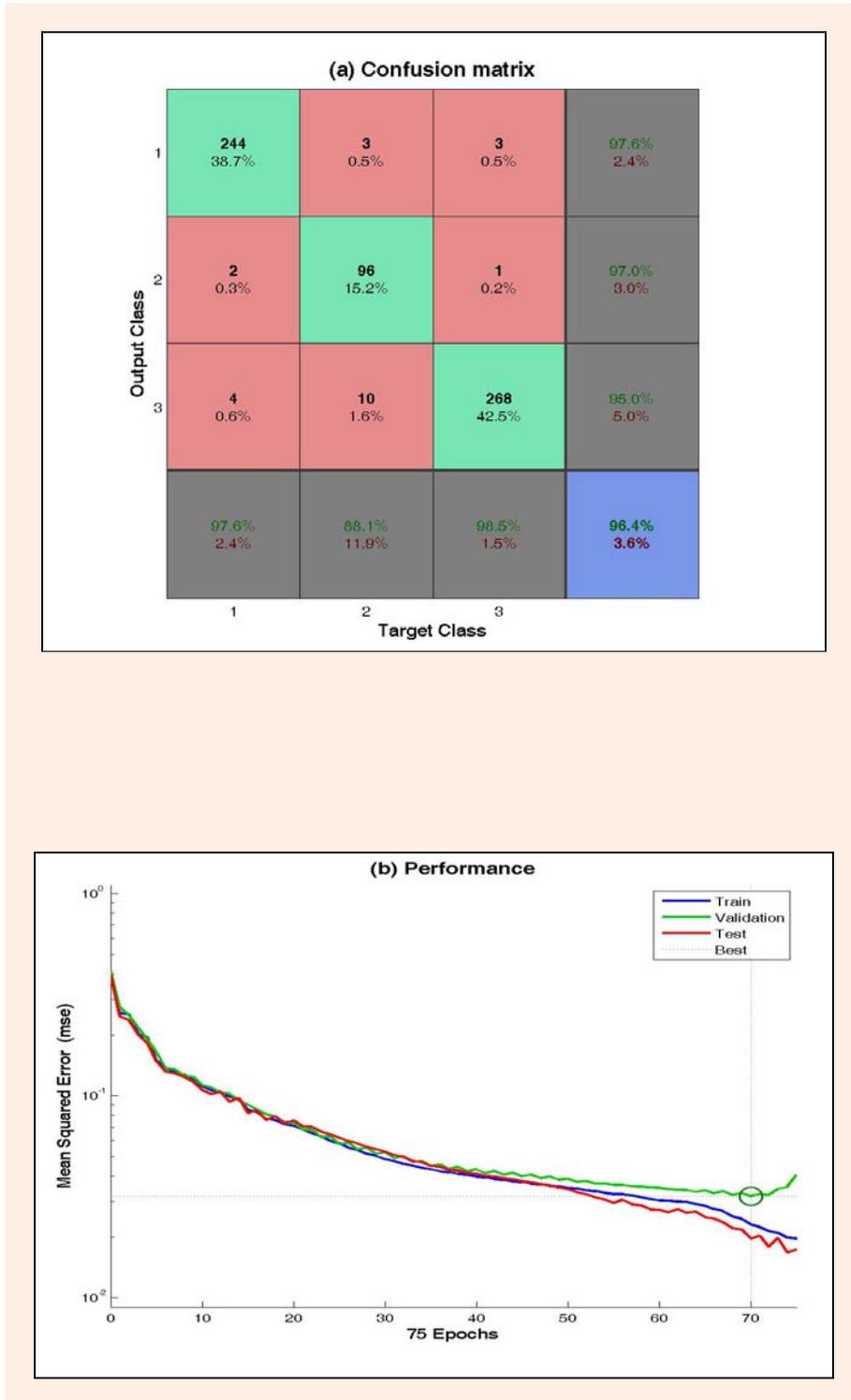
Figure 8. Classification results illustrating the outcome of the confusion matrix **(a)** and performance curves **(b)** for the trained ANN in respect to characteristics regarding the constancy of the executions.

and routines thus might enable new facilities for the support of sportsmen and injury prevention.

The target user group includes in the first instance inexperienced and elderly individuals, who can benefit from the modern sensor equipment and measurements in combination with the realization of the developed assessment routines. Their systematic integration in intelligent weight training machines would allow an automatic analysis of the quality of the execution on the basis of the pre-

defined criteria, thereby providing appropriate feedback during or just after the performed exercise.

The most suitable field of application of such developments including the intended design of automated resistance training equipment can be seen in the increasing amount of available regular but also exclusive fitness clubs. In these facilities the personal and individual care, assistance and mentoring of the members play major factors. Sportsmen can improve their technique on the

basis of the automated evaluation routines and the return of instant notifications regarding occurred mistakes, by receiving appropriate corrective advices and improvement suggestions. Based on this feedback information also the risk of injuries can be reduced, which is another big future objective of the approach.

At the same time, the application of the developed approach would bring valuable advantages to professional sportspeople. In this context, the aim of monitoring velocity characteristics and action forces of exercising movements might be to determine the contraction force specificity. Well-trained athletes need to optimize their training to their sport-specific requirements and to improve their functional ability more specifically. In order to achieve the desired adaptations it is therefore advisable to choose exercises that specifically meet the force-velocity needs of the sport. Hence, the presented approach would allow professionals but also their coaches to analyze in detail the athletes' executions and improve their performances by looking in real time at the measured force and displacement time series or also calculated acceleration, velocity and power properties. Consequently, the possibility of immediate control and comparison of the results could lead to a considerable training enhancement for elite sportsmen.

Limitations

The restrictions of the presented approach are that, for the moment, the implemented data analysis and feedback methods are narrowed down to the mentioned criteria such as time, constancy, velocity and completeness. In particular, it is not possible to observe other preconditions like, for example, the correct sitting position or placement of the feet, which would be important parameters for the application of the implemented models in conjunction with the sensor-equipped leg press machine. Furthermore, the developed routines are not able to directly monitor the posture of the body throughout the movement including, for instance, the knee or upper body and particularly the lower back motions. Such factors, however, might be for example detected and assessed on the basis of the integration of other measuring devices such as goniometers, torsiometers or pressure sensors.

Outlook

The future work of the presented research will concentrate on the adaptation of the developed models for different sensor-equipped machines including lat biceps curl, lat pull-down and shoulder press machine. At the same time, another particular aim will focus on the development of further models and solutions for the computer-based assessment of weight training data. One promising approach would, for instance, involve the implementation of fuzzy logic concepts, which are also commonly applied in the area of AI. As part of the probabilistic logic, such methods might be suitable for the realization of other effective possibilities for the automatic evaluation of weight training exercises.

It is intended to include the implemented procedures into the already mentioned mobile coaching system by integrating the ANT technology as well as computer devices into the measurement process. Thus, a bidirectional data transfer between the weight training machines and the implemented evaluation routines on the server could be accomplished. This system integration would contribute significantly to the idea of instant data acquisition, automated analysis and prompt feedback routines.

Conclusion

Computer-based feedback frameworks involving sophisticated assessment techniques become increasingly essential for the instant analysis and appropriate intervention during workouts. The present study suggests a novel evaluation approach integrating AI methods for the machine-aided appraisement of weight training exercises. The implementation involved the use of modern sensor technologies attached to the training equipment, allowing an effective acquisition and collection of sport-specific data. The gathered parameter values were applied for the automatic analysis of the performed exercises. The modeling of the data was based on supervised learning procedures integrating ANNs. The pre-processed sensor input was used for the classification and autonomous appraisal of the executions. The developed techniques showed good results and performance outcome, raising promise for their practical application in integrated feedback systems. Further research, optimizations and hardware realizations would then allow the intended implementation of a supportive coaching system that provides professional and hobby athletes as well as coaches with prompt assessment and feedback tools.

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Key points

- Artificial intelligence is a promising field for sport-related analysis.
- Implementations integrating pattern recognition techniques enable the automatic evaluation of data measurements.
- Artificial neural networks applied for the analysis of weight training data show good performance and high classification rates.

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