The Development of Cycling Performance during the Training Program: An Analysis using Dynamical Systems Theory

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Abstract

There is common agreement that an appropriate framework for training and adaptation needs to consider the complexity and non-linearity of athletic performance and its response to training. General concepts like dynamical systems theory (DST) deal with such characteristics under the idea of self-organizing systems but still lack of empirical verification in the field of training and adaptation. In this paper, first, a DST approach to training is detailed. Second, on the basis of empirical data of cycling training, it is evaluated whether training process related data support the proposed DST approach. Therefore, training and performance development of ten cyclists (recreational to competitive level) were monitored during a ten-week cycling training program. Additionally, changes occurring at the microscopic level in the neuromuscular system were analyzed by means of surface electromyography (EMG). The results underpin the non-linear and time-delayed relation of training and performance. Further, the performance development observed during the training program can be characterized by stable patterns in the performance dynamics, described as performance states and transitions between these states, promoting the concept of self-organizing states observable at the macroscopic level.

KEYWORDS: DYNAMICAL SYSTEMS THEORY, TRAINING PROGRAM, CYCLING, SYNERGETICS, ELECTROMYOGRAPHY

Introduction

In order to improve performance in competition, athletes must prepare themselves through a training process (Smith, 2003). From a global perspective, the training process involves the physical, technical, intellectual and psychological preparation of an athlete through physical and mental training (Harre, 1982). For the sports coach a thorough understanding of the relationship between training and performance is essential in order to organize the athlete’s training program (Jobson et al., 2009). However, the performance response to training is known to be highly individualized (Mujika et al., 1996; Hellard et al., 2002; Avalos et al., 2003; Hellard et al., 2006; Borresen & Lambert, 2009). In order to further the understanding of the individual training-performance-relationship, a growing interest in the application of systems theory for the training analysis exists (Busso & Thomas, 2006).

The systems theory attempts to abstract a dynamic process into a mathematical model, in which at least one input and one output are related by a transfer function (Busso & Thomas,
2006). With respect to the training process, the athlete is considered a system, in which the input (training) leads to an adequate output (performance). A modeling approach, based on systems theory, was first proposed by Banister and co-workers (Banister & Calvert, 1975; Calvert et al., 1976). Further refinements and modifications of the original model have led to a broad application of this approach for training analysis in several kinds of sports (review in Taha & Thomas, 2003). However, the empirical evaluations of the model indicated high variability in the modeled performance response to training (Mujika et al., 1996; Hellard et al., 2006; Taha & Thomas, 2003; Pfeiffer, 2008). Besides the simplification and some methodological limitations inherent to the used systems approach, possible reasons for the inconsistent findings can be seen in the fact, that the Banister model is based on a linear mathematical concept, but adaptation in the athlete is a non-linear phenomenon.

The common agreement on the complex nature of sport performance related phenomena is in contrast to the classical analytic reductionism approach utilized when analyzing athletes and training processes. By simply understanding the body as a machine divided into parts and the performance as the simple sum of different qualities, research based on this approach often offers poor explanations of athletic performance and may increase the distance between theory and practice that characterizes training science (Balague & Torrents, 2005). Consequently, alternative concepts, based on a complex understanding of performance need to be considered. The dynamical systems theory (DST) has developed in diverse sciences and was applied to the study of movement coordination (important first works by Kelso and co-workers; e.g. Kelso, 1995). It has emerged as a viable framework for modeling athletic performance with respect to processes of coordination and control in human movement systems, in which movement patterns emerge through processes of self-organization (Davids et al., 2003). By dealing with complexity and non-linearity, DST offers potential for the explanation of common phenomena in training and adaptation like individuality and non-repeatability of performance responses or sensitivity to small fluctuations that cannot be explained by classical concepts.

The understanding of the training process and the biological adaptation as a complex and non-linear dynamical system has led to a paradigm shift in the analysis of training responses from linear concepts to individual non-linear process-oriented concepts (Hohmann et al., 2000; Perl, 2001; Edelmann-Nusser et al., 2002; Hellard et al., 2002; Avalos et al., 2003; Balague & Torrents, 2005; Hellard et al., 2005; Pakenas et al., 2007; Pfeiffer, 2008; Jobson et al., 2009). Hohmann et al. (2000; 2002) suggested applying a synergetic concept of training, in which the training process and the resulting adaptation in the athlete is better understood as a complex dynamic system. Based on such understanding, alternative and non-linear concepts like neural networks (Hohmann et al., 2000; Edelmann-Nusser et al., 2002), the Performance-Potential metamodel “PerPot” (Perl, 2004) and non-linear extensions of the Banister model (Busso et al., 1997; Busso, 2003; Hellard et al., 2005) have been applied and revealed promising results for systems modeling of the training-performance-relationship.

In the following, a dynamical systems theory (DST) approach to training based on the synergetic concept of training proposed by Hohmann et al. (2000; 2002) and the synergetic concept of movement coordination from Witte et al. (2003) shall be formulated.

**A Dynamical Systems Theory (DST) Approach to Training**

The DST approach utilizes the synergetic concept (see Figure 1), a theory of self-organization and pattern formation in complex systems (Haken, 1983). In the synergetic concept, complex systems consist of several interacting subsystems which themselves may be composed of other
subsystems. One or more control parameters externally or internally influence the systems behavior. A system may become unstable and adopt a new macroscopic state, when control parameters reach a critical level. The few collective variables that macroscopically characterize the ordered state of the system are called the “order parameters”. According to the slaving principle, the order parameters govern (“enslave”) the behavior of the subsystems, which in turn, through their interaction, generate the order parameter. Stable patterns in the dynamics of the order parameters are called attractors and the change between two attractors is known as a phase transition (Haken, 1983).

The DST approach to training is illustrated in Figure 2. At the macroscopic level, it is assumed that the athletic performance ability represents the order parameter of the system. The training load is considered the control parameter of the system: During planning the training objectives are established and the training program is designed, that is, type, volume, intensity and frequency of training sessions are arranged in order to achieve the objectives. In the process-oriented model, the control parameter training load comprises the volume and intensity of training, and the frequency is represented in the time history of training load. At the microscopic level, the training load (i.e. volume and intensity) of each training session is known to induce stress in various functional subsystems as the basis for adaptations to occur (e.g. Keul et al., 1996; Hawley & Stepto, 2001). The complex interaction of the functional subsystems at the microscopic level leads to a self-organization of the system, detectable at the macroscopic level, through stable patterns in the dynamics of the order parameter, which in turn enslaves the subsystems’ behavior. Since each training session leads to an adaptive response of the organism and consequently changes the system itself, the same training load applied at a later time will produce a different response. In abstract terms, the change of the order parameter over time \( (dx/dt) \) is given as a nonlinear function \( F_\lambda(x(t)) \), with \( \lambda \) standing for a control parameter, depending on the current training load, the former training chronology and the individual characteristics of the athlete and, moreover, is sensitive to fluctuations in the athlete’s environment (e.g. Hellard et al., 2002). For this reason, the influence of the control parameter training load on the order parameter can be characterized as time-delayed (since adaptive responses are time-dependent) and non-linear. Consequently, the dynamics of the order parameter is relatively stable but not rigid and is not entirely predictable.
The neuromuscular system can be considered a subsystem of the athlete involved in the training process. Adaptations of the neuromuscular system to strength, power and endurance training are well documented (Hakkinen, 1989; Sale, 1992; Kraemer et al., 1996; Trappe et al., 2001; Neary et al., 2003). These adaptations can be associated with peripheral changes occurring at the skeletal muscle level as well as central changes, which include the neural activation of the motor units of the muscle. With respect to the neural activation, the intermuscular coordination refers to the interaction of the working muscles in a specific movement task, while the intramuscular coordination involves the recruitment, rate coding and synchronization of motor units within one muscle in order to generate force. By means of the surface electromyography (EMG), the activity of the motor units within the range of the detection electrodes can be globally measured. Since the acquired EMG signal depends on membrane properties of the muscle fibers as well as on the timing of the motor unit action potentials, it reflects both the peripheral and central properties of the neuromuscular system (Farina et al., 2004). One EMG signal parameter commonly used is the median frequency (MF) of the power density spectrum. Changes in the spectral parameters have been documented due to peripheral fatigue in the muscle (De Luca, 1984; Balestra et al., 2001), skill acquisition (Bernardi et al., 1996) and adaptations to strength and power training (Moritani, 1992) as well as endurance training (Lucia et al., 2000; Ganter et al., 2007).

**Aim of the Study**

Despite the common agreement that appropriate frameworks for understanding training and adaptation need to consider the complexity and non-linearity of athletic performance
(Hohmann et al., 2000; 2002; Perl, 2001; Edelmann-Nusser et al., 2002; Hellard et al., 2002; Balague & Torrents, 2005; Pakenas et al., 2007; Pfeiffer, 2008; Jobson et al., 2009), concepts like the proposed DST approach still lack of scientific empirical data and appropriate tools enabling the analysis and evaluation of self-organization phenomena in performance related variables throughout the training process. One explanation is the fact that the use of experimental research procedures is scarcely possible within the context of the training process, not only due to the singularity of the athlete’s response and the considerable number of variables involved (Foster et al., 1999; Hellard et al., 2002; Plisk & Stone, 2003). Studies, therefore, need to take the analysis of the individual effects of training into account and should in a first step focus on sports strongly associated with physiological adaptation, like endurance disciplines, in which training and performance are rather accessible for quantification.

Within this study an attempt is made to provide empirical support for the proposed DST approach on the basis of monitoring training and performance development during a ten-week cycling training program, while additionally monitoring changes occurring at the microscopic level in the neuromuscular system.

On the basis of the provided theoretical framework, the following hypotheses are formulated:

1. **Training-performance-relationship:** The relationship between the control parameter training load and the order parameter performance ability is non-linear and time-delayed.

2. **Dynamics of the system:** Stable patterns can be identified in the dynamics of the order parameter as well as phase transitions between intraindividual different stable patterns.

3. **Variability of the system and the subsystem:** The neuromuscular subsystem involved in training exhibits a higher variability compared to the order parameter and the variability is subject to change close to the phase transitions.

**Methods**

The study used a prospective non-experimental training design in combination with laboratory controlled performance measures.

**Participants**

Ten Sport Science students (9 male/ 1 female) participated in the study and ranged from recreational cyclists to regional competitive cyclists and triathletes (Table 1). Each participant has signed a written informed consent and was informed about the aim, the test procedures and associated possible risks.
Table 1. Age, sex, anthropometrics, heart rate (resting and maximum value), prior training experience, volume of the training and maximum performance (Pmax) in the first incremental cycling test of the participants.

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<tr>
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<th>Body mass</th>
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<th>Max. heart rate</th>
<th>Training experience</th>
<th>Prior training</th>
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Training

The athletes underwent a ten-week individualized cycling training program aiming at the improvement of aerobic and anaerobic cycling performance. All training sessions were conducted in the field using the cyclists' own personal bicycles and the program consisted of periods with varying training volume and intensity. Both aerobic and anaerobic training were performed by using various training methods including continuous, fartlek, interval and speed training, as well as sprints. The particular training schedule was dependent on the performance level and the individual preparation for upcoming competitions (e.g. road race or triathlon), but incorporated in any case high load as well as low load periods. For each training session, the duration, cycling distance, mean exercise heart rate (measured using a Polar S610, Finland) and the type of training (e.g. speed training) were recorded.

For the quantification of the training load, a training impulse score (TS), proposed by Banister (1991), which incorporates the duration of the training session (in minutes) and the training intensity, was used. The intensity is reflected by the mean exercise heart rate related to the individuals’ resting and maximum heart rate and a gender-specific correction factor, which weights the intensity with respect to the increase in blood lactate during exercise (eqn 1). Despite TS is itself expressed by a non-linear equation, it is used to consider both volume and intensity in one training parameter and since the individual heart rate parameters $HR_{\text{max}}$ and $HR_{\text{rest}}$ are not expected to significantly change during a ten-week training period.

$$TS = Ty \frac{HR_{\text{ex}} - HR_{\text{rest}}}{HR_{\text{max}} - HR_{\text{rest}}}$$

where,

$HR_{\text{ex}}$ - mean exercise heart rate [beats • min$^{-1}$]
HR\textsubscript{max} - maximum heart rate [beats \( \cdot \) min\(^{-1} \)]

HR\textsubscript{rest} - resting heart rate [beats \( \cdot \) min\(^{-1} \)]

T - duration of a training session [min]

\( y \) - correction factor for male (eqn 2) and female (eqn 3) gender (Banister, 1991):

\[
y = 0.64 e^{\frac{1.97 (HR_{\text{max}} - HR_{\text{rest}})}{HR_{\text{max}} - HR_{\text{rest}}}} \tag{2}
\]

\[
y = 0.86 e^{\frac{1.67 (HR_{\text{max}} - HR_{\text{rest}})}{HR_{\text{max}} - HR_{\text{rest}}}} \tag{3}
\]

**Performance measures**

To monitor performance development, a 30-second all-out cycling test (30-s test) on an electronically braked cycle ergometer (Cyclus2, RBM Elektronik Automation, Germany) was conducted three times a week (Monday – Wednesday – Friday), between training week 2 and 10. The test protocol was similar to that of the Wingate Anaerobic Test (WanT; Inbar et al., 1996), but in contrast to the WanT, the test was performed in isokinetic mode (pedaling rate limited to 110 rpm) and with a flying start, in order to keep the movement velocity constant throughout the test. Power output was sampled at 3 Hz and averaged over 30 s, giving the test performance (\( P_{30} \)) which was related to body mass (unit: W/kg). \( P_{30} \) corresponds to the mean power of the WanT and can be considered a measure of the actual anaerobic performance, more precisely the anaerobic capacity (Vandewalle et al., 1987; Inbar et al., 1996; Bachl & Baron, 1998), which is known to contribute to cycling performance (Neumann, 1992; Tanaka et al., 1993; Davison et al., 2000; Atkinson et al., 2003). The validity, reliability and sensitivity of the test are discussed in Inbar et al. (1996). The authors state that the test can be regarded valid for the estimation of the anaerobic performance capacity and a sufficient reliability is accomplished through a standardized protocol. Moreover, the WanT is also sensitive to changes in performance occurring during certain training regimen. Our previous investigations indicated a very high day-to-day reproducibility of \( P_{30} \) for the applied test protocol (intra-class correlation = 0.97; Ernst et al., 2008). It should be noted that the 30-s test itself can be characterized as an anaerobic training stimulus with very short duration and maximum intensity but was not considered in the TS scores. Own unpublished data revealed no performance improvements in \( P_{30} \) in a control group with no specific cycling training but only three 30-s cycling tests per week over a period of eight weeks.

In addition to the regular anaerobic performance measures, cycling performance was assessed during an incremental cycle ergometer test (Cyclus2) to exhaustion in week 1 and week 10 of the training program. Blood lactate concentration was determined from capillary blood samples drawn from the hyperaemic ear lobe using a photometric method (Miniphotometer plus LP 20, Hach Lange, Germany) at the end of each increment of the test (starting with 80 W [women] / 100 W [men] followed by 40 W increments every 3 min) and heart rate was continuously measured. The individual anaerobic threshold was obtained using the “\( +1.5 \text{ mmol/l-method} \)” (Dickhuth et al., 1991) and results of the test in week 1 were used to derive the individual heart rate ranges corresponding to different training intensities in order to
control the following training sessions. Maximum power output (Pmax) maintained during the last increment was determined as an indicator of cycling performance, integrating the aerobic and anaerobic performance components (Hawley & Noakes, 1992; Balmer et al., 2000; Beneke et al., 2000; Bentley et al., 2001).

**EMG measures**

During each 30-s test, the surface electromyogram (EMG) of the muscle rectus femoris of the right leg was continuously recorded using a Biovision EMG-system (Germany; analogue RC filter: 10-500 Hz bandwidth, 1000 Hz sampling rate). In order to ensure reproducible EMG measurements, the positions of the EMG electrodes as well as the skin impedance were controlled and standardized. For the analysis, the successive movement cycles (according to one complete pedaling revolution) of the whole test (except the initial and final five cycles) were extracted and the time-dependent EMG power spectra as well as the instantaneous median frequency computed for each cycle by using an autoregressive model (Arnold et al., 1998). Subsequently, the mean median frequency (MF) was calculated for each cycle by averaging the instantaneous median frequency over a period of 200 ms when the muscle is active (prior to EMG offset). Finally, for each 30-s test the following parameters of MF were obtained, considering all cycles of the test: mean (σ), standard deviation (SD) and coefficient of variation (CV). This method has been previously used and described elsewhere for the analysis of arm strokes during swim bench testing and has yielded acceptable reproducibility of EMG MF in dynamic conditions (Ganter et al., 2007).

**Data analysis and statistics**

The overall changes obtained in $P30$ from the beginning to the end of the training period were compared to the changes in $P_{max}$ in the incremental cycling test in order to evaluate to what extent performance development is comparable between different tests.

The variables used for the analysis of the system’s behavior are $P30$ (order parameter), $TS$ (control parameter) and EMG MF (subsystem’s parameter). If not otherwise stated, results are presented as mean (SD).

*Training-performance-relationship.* The original time series of $P30$ and $TS$ were transformed into series containing nine consecutive weeks (week 2 – week 10) with the average of $P30$ and the sum of $TS$ per week, respectively. Development of performance in relation to training load was illustrated by plotting $P30$ vs. $TS$ and visually analyzed in each subject.

*Dynamics of the system.* To analyze the dynamics of the order parameter, the original time series data of $P30$ were transformed to a new time scale with a time interval of one day. Since performance was not tested every day, missing performance values between two consecutive tests were linearly interpolated. Transformation and interpolation of the performance data were done for better illustration of the dynamics. Despite the linear interpolation technique may not reflect real performance progress between testing sessions, it seems reasonable since $P30$ was assessed very frequent ($n = 15-21$ tests within 56 days). For the illustration of the dynamics of the order parameter, phase plots were generated with $dP30/dt$ vs. $P30(t)$. Different states in the order parameter are qualitatively identifiable as stable patterns in the phase plots and were referred to as $St1$ (first state) and $St2$ (second state) with the period between the two states is referred to as the phase transition ($PT$; see example data in Figure 3). If different states were identified, the time of $PT$ was estimated by analyzing the running total range of $P30$ for the nine consecutive weeks (week 2 – week 10), calculated for each week as the range between minimum and maximum value of $P30$ in the period beginning with the preceding and ending
with the subsequent week. The time of $PT$ (within two consecutive weeks) can thus be characterized by a high range followed by an immediate reduction (see Figure 4).

Figure 3. Phase plot of a fictitious time series $P30(t)$ (chart in the upper right). From the phase plots the states of the system as stable patterns (St1 and St2) as well as the phase transition (PT) are identifiable.

Figure 4. Sample data of athlete M8 showing the running total range of $P30$ (Range $P30$: grey bars) and the estimated time of phase transition (PT). The calculation of Range $P30$ is illustrated for week 3 as the range between minimum and maximum value of $P30$ in the period between week 2 and week 4. Example calculation: Given the values 9.11, 9.70, and 10.53 W/kg for $P30$ in week 2, 3, and 4, respectively, Range $P30$ in week 3 is calculated as the difference between maximum and minimum values of $P30$, namely, 10.53 – 9.11 = 1.42 W/kg. Accordingly, for calculating Range $P30$ in week 4, $P30$ values of weeks 3, 4, and 5, namely, 9.70, 10.53, and 10.56 W/kg are considered, giving 10.56 – 9.70 = 0.86 W/kg for Range $P30$. 
Variability of the system and the subsystem. Variability of the order parameter $P_{30}$ was determined as the within subject coefficient of variation of all test performances ($CV_{P_{30}}$) during the training period. The variability of the subsystem’s parameter $EMG \, MF$ was determined as the within subject average of the coefficient of variation ($CV_{MF}$), calculated for each test as described in the “EMG measures” section. In order to analyze within subject changes in the subsystem’s variability close to the phase transitions, all tests in the two weeks preceding the phase transition were compared to the tests in the following two weeks with respect to the $CV$ of $EMG \, MF$.

**Results**

Overall performance improvement from the beginning to the end of the training period was $14.9 \, (10.9) \%$ and $8.1 \, (6.2) \%$ in $P_{30}$ and $P_{max}$, respectively. Participant $M2$ was the only athlete with a slightly decreasing $P_{30}$ (- 1%), while $P_{max}$ was only slightly increased (2%). The other athletes ($M3$, $M5$) with a minor $P_{max}$ increase (2%) showed $P_{30}$ improvements of 19% and 20%, respectively. The highest improvement in $P_{max}$ was observed for athlete $M1$ with 20% combined with a 16% increase in $P_{30}$. Further, the highest $P_{30}$ increase of 38% was observed for $M7$ coming with a 12% increase in $P_{max}$.

**Training-performance-relationship.** Sample data of training load distribution and performance development over the training period are shown in Figure 5 for two athletes, indicating an increasing trend in $P_{30}$ and a decreasing trend in $TS$ over the training period. The transformation of the data considering $P_{30}$ vs. $TS$ per week is presented in Figure 6.

**Dynamics of the system.** The constructed phase plots for all athletes including the identifiable performance states are shown in Figure 7. With respect to the training load distribution, the identified performance states and phase transitions are illustrated for four athletes in Figure 8.

![Figure 5. TS (in arbitrary units) and P30 for athletes M3 (bottom) and M8 (top).](image-url)
Figure 6. P30 (average per week) versus TS (sum per week) from week 2 to week 10 for athletes M3 (bottom) and M8 (top; grey line: cubic spline curves).

Figure 7. Phase plots (dP30/dt vs. P30) for the athletes M3, M8 (top left), M1, M7 (top right), M4, M6, W1 (bottom left) and M2, M5, M9 (bottom right; cubic spline curves) with the assignment of identifiable performance states (St1 and St2).
Variability of the system and the subsystem. Variability in $P30$ with 5.4 (2.7) % was lower compared to 13.4 (3.0) % in $EMG MF$ (Table 2). Table 2 also shows the within subject changes in the variability of $EMG MF$ close to the phase transitions.
Table 2: Coefficient of variation (CV) of P30 and EMG MF over the whole training period and EMG MF compared between the tests in the 2-week-period preceding (St1) or following (St2) the phase transition for all athletes.

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<th>CV [%]</th>
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<td></td>
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<td>[CV in %]</td>
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</table>

Discussion

**Overall performance development.** The overall mean performance improvement observed in this study was 14.9% for P30. There are only few studies investigating the effects of an endurance training program on anaerobic performance in trained cyclists. A study that utilized the \textit{WanT} found 6% and 3% increase in mean power after four weeks of additional sprint training and endurance training alone, respectively (Creer et al., 2004). Inbar et al. (1996) reported results of different training studies, in which performance improvement after eight weeks of training varied between 7% (not statistically significant) for the moderate aerobic training and up to 20% improvement for the mixed aerobic anaerobic training. Another study of Touchberry et al. (2004) found a non-significant 1% increase in mean power after twelve weeks of training. The results, however, showed large interindividual variations. Direct comparison of our results to other studies is difficult because of the different subject, training and test characteristics.

Compared to the average performance improvement in P30, the increase in the incremental testing performance (\(P_{\text{max}}\)) was lower (14.9% vs. 8.1%). The differences may be attributed to the specificity of the test, since \(P_{\text{max}}\) integrates the aerobic and anaerobic component and P30 mainly the anaerobic component of cycling performance. With respect to improvements or stagnations in performance, the results, however, showed qualitatively good agreement. Since exhausting incremental tests are not feasible for frequently monitoring actual performance during training, the short modified \textit{WanT}-protocol was chosen. There is reasonable evidence for the anaerobic contribution to complex cycling performance, its proportion, however, is largely dependent upon the characteristics of the cycling event and not yet completely understood (Neumann, 1992; Atkinson et al., 2003). Studies with sub-elite cyclists suggest that the higher-level athletes not only provided better aerobic performance but also anaerobic
performance as indicated by the \textit{WanT} (Tanaka et al., 1993). The relative \textit{WanT} performance was also found to be a good predictor of hill climb cycling performance in competitive cyclists (Davison et al., 2000).

\textit{Training-performance-relationship.} Individual performance progressions presented in Figure 5 show typical characteristics of performance curves, with higher variation at the beginning of training, the development of a more stable level after a certain training period and, subsequently, an asymptotic behavior. The representative sample data illustrated in Figure 6 indicate the non-linear and time-delayed characteristics of the relation between training and performance, suggesting that actual performance progression is largely dependent on previous training history. It can be shown that, at the beginning of the training period, performance increases with the training load. A subsequent stabilization and/or further increase in performance are observable once training load is again reduced. The results are consistent with practical experiences and compare well to data shown by Hristovski et al. (2010) illustrating the “memory effect” of training. So at a certain performance level or stage of training, performance tends to increase with training load (Foster et al., 1996). However, the impact of training load has an upper limit above which performance could decline because of accumulated fatigue induced by high load periods (Hellard et al., 2005). By eliminating the accumulated fatigue during subsequent phases of reduced training, effects of lasting performances (“memory effect”) or improved performances are well known and used in the tapering periods prior to competitions (Mujika et al., 1996). It has to be noted that no considerable (at least mid-term stable) performance decline was observed in the current study, suggesting that training was not inducing overtraining-like effects (Smith, 2003).

\textit{Dynamics of the system.} On the basis of phase plots and the running total range of \textit{P30} an attempt is made to describe the dynamics of the system. In fact certain patterns can be observed which may be qualitatively described as the emerging of different states in the performance dynamics (Figure 7). An emerging performance state (\textit{St2}) can be qualitatively characterized by a higher stability (= lower variability) compared to the lower performance states (\textit{St1}) and the phase transition (\textit{PT}) between them. By comparing athletes \textit{M3} and \textit{M8} (Figures 5, 6, 7, 8) the emergence of the higher stable state (\textit{St2}) occurs earlier in the training period for \textit{M8}, with the attribution of the first state (\textit{St1}) to the initial performance level, but without exactly knowing how stable this first state in the long-term has been for \textit{M8} beforehand. Nonetheless, a transition early in the training period, here referred to as a phase transition can be observed. By quantitatively analyzing the performance dynamics, the periods of emerging states or the phase transitions between different states may be allocated. The results show that if different performance states are identifiable, the occurrence and time frames of the transition periods are highly individual. With respect to the current training load, with the weekly \textit{TS} scores comprising volume, intensity, and frequency of training, phase transitions could be attributed to periods with moderate loads either following high or reduced load phases (Figure 8). In addition, they could also be allocated to high load periods, suggesting that the occurrence is, among other things, influenced by performance level and training history. Keeping in mind that the \textit{TS} score does not discriminate between the contributions of volume, intensity and frequency to training load, \textit{PT} for \textit{M8} may be attributed to the period when training load increases and, therefore, becomes effective, whereas for \textit{M3} the \textit{PT} may be observed not until training load is sufficiently reduced (Figures 6 and 8). Other qualitative patterns observed were, first, leaving a stable performance state towards the end of the training period (athlete \textit{M2}) and, second, the non-occurrence (or non-identifiability) of at least mid-term stable performance states (athletes \textit{M5}, \textit{M9}; Figure 7). In the first case, the pattern may result from the excessive reduction in load towards the end of the training, leading
to a preliminary stage of detraining (Neufer, 1989). For the second case, one may speculate that other stressing factors than training load are the reason for short-term fluctuations in performance and thus preventing the emergence of a stable state. However, this cannot be fully addressed with the available data.

The concept of identifying performance attractors has been used in studies by means of neural networks (Hohmann et al., 2000; Edelmann-Nusser et al., 2002). Despite these studies were able to model competition performances of elite swimmers, the temporal characteristics of the performance states have not been addressed. Analyses of frequent performance measures in the training of swimmers revealed differences in the dynamics of emerging performance states between elite and junior athletes also highlighting the specificity of responses to training (Ganter et al., 2008; Witte & Ganter, 2010). A recent work by Hristovski et al. (2010) observed collective variables (order parameters) at different levels of exercise-induced psychobiological adaptation, namely, at performance, electrophysiological, kinematic, and psychological level. They showed phenomena indicating the self-organized evolution of soft-assembled cooperative states on different time scales under the control of constraints (control parameters), for instance, in the study of fatiguing exercises.

Variability of the system and the subsystem. The variability in the order parameter ($P30$) has shown to be lower than in $EMG\ MF$, as a measure of variability in the subsystem, for nine out of ten participants (Table 2). Only for athlete $M7$ the variability was quite similar, which may be attributed to the high performance improvement observed. When interpreting the differences, the proportion of variability induced by the measuring method, needs to be taken into account. Due to the stochastic nature of surface EMG signals, some natural variability in $EMG\ MF$ can be expected. Previous studies, however, indicated acceptable reproducibility of the method used (Ganter et al., 2007; Ernst et al., 2008).

With respect to the within subject changes of the variability in the subsystem, the results indicated a trend of reduction for $EMG\ MF$ after the phase transition in five out of eight participants, in which different performance states were identifiable (Table 2). Changes in EMG spectral parameters in the course of endurance training have been reported (Lucia et al., 2000; Ganter et al., 2007) and can be associated with morphological adaptation of the skeletal muscle and adapted neural activation also occurring in cycling training (Hawley & Stepto, 2001). Despite several factors influence the characteristics of the surface EMG signal and, therefore, need to be controlled, the signal reflects to some extent the function of a part of the neuromuscular subsystem.

Practical implications for training. This study aimed at analyzing data of a cycling training program in order to evaluate whether it provides support for a DST approach to training. Cycling in a first instance was chosen, because cycling training can be strongly associated with physiological adaptation and training and performance parameters are quantifiable. Consequently, the results of the study have no direct practical implications for the training in cycling. Rather, the DST approach and the concept of self-organization of performance states in the training process would have some practical implications on training planning. With regard to this concept, Hohmann et al. (2000; 2002) state that a certain range should exist for training loads to be appropriate to initiate self-organization of the transient state of optimal performance in the particular athlete. Consequently, a too detailed prescription of training load is not necessary as long as the individual responses to the training stimuli will be continuously evaluated. Similarly, Hellard et al. (2002) summarize that adaptational responses to training are always specific to the individual athlete and, to a certain extent, unpredictable. Accordingly, they demand to reconsider the “closed” classical planning models to an open conception of
planning, which “implies ... the development and regulation of the initial strategy in accordance with the unforeseen emergence of adaptational responses ... and in accordance with the unpredictable evolution of the athlete’s overall environment” (Hellard et al., 2002, p. 87).

Limitations of the study. Limitations of the study can be seen in the non-experimental training design and the methods used for assessing training and performance. The observational approach in cycling training combined with an exploratory data analysis does not allow to confirm, but rather to support or non-support the stated hypotheses. Consequently, generalization of the findings is limited, unless tested in other settings (sports and athletes). Despite these limitations, observational studies are necessary in the context of training processes of elite athletes, since experimental procedures are scarcely possible due to the singularity of the athlete’s response and the considerable number of variables involved (Foster et al., 1999; Hellard et al., 2002; Plisk & Stone, 2003). Further limitations can be associated with the method used to quantify training load and performance in cycling as well as the EMG procedures used to infer adaptation of the intramuscular coordination. Despite endurance sports like cycling are advantageous for assessing training loads compared to more technique-oriented sports, the approach used to calculate the training impulses on the basis of heart rate responses has some shortcomings when assessing high or intermittent intensity training. Under the assumption that, if macroscopic patterns exist in the dynamics of the complex performance ability, they should also be identifiable in the dynamics of the anaerobic component of performance, the proposed test procedure to assess performance has been used under practical considerations with the previously discussed limitations in validity.

Future studies. For further verification of a DST approach to training, systematic prolonged analyses of training processes in different sports with athletes at various performance levels are necessary. To enable quantitative analyses also in elite sports, training and performance parameters are required to be monitored continuously with least disturbance to the training process. Therefore, technical advances would be valuable like, for example, the recent development of cycling power output measuring devices that enable training and performance assessment even under field conditions. On the basis of such data, retrospective analysis of critical training periods is possible which cannot be adequately mimicked in experimental approaches. Following a holistic perspective, the integration of assessing additional physiological, psychological and social parameters is necessary in order to identify further key variables characterizing different performance states. To further the systems modeling of the training-performance-relationship non-linear methods like, for example, PerPot, fuzzy logic or neural networks (Balague & Torrents, 2005) can be valuable for analyzing data related to training processes.

Conclusion

This study tried to evaluate whether training and performance data obtained from a group of cyclists during a ten-week cycling training program support a proposed DST approach to training. The results suggest that, at the macroscopic level, performance development observed during the training program shows, to a certain extent, a self-organizing behavior that can be characterized by stable patterns in the performance dynamics, described as performance states and transitions between these states. Further, the analysis at the microscopic level, in terms of spectral EMG parameters, at least in part supports the hypothesis that changes are observable close to the phase transitions. A DST approach may have direct implications on concepts of training planning and the identification of performance states in training in order to optimize training and performance response in the particular athlete in a next step. However, to bring
forward a viable framework for training and adaptation, the search and study of selforganization phenomena in the adaptive behavior of the athlete needs to be continued, by identifying potential collective variables or order parameters reflecting macroscopic changes under the influence of control parameters. Moreover, suitable tools need to be developed or utilized to enable extensive analysis of training processes, particularly for elite athletes, in various sports in order to further the understanding of the training-performance-relationship.

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