MODELLING AND PROGNOSIS OF COMPETITIVE PERFORMANCES IN ELITE SWIMMING

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The study demonstrates that the performance of an elite female swimmer in the finals of the 200 m backstroke at the Olympic Games 2000 in Sydney can be predicted by means of the nonlinear mathematical method of a neural back-propagation network. The analysis included the performance output data of 19 competitions prior to the Olympics within a time period of 95 successive weeks and the training input data of the last four weeks prior to each competition. The training data were divided into two phases: (1) a two-week taper cycle, and (2) an earlier two-week high load cycle. The trained neural network was not only able to model the 19 competitive performances, but also to predict the performance in the semi final of the Olympic Games in Sydney on the basis of the two sets of training data during the preparation before that specific competition.

KEYWORDS: synergetics, dynamical system, training analysis, competition, single-case study, time-series analysis

INTRODUCTION: The thorough analysis of periodized training processes is one of the most important issues in training science. It helps the coach of elite sports in monitoring training and peak athletic performances in crucial competitions. Contemporary science, theory and training methods have commonly used linear mathematical concepts like differential equations or regression analysis to model the adaptive behavior as the result of different training parameters. Based on that cybernetic approach, several studies focussed on the adaptation of swimmers to certain training regimen (Calvert, et al., 1976; Banister, & Calvert, 1980; Banister, 1982; Monika, et al., 1986; Busso, et al., 1990; Fitz-Clarke, et al., 1991; Hohmann. 1992; Mujika, et al., 1996; Busso, et al., 1997; Hooper & Mackinnon, 1999; Chatard & Mujika, 1999). In this type of cybernetic thinking, the system athlete functions similar to a technical closed circuit, where a definite amount of training input leads to an equivalent raise in the performance output. As we know today, linear models of dynamical systems like an athlete are not adequate to model much beyond the simplest physical phenomena. Therefore, it should come as no surprise, that these models cannot deal with the considerably more complex nature of athletic behaviour, which is highly influenced by the training regimen and the social embedding of the coach-athlete partnership.

Based on these findings, the present study concentrates on a synergetic concept of training adaptation and shows that the dynamic system training process can be modeled with nonlinear methods.

METHODS: To understand the nature of a complex dynamic system, it is necessary to observe the system unfold over time. Consequently, the training input data and performance output data have to be interpreted as mutual interacting time series. As most of the complex systems show feedback mechanisms, special mathematical tools are needed to detect the presumably nonlinear behavior of dynarnical systems. At least three methods are frequently used for this purpose (Schroeck, 1994): (1) Fourier-Analysis, (2) Coherent State Analysis, and (3) Neural Networks. Fourier or Spectral Analysis is useful when the system is known to possess periodic behavior, which can be divided into different temporally periodic components. This ,,harmonic" analysis does not work well in situations that do not exhibit regularly occurring patterns and stationary signals, or when the system is embedded in a highly noisy background, or when the cost of acquiring many data points is prohibitive. Coherent State Analysis is able to detect fundamental patterns of the same family, even when they do not occur regularly or when they are stretched or condensed in time. Neural Networks recognize global patterns in the linear as well as nonlinear behavior of a complex dynamic system in a coherent way, so that they are useful for the analysis of synergetic systems. A Neural Network is a signal processor that possesses the following attributes: a) it is nonlinear in the signal, b) it samples the signal nonlocally, c) it can process nonstationary signals, d) it is adaptive or capable of learning, and e) it is stable under small changes of input and in the presence of noise. Since training and adaptive behavior are nonstationary processes, and furthermore, in most cases training and performance data in time series are not available in great numbers, Neural Networks seems to be the best method to be used in training analysis. The conclusion that neural networks are worthwhile tools for training analysis was supported by a study of Hohmann, et al. (2000), who could properly model the training process of an elite swimmer with the help of a neural backpropagation network.

Data Collection. The training process lasted a total of 95 weeks from week 0111998 to week 3912000. According to the system of Fry, Morton, & Keast (1991) it was divided into different preparation macrocycles including the final competitions. The macrocycles consisted of 6-14 weeks (microcycles) of training preparation and 1-3 weeks of competitions.

The data consisted of the competitive performances and the documented training loads in three zones of swim training intensity and two categories of dry-land training. The three zones of training intensity were controlled by frequent lactate testing in the course of the training process. The documented categories of training were: 1) compensation and maintenance aerobic endurance training at and slightly above the aerobic threshold (End–I: 2-3 mmol/l blood lactate); 2) developmental and overload aerobic endurance training at and slightly above the anaerobic threshold (End_II: 4-6 mmolll blood lactate); 3) anaerobic power training, speed training and competitions (End_III: 6-20 mmolll blood lactate); 4) dry land strength training (Strength); and 5) dry land general conditioning training (General Conditioning). The competitive performances in the 200 m backstroke events were transformed according to the pointage system of the *Ligue Europèene* de Natation into LEN-points. The LEN-point table 1997-2000 which ranges from 1 to 1200 points was used. The actual World Record (e.g. in the female 200 m backstroke 2:06,62 min) served as the reference value for 1000 points.

Data Analysis. In the present study a neural backpropagation network (*multilayer* perceptron, DataEngine Inc., Aachen, Germany) with three layers was used (Hohmann, et al., 2000). Two analyses were conducted: 1) To determine the influence of the two week taper cycle prior to the 19 competitions. The taper has the function to allow the athlete to recover from the high training loads before and to peak in hislher performance; 2) to determine the influence of the high load training phase which includes weeks three and four prior to the 19 competitions. This crash cycle normally contains very intensive and exhaustive training, and it is its purpose to create a state of slight overreach in the athlete (Kreider, et al., 1998). That state of transient fatigue allows the athlete to reach an accumulated and thus optimal supercompensation after the later taper.

For both analyses a neural network consisting of 10 input neurons was created. Each neuron represented the weekly training volumes in one of the five training categories in one of the two weeks of the investigated training phase. Two hidden neurons served to represent the black box of the system athlete and one output neuron to represent the competitive performance. Since 19 sets of training and performance data are not very many, an already existing pre-trained neural network was used. It was created earlier when analyzing a female olympic champion in the 400 m freestyle who trained with the same coach in the same training group (Hohmann, et al., 2000).

In the first step, the validity of the two neural network solutions for the crash resp. of the taper phase was tested thoroughly, following the validation procedure 'leave-one-out'. Therefore, in

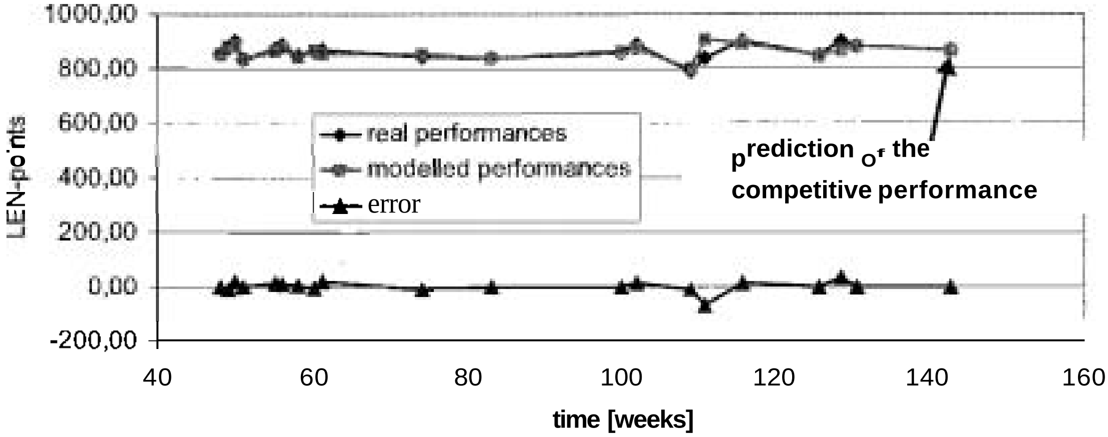

Figure 1 - Comparison of the 20 real competitive performances and the mean values for the performances modeled by two neural backpropagation networks on the basis of the training data from the two-weeks crash phase and the two-weeks taper phase prior to the competitions.

both cases the pre-trained multilayer network was trained nineteen times in a different way: Each of the 19 neural networks was provided with different 18 sets (network 1 with the sets 2-19, network 2 with the sets 1 plus 3-19, and so on) out of the 19 training input and performance output data, to learn the interrelation between the training input and the performance output. The training phase aimed at the weighting of all 13 neurons on the three layers and consisted of 10,000 repetitive calculations of the neuron weights.
In the second step, each of the 19 trained networks was tested with the left out competition. This forced the neural networks to estimate the missing competitive output data based only on the formerly learned weights of the connected neurons on the three layers and the given training data. The tests showed that all 19 networks were able to predict the performance in the left out competition sufficiently (Figure 1). The leave-one-out procedure made clear that the use of a pre-trained network was acceptable, and that none of the 19 training processes led to strange adaptations in the athlete.
In the third step, one network for the crash and one for the taper phase were trained on the basis of all 19 training and performance data sets. To model the performance at the Olympic Games, these two networks were paired with the training input data before that competition.

RESULTS AND DISCUSSION: In order to predict the competitive performance, the mean of the two values that were predicted by the neural networks on the basis of the crash cycle resp. of the taper cycle was calculated. (Table 1). The mean error of the averaged forecast of the two models was 12.02 LEN-points, which was equivalent to differences of plus 0.62 s or minus 0.61 s in the mean time of all the nineteen 200 m backstroke races of 2:12,94 min.

Table 1 Means and Standard Deviations of the Error of the Modelling (difference in LEN-points between the true competition values and the neural network predictions).

	Models #1-19 taper cycle	Models # 1-19 crash cycle	Averaged forecast of the two models
Mean error	14,78	20,16	12,02
Standard deviation	15,76	17,73	15,82

The results in Figure 1 show that the prognosis obtained with the two neural network solutions #20 lead to an error of only 1.24 LEN-points, which was 0.11 percent off of the final performance at the Olympic Games of 870 LEN-points. Compared to the chronometric time of the athlete in the Olympic 200-m-backstroke race of 2:12,64 min, that average error is equivalent to a difference of plus 0,04 s or minus 0,04 s.

CONCLUSION: The neural network method is a worthwhile tool to enhance the monitoring of a training process, especially then, when the data basis resulting from the training record of the coach is too small or not adequately scaled to allow training analysis with the linear methods commonly used up to now. Furthermore, the method is not only able to ,,learn" the individual adaptative behavior of the athlete. After the learning procedure the neural network is also able to calculate a simulation of the prospective performance responses of the athlete under the influence of a slightly changed structure of the training input. So, the trained neural network allows the coach to simulate the effects of certain modifications of the training program on the competitive performance of the athlete. This makes the planning and monitoring of a training process more effective.

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