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TABLE OF CONTENTS

Editorial

Arnold Baca

Department of Biomechanics, Kinesiology and Applied Computer Science,

ZSU, University of Vienna

Dear readers:

Welcome to the winter 2008 issue of the **International Journal of Computer Science in Sport (IJCSS)**.

Three full papers, three project reports and one extended report from industry have been included within this issue.

K. Tanaka and **Y. Kurose** propose a model to understand tactical behaviour in Karate matches. The model takes into account that offensive and defensive states do not necessarily alternate and includes a third state, which is neither offensive nor defensive.

In the paper by **M. Pfeiffer** two antagonistic concepts for modeling the relationship between training and performance are compared. In particular, the model-fit and the accuracy to predict future performance are analysed.

T. Jaitner and **M. Trapp** present a software approach based on a service oriented architecture that supports dynamic integration of heterogeneous devices in a sports-specific environment. The concept is illustrated by an application from group training in cycling.

An antagonistic model and neural networks are used to model individual performances of archers in the project reported by **N. Ganter, K. Witte, S, Giggel** and **J. Edelmann-Nusser.**

N. Roznawski and **J. Wiemeyer** inform on an e-learning project that tries to implement interaction and interactivity using a blended-learning scenario.

Global positioning system (GPS) technology is used to analyse performance in long-distance rowing in the report by **R. Cejuela**, **J. A. Pérez-Turpin**, **J. M. Cortell**, **J. Llopis** and **J. G. Chinchilla**.

An extended report from **D. Zhong** rounds off this issue. Within this paper a possible solution to build a “Sport and Wellness Ecosystem” is described from an industrial perspective.

I hope you enjoy this issue.

If you have any questions, comments, suggestions and points of criticism, please send them to me.

Best wishes for 2009!

Arnold Baca, Editor in Chief
University of Vienna, arnold.baca@univie.ac.at

An Analysis Method of Tactics in Karate Matches Using a Bayesian Network Model

Kazumoto Tanaka, Yoshinobu Kurose

Dept. of Information and Systems Engineering, School of Engineering,

Kinki University, Japan

Abstract

This study proposes a model using a Bayesian network to understand tactical behavior in Karate matches. The model is a probabilistic causal model consisting of the states of two competitors engaged in combat. Each state node of the model outputs a probability distribution of the occurrence of offensive, defensive, and evaluative actions. Using the model, we also propose an analysis method of Karate tactics that can obtain the high likelihood processes for a competitor for the case in which the competitor's offensive action ends in success. The extracted processes indicate competitor's tactical pattern. For an experiment of the method, we collected action data from the videos of Karate matches in which elite competitors had competed, and trained two elite competitor's model. The method has extracted the elite competitors' tactical actions correctly using the trained models.

KEYWORDS: TACTICS ANALYSIS, COMBAT SPORTS, KARATE MATCH, BAYESIAN NETWORK, PROBABILISTIC CAUSAL MODEL

Introduction

In sports technique analysis, various studies have been conducted using soft computing methods (Bartlett, 2004). In particular, neural network modeling and stochastic modeling are often utilized in order to analyze tactical techniques in sports games. For tactical analysis, it is necessary to build a state-transition model that can represent the game context to be analyzed. As a stochastic approach, the Markov chain has often been used for modeling state transitions. A four-state Markov process model has been developed for evaluating tactical decisions in football games (Hirotsu and Write, 2002). The model is composed of the team states that indicate ball possession or a goal. For estimating pinch-hitting strategies in baseball games, a Markov transition matrix that consists of top inning states and bottom inning states and calculates the probability of winning has also been formulated (Hirotsu and Write, 2003). As a neural network approach, DyCoN (McGarry and Perl, 2004) is a powerful modeling method that was developed based on the Kohonen Feature Map (KFM) for efficient and continuous self-organization. Offensive tactics in handball games have been analyzed using a DyCoN-network trained with feature vectors, each of which represents an offensive state sequence (Pfeiffer and Perl, 2006). In the case of volleyball, the sequence of the feature vector that represents the positions of team competitors on a court was used to train a DyCoN-network, which provided a visual representation of tactical formations (Jäger and Perl, 2007).

As stated above, team ball sports are often used to study game tactics. In contrast, little attention has been given to combat sports. Although punching skills in boxing have been considered in experiments using a sandbag (Hristovski, Davis, et al. 2006), very few attempts have been made to model the tactics of combat sports under the circumstances of interaction with an opponent. Compared with team ball sports, the notable features of combat sports are as follows:

(1) The offensive and defensive states do not necessarily alternate. For example, one competitor can continuously make unilateral attacks, or both competitors can attack one another at the same time.

(2) In a third state, which is neither offensive or defensive, competitors evaluate each other for planning next move.

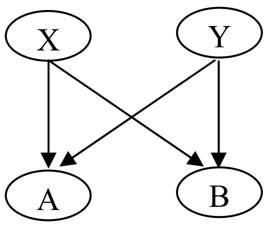
According to these features, the models described above, which assume that the offensive and defensive alternate with one another as separate states, are not suitable for combat sports. The present study proposes a model using a Bayesian network (Pearl, 1988) to understand tactical behavior in Karate matches. The proposed model is a probabilistic causal model consisting of the states of two competitors engaged in combat. Each state node of the model outputs a probability distribution of the occurrence of offensive, defensive, and evaluative actions.

Bayesian Network

The Bayesian network is a probabilistic graphical model that can be used for probabilistic reasoning. The graph in Figure 1 illustrates a Bayesian network for diagnosis. Suppose that there are two diseases, X and Y, that cause symptoms A and B. Each node has three possible values, N (Null), Sl (Slight), and Se (Serious), and a conditional probability table. When the value of a symptom node is given, the network can compute the likelihood of each disease level using the Belief Propagation Method.

X: N	X: Sl	X: Se
0.7	0.2	0.1

Y: N	Y: Sl	Y: Se
0.8	0.1	0.1



X	Y	A: N	A: Sl	A: Se
N	N	0.9	0.1	0.0
N	Sl	0.5	0.4	0.1
N	Se	0.5	0.3	0.2
Sl	N	0.3	0.5	0.2
Sl	Sl	0.3	0.6	0.1
Sl	Se	0.2	0.5	0.3
Se	N	0.3	0.4	0.3
Se	Sl	0.3	0.5	0.2
Se	Se	0.2	0.3	0.5

X	Y	B: N	B: Sl	B: Se
N	N	0.9	0.1	0.0
N	Sl	0.6	0.4	0.0
N	Se	0.6	0.3	0.1
Sl	N	0.4	0.5	0.1
Sl	Sl	0.4	0.5	0.1
Sl	Se	0.3	0.5	0.2
Se	N	0.4	0.5	0.1
Se	Sl	0.4	0.4	0.2
Se	Se	0.3	0.4	0.3

Figure 1. Example of a Bayesian network.

Methods

The action that a competitor decides and executes is causally related to the context in the match before the action. We call this action a *current action*. Let X be a context. X can be described as a sequence: X1X2・・・XN, where Xi denotes an action in the context and the suffix 'i' indicates the order of the action. We call the sequence a *past action set*. A causal model among the current actions and the past action sets for two competitors are illustrated in Figure 2. The state node Ac (Bc) indicates the current action of competitor A (B). The state node Ap (Bp) indicates the past action set of competitor A (B).

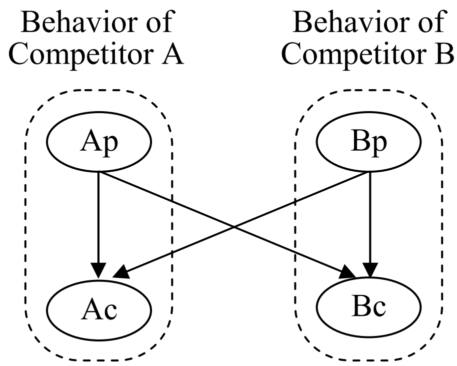


Figure 2. Causal model (Bayesian network model) for analyzing tactical behavior in a Karate match.

It is necessary to collect action sequences in Karate matches for training the causal model, namely, the Bayesian network model. First, for the expression of the action sequences, the 31 action labels shown in Table 1 were used to indicate the competitor's footwork, punches, kicks, feints, and guards.

The procedure for collecting action sequences is shown below and is illustrated in Figure 3.

Step 1: Each action in the Karate match video images was labeled by visual observation, and we obtained time-series action labels.

Step 2: Each range of actions having the same label was merged into one region.

Step 3: The action sequences obtained by the merging process were re-segmented at each boundary of the region.

After the procedure, we extracted sub-sequences composed of (N+1)-actions to train the Bayesian network model as illustrated in Figure 3. A sub-sequence is separated into two parts: a *current action* and a *past action set* (composed of N-actions). The N-value was given such that an appropriate model could be constructed.

Since we have supposed that tactical skill differs among individuals and depends on each competitor, we selected two elite competitors (A1 and A2) and constructed two models: a model in which competitor A (see Figure 2) corresponds to elite competitor A1 and a model for elite competitor A2. For the sake of training the two models, we collected 1600 sub-sequences from the videos of Karate matches (e.g., National Sports Festival in Japan, Japan Karate Championships, and World Karate Championships) in which the elite competitors had competed.

Table 1. Action Labels in Karate Matches.

1: Standing with Defense Posture	17: Punch(2) to Opponent Face (Failure)
2: Standing with No Guard	18: Punch(1) to Opponent Body (Success)
3: Jumping with Defense Posture	19: Punch(1) to Opponent Body (Failure)
4: Jumping with No Guard	20: Punch(2) to Opponent Body (Success)
5: Forward Step (High-speed)	21: Punch(2) to Opponent Body (Failure)
6: Forward Step (Moderate-speed)	22: Kick to Opponent Face (Success)
7: Forward Step (Low-speed)	23: Kick to Opponent Face (Failure)
8: Back Step (High-speed)	24: Kick to Opponent Body (Success)
9: Back Step (Moderate-speed)	25: Kick to Opponent Body (Failure)
10: Back Step (Low-speed)	26: Feint Punch to Opponent Face
11: Side Step (High-speed)	27: Feint Punch to Opponent Body
12: Side Step (Moderate-speed)	28: Feint Kick to Opponent Body
13: Side Step (Low-speed)	29: Blocking Attack to Face
14: Punch(1) to Opponent Face (Success)	30: Blocking Attack to Body
15: Punch(1) to Opponent Face (Failure)	31: Rapid Stop of Footwork
16: Punch(2) to Opponent Face (Success)	-

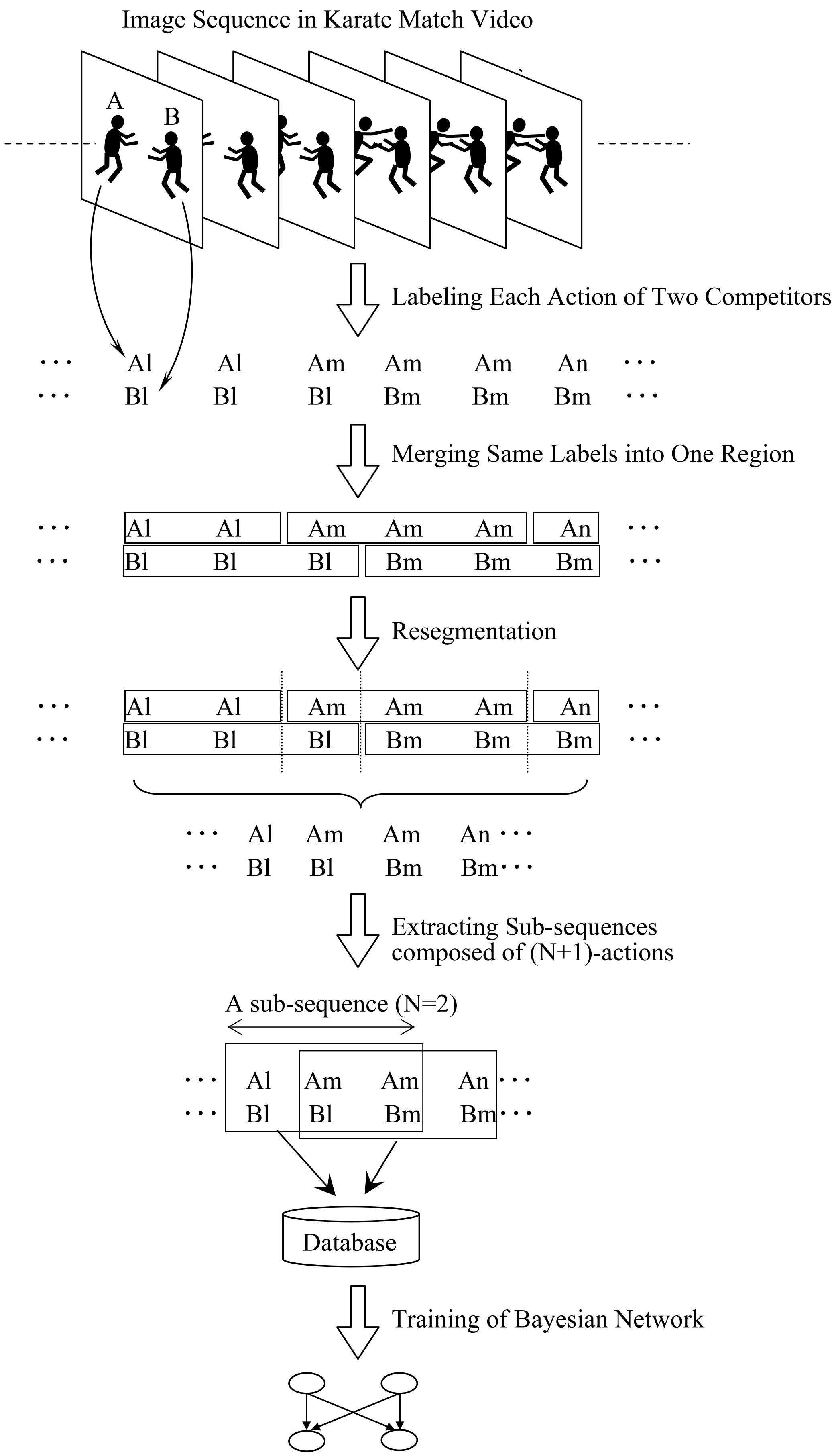


Figure 3. Procedure for Action Sequence Extraction and Training Causal Model.

The method of the tactical analysis on competitor A's offensive action (success) is described in the following:

Step 1: The proposed method calculates each probability distribution of the output of the nodes Ap and Bp (i.e., the likelihood of each past action set of the nodes Ap and Bp is obtained), provided that the offensive action (success) of the node Ac is true (i.e., current action of the competitor A is the offensive action (success)).

Step 2: The past action set of which the likelihood is greater than a given threshold value is selected by the proposed method.

Step 3: The proposed method calculates the probability of competitor A's offensive action (success) and that of the same action (failure), under every condition in which a combination of the selected Ap's past action set and the selected Bp's past action set is true.

Step 4: The combinations, which cause the probability of the offensive action (success) to be greater than both a given threshold value and the probability of the same action (failure), are selected by the proposed method.

Step 5: The proposed method calculates the probability distribution of the output of node Bc, under every condition in which the selected combination and the offensive action (success) are true.

Step 6: The current action of node Bc for which the likelihood is greater than a given threshold is selected by the proposed method.

According to the proposed method, we can obtain the high likelihood processes for the two competitors for the case in which competitor A's offensive action ends in success. We can safely say that the extracted processes indicate competitor A's tactical pattern.

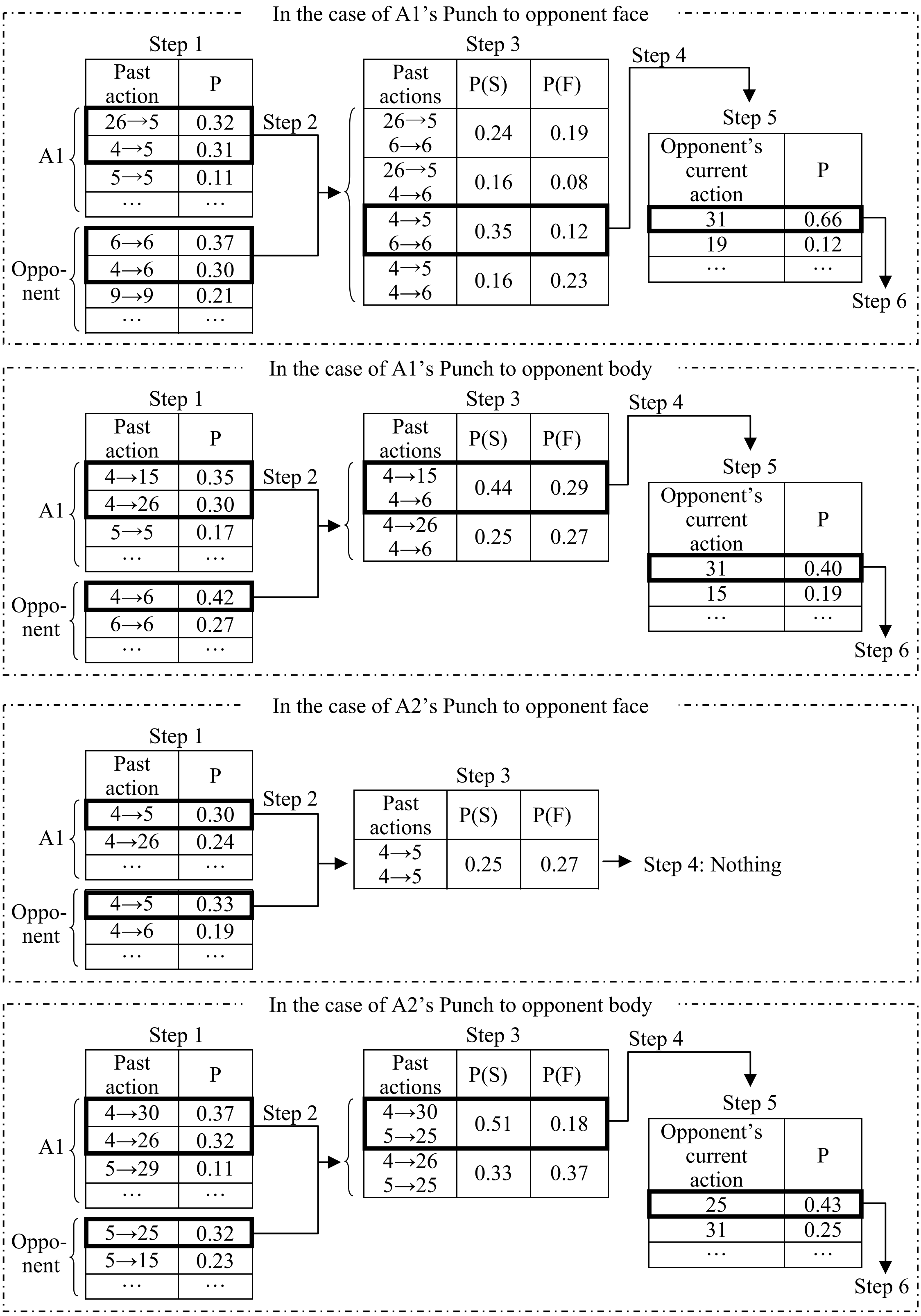
Results

We have analyzed the processes in which the elite competitors succeeded in a punching attack because the competitors had hardly used any kicking techniques. The results for each step of the tactical analysis method, in the case of $N = 2$, are shown in Figure 4. The threshold values for the method (Steps 2, 4, and 6) were set at 0.3. The processes with high likelihood for the elite competitors for the case in which their punching attacks end in success are shown in Table 2.
The obtained processes indicate the specialties of the elite competitors. Each of the processes can be interpreted as follows:

(1) Competitor A1 suddenly steps toward the opponent while the opponent steps forward, and competitor A1 then punches the opponent's face at the same time the opponent rapidly stops stepping forward.

(2) Competitor A1 punches the opponent's face (failure) while the opponent steps forward, and competitor A1 then punches the opponent's body at the same time the opponent rapidly stops stepping forward.

(3) When the opponent tries to kick competitor A2's body after stepping forward, competitor A2 blocks the kick and punches the opponent's body.



P: probability. P(S): Success probability. P(F): Failure probability.

Figure 4. The results for each step of the tactical analysis method for the elite competitors.

Next, we tried to analyze the case of N = 3, but could not obtain any processes with a high likelihood. Finally, we tried to analyze the case in which the current action of competitor B is an offensive action (success), whereby the elite competitors allow their opponents to score. However, no processes with a high likelihood could be obtained.

Table 2. Extracted processes with high likelihood for the elite competitors

(1) Process in which competitor A1 succeeds in punching his/her opponent's face.

Competitor	Extracted Sequence (→ Flow of Time)		
A1	Jumping with No Guard	Forward Step (High-speed)	Punch(1) to Opponent Face (Success)
Opponent	Forward Step (Moderate-speed)	Forward Step (Moderate-speed)	Rapid Stop of Footwork

(2) Process in which competitor A1 succeeds in punching his/her opponent's body.

Competitor	Extracted Sequence (→ Flow of Time)		
A1	Jumping with No Guard	Punch(1) to Opponent Face (Failure)	Punch(2) to Opponent Body (Success)
Opponent	Jumping with No Guard	Forward Step (Moderate-speed)	Rapid Stop of Footwork

(3) Process in which competitor A2 succeeds in punching his/her opponent's body.

Competitor	Extracted Sequence (→ Flow of Time)		
A2	Jumping with No Guard	Blocking Opponent Attack to Body	Punch(1) to Opponent Body (Success)
Opponent	Forward Step (High-speed)	Kick to Opponent Body (Failure)	Kick to Opponent Body (Failure)

Discussion

The extracted processes for competitor A1 indicate that the competitor succeeds in a punching attack when his/her opponent stops stepping forward as a result of rapid footwork or a previous punch. Competitor A1 is good at taking advantage of such opportunities. According to the other extracted process, competitor A2 excels in the execution of punching attacks while blocking his/her opponent's kick. In Japanese martial arts, an old teaching states that "the timing of a successful attack is immediately after the beginning or end of an opponent's movement". The results of the experiment support this teaching.

In the case of N=3, tactical processes could not found because the number of sub-sequences (=1600) for the model training was too few compared with the number of combinations of past action (=31x31x31). To solve this problem, it is necessary to automate the action labeling, which was done by visual observation (see the procedure for collecting action sequences in p. 3), to collect a lot of sub-sequences. Image Recognition technology will support an automatic labelling method.

Next, the result that successful processes with high likelihood for competitor B were not found indicates that elite competitors seldom repeat the same mistake.

We asked a Karate specialist's opinion who knows both competitor A1 and A2 well, and found that the opinion coincides with the results. Therefore, we can safely say that the proposed method has extracted tactical actions correctly. The function of the proposed method is data mining from a database of action sequences.

Conclusions

We have proposed a model using a Bayesian network to understand tactical behavior in Karate matches. The model is a probabilistic causal model consisting of the states of two competitors engaged in combat. Each state node of the model outputs a probability distribution of the occurrence of offensive, defensive, and evaluative actions. Using the model, we have also proposed an analysis method of Karate tactics that can obtain the high likelihood processes for a competitor for the case in which the competitor's offensive action ends in success. The extracted processes indicate competitor's tactical pattern. For an experiment of the method, we collected action data from the videos of Karate matches in which elite competitors had competed, and trained two elite competitor's model. The method has extracted the elite competitors' tactical actions correctly using the trained models.

Acknowledgement

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Modeling the Relationship between Training and Performance - A Comparison of Two Antagonistic Concepts

Mark Pfeiffer

Department of Training and Movement Science, University of Bayreuth

Abstract

Few attempts have been made to apply systems theory to the description of human responses during physical training. Initially, Calvert, Banister, Savage & Bach (1976) proposed describing systems behavior with two antagonistic transfer functions ascribed to fitness as a positive and fatigue as a negative response to physical training. Performance, i.e. system output, was thus the balance between fitness and the fatigue effects calculated by a system of differential equations. This approach has been used in several studies to model the relationship between training and performance, but recently some authors have criticized the FF-Model for its methodical limitations and inconsistent empirical findings. Largely decoupled from this discussion another antagonistic model has been developed by Perl (2002). In order to analyze and optimize physiological adaptation processes, the so-called PerformancePotential-Model (PerPot) helps to simulate the interaction between training load and performance by using a dynamical state-event-model with adaptive delay in effect. To compare these two antagonistic models with regard to some critical considerations two training studies (untrained subjects) on a cycle ergometer were carried out. The results show, that in nine out of fifteen cases, better model fit to real performance data is achieved with PerPot. The prediction of the performance values for the final two weeks of the training experiment were, indeed, on average of higher quality for PerPot. But regarding to the individual cases with the FF-Model, prediction of values succeeds to a smaller middle percentage deviation in eight of the fifteen subjects. Furthermore, in both models a better model-fit and prediction accuracy was achieved by equidistant time interval between the training and testing sessions.

KEYWORDS: MODELING, TRAINING, ANTAGONISTIC TRAINING THEORY

Introduction

The analysis and understanding of training processes, i.e. the effect of training load on sports performance, are of extreme importance to training science and the practice of sport. In its research methodology, training-effect analysis has traditionally oriented itself, like other areas of science such as medicine, biology or psychology, on the prinicple of reductionism (cf. Gerok, 1989, etc). Here individual variables are isolated from the network of interactions, and interacting factors eliminated, as far as possible. Under these conditions, individual variables of a training process can be readily investigated and certain component phenomena scientifically grounded. Insodoing, training effects are typically evaluated using inferential statistical methods and models (eg. pre-post test-design). Increasingly in the recent past, however, it has been shown that deterministic, linear models are inadequate in understanding

and explaining simple biological mechanisms (Gerok, 1989) as well as complex forms of human behaviour (Tschacher & Brunner, 1997, Kriz, 1999). Nevertheless, the classical reductionistic approach to investigating individual component processes under simplified experimental conditions has not become superfluous as a consequence, to the contrary (Hughes & Franks, 2004; Balagué & Torrents, 2005). Indeed, to grasp the structure of the complex system of the training process, it is necessary to understand its essential building blocks. Despite this, deterministic, group statistical models are inappropriate for the understanding of complex training processes, if only because of their large number of various adaptive systems even down to the cellular level (Mester & Perl, 2000).
These problems more or less led to a paradigm shift in the approach to adaptation phenomena as complex dynamical systems and resulted in the abandonment of general, linear, structure-oriented models in favour of individual, non-linear, process-oriented models[1]. At present the most common theoretical approaches to physical adaptation processes in the field of sports are based on an antagonistic understanding of training effects. The basic assumption of an antagonistic concept used to model the interaction between physical training and performance is that the training (input) has two concurrent effects on performance (output) - a positive as well as a negative. Depending on the respective delays in the negative and positive effects, a training impulse can cause positive or negative results in the initial performance. This dynamics principle is "given by interactions of organs or components of an organism, which produce and transport substances with certain delays and so change the organism's state" (Perl, 2005). The two currently most common antagonistic models are the Fitness-Fatigue-Model (FF-Model) and the Performance-Potential-Model (PerPot).

Fitness-Fatigue-Model (FF-Model)

In the middle of the seventies Banister and colleagues suggested a system theory founded model to describe and analyze physical adaptation due to physical training (Banister, Calvert, Savage & Bach, 1975, Calvert et al., 1976). In the so-called Fitness-Fatigue-Model the athlete is viewed as a system with training impulse as the input and performance as the output. The functional relationship between training impulse and the system's response is described by two differential first-order equations ascribed to the antagonistic effects called fitness and fatigue. Thus fitness increased by physical training depicts a positive effect on performance as well as fatigue, which is affected negatively. For a general solution to these equations the convolution product of training impulse and time decay function has to be calculated. The final form of the FF-Model had two exponential functions that comprised fitness on the one hand and fatigue on the other (Calvert et al., 1976). Morton, Fitz-Clarke and Banister (1990) simplified the two-component FF-Model with three exponential functions to a form that had only one fitness and one fatigue function. In a further study Busso, Carasso & Lacour (1991) showed that adding up to four further components was not statistically supported. So in further studies a framework predominated, with two exponential functions which described the training-influenced change over the course of time in fitness ($\Delta g_i(t)$) and fatigue ($\Delta h_i(t)$) (for mathematical details see the "Methods" chapter of this paper). Finally, predicted performance ($p(t)$) was deduced by superposition of the contribution of training units (w) to fitness ($g(t)$) and fatigue ($h(t)$) (figure 1).

[1] The paradigm shift taking place in the understanding of sports performance is discussed by Balagué and Torrents (2005).

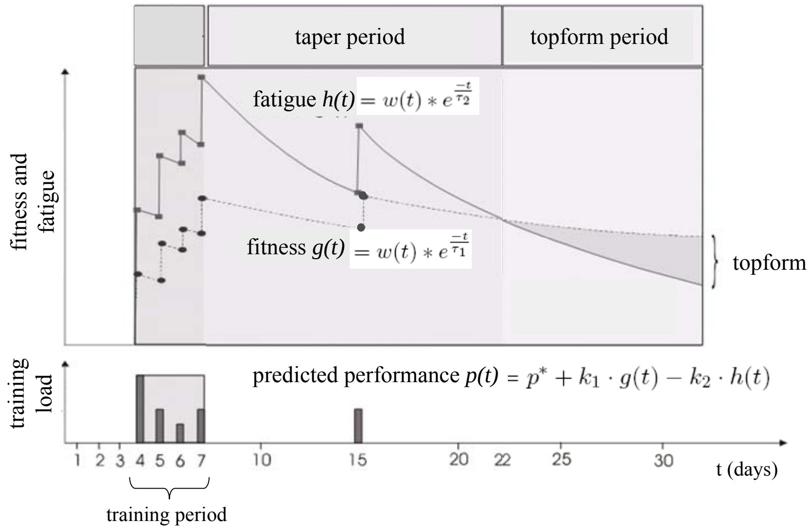

Figure 1. Principle example of the antagonism of the Fitness-Fatigue-Model including equations (reprinted from Banister & Hamilton, 1985).

The constants τ_1 and τ_2 are the decay time constants of fitness and fatigue, however the factors κ_1 and κ_2 weighting the training magnitude to fitness and fatigue expressed in arbitrary units. Whereas the time constants (t) describe the decay in the course of time expressed in days, the magnitude factors (κ) depend on the units used to measure the training load and performance and have no direct physiological basis. The time constants and the magnitude factors have to be determined for the individual through the use of an iterative process repeated for each subject. To obtain the best model-fit parameters, the non-linear least squares iterative method is used, by minimizing the residual sum squares between modelled and actual performance (Hellard, Avalos, Lacoste, Barale, Chatard & Millet, 2006). By calculating individual specific model parameters, the effect of known training response determinants such as past activity, initial fitness and genetic predisposition may be incorporated (Taha & Thomas, 2003).

Busso et al. (1991) investigated whether a better model-fit could be achieved by using a one- or a two-component FF-Model. The values determined by the two-component model were higher without exception than those for the one-component solution, but the result was not statistically significant. Nevertheless the authors conclude that a system model composed of two antagonistic first-order transfer functions will provide a proper representation of the training responses.

Referring to different time parameters reported in further studies Busso, Denis, Bonnefoy, Geyssant and Lacour (1997) infer that this was indicative of changing model parameters throughout the course of the training period causally founded in variable training intensity. As a result, they proposed using a model with time-varying parameters in which a recursive least square method was employed to recalculate the parameters stepwise each time data are collected. In the research presented here, two recreational cyclists were studied during two periods of intensive training (14 weeks). Unsurprisingly, better model-fit was obtained for the time-varying model for both subjects. The authors suggest that variations in model parameters reflect changes in training responsiveness, but restrictively these variations cannot be directly interpreted as modifications in the underlying physiological structures. However the time-varying model can be a useful tool to learn more about the chronological progression of adaptation to physical training (Busso et al., 1997).

The FF-Model has been used time and again to analyse training processes in competitive sports as well as in training studies with recreational athletes or untrained subjects. In several studies, attempts have been made to relate the model components of fitness and fatigue to physiological responses (Banister, Morton & Fitz-Clarke, 1992) (Tab. 1).

Table 1. Overview of existing approaches used the FF-Model.

Reference	*Year*	*Sport*[1]	*N*	*Duration*	*Physiological Parameters*	*Model-fit*²	*Model*
Banister & Hamilton	1985	Distance Running (C)	5 (♀)	43 wks	Iron status variables, Ferritin	-	time-invariant
Banister et al.	1986	Running (C)	? (♂)	52 wks	-	-	time-invariant
		Soccer (C)	1 (♂)	22 wks	VO_{2max}	-	time-invariant
		Swimming (C)	1 (♂)	18 wks	-	-	time-invariant
		Distance Running (C)	5 (♀)	43 wks	Iron status variables	-	time-invariant
Busso et al.	1990	Weight Lifting (C)	6 (♂)	52 wks	Hormones: Testosterone concentration, Cortisol ratio	R^2=.50 - .97	time-invariant
Morton et al.	1990	Running (R)	2 (♂)	4 wks	-	R^2=.71; .96	time-invariant
Busso et.al.	1991	Cycling (U)	8 (♂)	14 wks	-	R^2=.764 - .938	time-invariant
Banister et al.	1992	Running (R)	2 (♂)	4 wks	LDH, CK, AST	R^2=.71; .96	time-invariant
Busso et al.	1992	Weight Lifting (C)	6 (♂)	52 wks	Hormones: Testosterone concentration, Cortisol ratio, LH	R^2=.29-.85	time-invariant
Candau et al.	1992	Cross-Country-Skiing (C)	3 (1♀/2♂)	33 wks	Iron status indices	-	
Busso et.al.	1994	Hammer throw (C)	1 (♂)	37 wks		R^2=.91	time-invariant
Mujika et al.	1996	Swimming (C)	18 (8♀/10♂)	50 wks	-	R^2=.45 - .85	time-invariant
Busso et.al.	1997	Cycling (R)	2 (♂)	14 wks	VO_{2max}	R^2=.879 - .875	time-varying
						R^2=.666 - .682	time-invariant
Banister et al.	1999	Triathlon (C)	11 (♂)	14 wks	VO_{2max}	-	time-invariant
Busso et al.	2002	Cycling (U)	6 (♂)	15 wks	VO_{2max}	R^2=.957 - .982	time-varying
Millet et al.	2002	Triathlon (C)	4 (3♀/1♂)	40 wks	Heart Rate	r=.37 - .74	time-invariant
Busso	2003	Cycling (U)	6 (♂)	15 wks	VO_{2max}	Adj. R^2=.857; .944 (Mean)	time-invariant
Millet et al.	2004	Triathlon (C)	4 (3♀/1♂)	40 wks	Heart Rate,	r=.32; r=.30	time-invariant
Wood et al.	2005	Running (R)	1 (♂)	12 wks	VO_{2max}, VTRS, POMS	R^2=.92	time-invariant
Hellard	2006	Swimming (C)	9 (5♀/4♂)	60 wks	Blood lactate	R^2=.79	time-invariant

[1] C = Competitive (Elite) Sport; R = Recreational Sport; U = Untrained Subjects
[2] R^2 = coefficient of determination; Adj. R^2 = adjusted coefficient of determination; r = correlation coefficient

Recently some authors criticized the FF-Model concerning (1) its inability to predict future performance with accuracy, (2) differences between the estimated time course of change in performance and experimental observations, (3) the ill-conditioning of model parameters and

(4) the model was poorly corroborated by physiological mechanisms (Taha & Thomas, 2003; Hellard et al., 2006).

Performance-Potential-Model (PerPot)

In the recent past another model to investigate adaptive physiologic processes by means of antagonistic dynamics has been developed by Perl (Perl, 2001; Perl, 2002; Perl, 2004). In order to analyze and optimize physiological adaptation processes, the so-called Performance-Potential meta-model (PerPot) helps to simulate the interaction between training load and performance.

The starting point of the new model was the fact that adaptation to physical training is mainly (1) dominated by the individual conditions, (2) an extremely complex process and (3) characterised by diversity of parameters and their interrelation (Mester & Perl, 2000). Starting from these aspects, the primary aim of the research work was to model adaptation phenomena such as super-compensation, collapsing effect and the so-called U-function of protein metabolism (Mader, 1988, 1994). In addition the phenomenon of constant and moderate training leading to performance asymptotically tending to an upper limit was to be be modelled.

PerPot is based on a meta-model, where an output potential (the performance potential) is influenced by input load (training) – itself dynamically controlled by two internal buffer potentials, the strain potential and the response potential. Both potentials are influenced by each training impulse in equal measure and affect performance in an antagonistic way. Whereas the response potential raises the performance potential delayed by a numeric factor (DR), the strain potential reduces the performance potential also delayed by a factor (DS) (figure 2). The effect on performance is basically dependant on the course of time (t). For the mathematical calculation of the model potentials, differential equations are used in discrete steps. This means that the actual potential level results out of the prior potential level and the corresponding flow between the relevant potentials. Contrary to the FF-Model the chronological interval (time scale for Δt) can be chosen freely[2]. Because of an internal normalization of the potentials (values from 0 to 1), PerPot is independent of the scales of load and performance. Also, the time-scale does not play any role because the time units are embedded in the delays. Therefore, PerPot can be used for modelling arbitrary types of load–performance interaction (Perl, 2004).

The basic structure of PerPot was added to by an overflow pathway, which allows modelling of a collapse effect (Perl, 2003; Perl, 2004). That means, if the load integral over a period of time becomes too high, the performance breaks down spontaneously. This collapsing effect, known as the “overtraining” phenomenon, can be described by PerPot because the potential capacities are limited. If in particular the strain potential reaches beyond its upper limit, an overflow is produced, which reduces the performance potential with only small delay (DSO) (figure 2).

[2] the mathematical details are explained in the chapter “Methods” of the present contribution

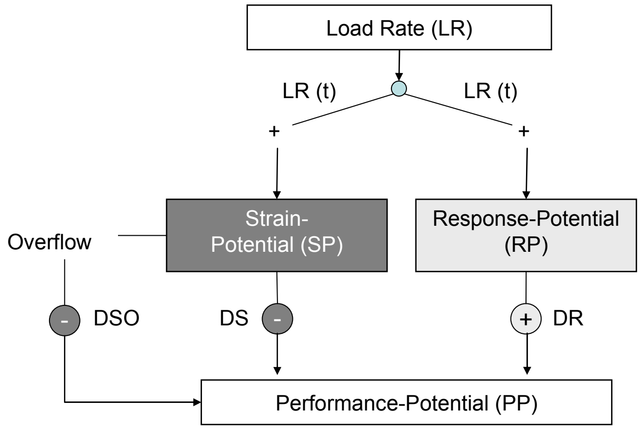

Figure 2. Basic antagonistic structure of the Performance-Potential meta-model (PerPot) containing strain overflow (reprinted from Perl, 2001).

In the manner described for the FF-Model, it is necessary to adapt the PerPot parameters to the individual conditions based on empirical data. The delay values and the capacity parameters of the potentials (maximum and start-capacity) have to be determined using a simulation-based calibration to achieve the best approximation to the real performance data. As a calibration criterion, the method of minimizing the residual sum squares between predicted and actual performance (model-fit) is applied. After an appropriate calibration, the two flow delays, DS and DR, determine the characteristic behaviour of the model and so, like a fingerprint, encode the characteristics of the modelled systems. The manner in which internal potentials control each other in order to take joint control of the input-output-behaviour is reminiscent of several examples of physiological antagonism (Perl, 2004). Upon obtaining good results from the theory based simulation and validation, PerPot was successfully applied to empirical data (Perl & Mester, 2001).

Due to the fact that training in general as well as training intensity changes the physiological status of an athlete, which in turn influences the delay values, PerPot allows the determination of model parameters by two procedures: constant delay values over the whole process (global) or varying delay values step by step in time (local). The latter is comparable to the time-varying FF-Model (see above) and reflects physiological phenomena of training like the improving adaptability of organic components. The change in physiological conditions in long term training prompted the development of a two-level PerPot with changing delay values. The dynamics of these long-term effects can be modelled using two exemplars of PerPot, where the performance output of the internal long-term model modifies the delay values of the external short-term model (Perl, Dauscher & Hawlitzky, 2003).

In previous applications with empirical data, PerPot was mainly used to study the interrelation between running speed and heart rate during a running race (Perl & Endler, 2006), to analyse the dynamic interaction between teams in games (handball) (Perl, 2006) or to get information about the effect of training on protein metabolism (Perl & Mester, 2001). Scientifically and statistically proven studies to validate PerPot with regard to simulating the training-performance relationship are quite rare. In order to compare the FF-Model and PerPot, Ganter, Witte and Edelmann-Nusser (2006) modelled the relationship between training and performance over an eight week cycling training program, with a prediction of the performances - measured in a 30-seconds-all-out test (Wingate-Test) - in the last week (two values). The model-fit obtained for PerPot provides an inconsistent result, with coefficients of determination ranged between r^2=.134 and r^2=.928. In the same way the quality of prediction, measured by the mean relative difference between the predicted and

actual performances of the last week of training, varied between 1.66 and 8.29 percentage (further aspects of this study are described in chapter "discussion").
The aim of the study conducted by Torrents, Balagué, Perl and Schöllhorn (2007) was to observe the differences of a linear tool (cross correlation) and PerPot in analysing the interaction between training and different parameters of strength performance in aerobic gymnastics (two subjects). As for PerPot, the scientific interest was to study the differences in delay characteristics of strain and response by using two kinds of training impulses (quantitative and qualitative). Thus, the approximation quality of the PerPot simulation was only specified in the value of average relative deviation between modelled and real performances (5.06% to 10.62%). The interpretation of and comparison to reported findings of this parameter is rather difficult and can only be done with regard to the semantic background. The average relative deviation has no mathematical limits, so that no general statistical convention exists. The authors fail to discuss the quality of the determined model-fit. Nevertheless, the calculated delay values were interpreted.
Altogether there are hardly any empirical findings - in contrast to the FF-Model – suitable for validating PerPot for modelling short- and long-term training adaptation. Moreover, PerPot has scarcely been recognized in the international community of training science or in sports medicine.

Discussion of the current research

In a review article by Taha and Thomas (2003) the current status of research on systems modelling the relationship between training and performance were discussed with regard to different models stemming from the original Banister FF-Model. The authors criticized the applied models concerning:
(1) Descriptive ability: The ability of the model to describe actual or future performance varies in the different studies, depending on the degree of external influences on the athlete's life, the precise quantification of training load and the changes in model parameters over a longer period of time. Nevertheless, the time-varying model (recalculating model parameters each time data are collected) of Busso et al. (1997) did obtain better results in describing the actual performance than the standard time-invariant model (using only one initial set of model parameters). However, unless it is possible to predict the change of the parameters themselves, this approach makes it impossible to use the model and its parameters to predict the response to future training.
(2) Quantification of training inputs: The existing concepts of quantifying training do not consider the specific effects of training, resulting in equally modelled effects from long, low intensity training sessions and short, high intensity training sessions.
(3) Relationship to underlying structures: Most studies were unable to identify significant relations between calculated fitness and fatigue components of the model and physiological parameters. Observed physiological variables such as resting heart rate or blood volume showed no fatiguing or negative effect with training, while not necessarily reflecting the athletic performance either. Other physiological parameters such as serum testosterone were positively related to both modelled fitness and modelled fatigue.
(4) Several modelling studies with various groups of study participants showed differences between the estimated time course of change in fitness and performance and their experimental observations, especially in response to short-term training.
Hellard et al. (2006) pick up several of these critical aspects and add the problem of ill-conditioning of model parameters. The authors advise carrying out further studies to determine whether the parameter estimation of the FF-Model would be more accurate under standardized experimental conditions. In point of alternative methods, the authors refer to the

PerPot meta model, which "seems conceptually very rich, because it takes into account the collapse effect in the wake of an overload training period, atrophy following a period of detraining, and the long-term behaviour of the training-performance relationship" (Hellard et al., 2006, 519).
The critical overview to investigations using the FF-Model up to now and the rare and inconsistent findings on PerPot prompted us to compare these antagonistic models with regard to (1) model-fit and (2) prognostic accuracy. To this end, two quasi-experimental studies were conducted.

Methods

Experimental methods

Subjects: The participants for two studies included three female and three male, college-aged students, with no known cardiovascular/pulmonary disease, medication or tobacco consumption or other medical contraindications, exercising as determined by self-response. The active but not endurance-trained, subjects volunteered for an endurance training program on a cycle ergometer. Subjects were encouraged not to participate in any other specific training during the study period. The experimental procedure and possible risks of the study were explained to each subject who gave their written informed consent before participation. The studies were conducted in laboratories at the Institute of Sport Sciences of the University of Bayreuth and approved by the Ethics Committee. All subjects were familiarised with the testing procedures by completing three performance tests (see below) one week prior to the commencement of the training experiment.
Training protocol: The protocol involved in Study 1 seven weeks (wks) and in Study 2 ten wks of bicycle ergometer (Cyclus 2, RBM GmbH, Leipzig, Germany) exercise, carried out in Study 1 three times weekly (Monday, Wednesday, Friday) and in Study 2 twice weekly (one and four days rest between training sessions), each session lasting 45 minutes. A previously determined and constant over the whole session (continuous method) resistance load was used. Each of the subjects completed various endurance training programs (TP) at cadences between 70 to 90 revolutions per minute (rpm), which was displayed in full view of the subject. The training load was quantified for each session in watts. Whereas in Study 1 the training and testing period was six wks followed by one wk testing only (once-weekly), in Study 2 this relation was nine wks and one wk (twice-weekly).
TP-A: Training was scheduled progressive-regressive to obtain an adaptation characteristic in the manner of tapering concepts. During the first four wks (Study 1) and six wks respectively (Study 2) workload was progressively boosted from 35% to 50% of power workload (watt) at VO2max[3] (pVO2max) of each subject, followed by two wks regressive reduction (50-30% of pVO2max).
TP-B: In Study 1 the resistance load was freshly determined for each training session at random within the range of 25-50% of pVO2max. The same procedure was used in Study 2, but within a range of 30-50% of pVO2max in wk 1-4 and 40-60% of pVO2max in wk 5-10. This training concept of varying loads was inspired by the differential training concept (Torrents, Ballagué, Perl & Schöllhorn, 2007) theoretically provoking a fluctuating increase in performance.
TP-C: Constant and moderate training (45% of pVO2max) to allow the performance asymptotically to tend to an upper limit.

[3] All values consecutively reported in percentage of VO_{2max} refer to the maximal workload (watt) measured in a maximal aerobic power test (VO_{2max}) until exhaustion with a continuous incremental testing protocol conducted one week before beginning the training experiment.

Performance testing: On each training day performance was tested on a cycle ergometer (Cyclus 2, RBM GmbH, Leipzig, Germany) prior the exercise in an all-out test. The all-out test should be able to be performed, as far as possible, without prolonged damage to physiological structures or functions, and not represent an additional training intervention. In various bicycle ergometer studies, it has been shown that endurance-oriented training additionally leads to a significant improvement in maximal performance output or maximal work performed (Izquierdo, Ibanez, K, Kraemer, Larrion & Gorostiaga, 2004). Moreover, the literature relates a relationship between aerobic and anaerobic performance components. Balmer, Davison and Bird (2000) were able to prove that the peak power output of a short all-out test represents a satisfactory predictor for mean power output of an individual time trial (16.1km). Similar findings are to be found in Baron (2004) and Stapelfeldt, Lohmüller, Schmid, Röcker, Schumacher and Gollhofer (2006).

Procedure: The cycle ergometer was calibrated to the individual conditions before data collection, which included adjusting the saddle height to accommodate partial knee flexion of 170-175° during the down stroke. Afterwards each subject began a 5-minute warm-up phase pedalling at 30% of pVO2max comprising three 8-second sprints at 100% of pVO2max. Closing the warm-up the subjects pedalled against no resistance at 60 rpm for 2 minutes. Following completion of the warm-up the testing procedure started as follows.

Study 1: The subjects completed an 8-s maximal cycling sprint test (isokinetic) limited to 100 rpm (cf. Baron, Bachl, Petschnig, Tschan, Smekal & Pokan, 1999; Baron, 2004; Stapelfeldt et al., 2006). The test was started by pedalling 20 seconds against a resistance of 30N. After a short countdown (tree - two - one - go), the subject maximally accelerate for 9 seconds against an automatically controlled resistance, so that the subject could not exceed the limit of 100 rmp. To minimize any possible effect of a subject's anticipation of the end of the test exercise, the last second was ignored for purposes of performance measurement. Peak Performance (PP), the highest power output (average of 1 second) and Mean Performance (MP), the average power output within the 8 seconds were calculated to quantify the performance.

Study 2: According to Williams, Barnes and Signorile (1988) a 15-s-Wingate-Test was adapted to measure the subject's performance. The starting procedure was as like in study 1 (see above). Subjects were verbally encouraged to maximally accelerate and maintain maximal pedalling velocity for 15 seconds against a preselected load, which was calculated as follows:

$$\text{resistance} = \frac{\text{body mass} \times \text{F} \times 52}{12}$$

where F is a weighting factor of 1,4 N per kg body weight for men and 1,2 N per kg for female. To characterize the temporal changes in performance, the following mechanical parameters were computed: Peak Power (PP), the highest power output value (average of 0,33 seconds); Mean Power (MP), the average power generated during the 15 seconds; Fatigue-Index (FI), the relative decline in power output from peak power to that produced at the end of the test. Williams, Barnes and Signorile (1988) identified a high correlation between PP and MP, while in comparison these mechanical parameters were not correlated with FI.

Table 2 gives an overview of the main experimental information of the conducted studies.

Table 2. Overview of the main methodical variables of both experimental studies

	Study 1	Study 2
Subjects (TP/gender)	3 (A ♂, B ♂, C ♀)	3 (A ♂, B♀, C ♀)
Length of study	6 wk (5 wks training & testing; 1wk testing only)	9 wks (8 wks training and testing; 1 wk testing only)
Training sessions per week	3	2
Training unit (input)	Watt	Watt
Performance Test	8s-All-Out-Test (isokinetic, 100 rpm)	15s-Wingate-Test (Williams, Barnes & Signorile, 1988)
Performance units (output)	• Peak Power (PP) • Mean Power (MP)	• Peak Power (PP), • Mean Power (MP) • Fatigue-Index (FI)

Modeling training effects on performance

The FF-Model and PerPot was used to simulate the training effects on performance data in both studies. Having given a detailed explanation of the fundamental ideas and developments of the two antagonistic models in the introduction above, in the following only the mathematical specifications used in the presented research are explained.

FF-Model: The two-component FF-Model relates to the basic framework by Morton et al. (1990) as described above. The following functional relation between the training load w(t) and an output of the physiological system g(t) and h(t) respectively is assumed:

$$\frac{\partial g(t)}{\partial t} + \frac{1}{\tau_1} \cdot g(t) = w(t)$$
$$\frac{\partial h(t)}{\partial t} + \frac{1}{\tau_2} \cdot h(t) = w(t) \qquad (1)$$

By using the convolution product the differential equations can be solved by the functions of fitness g(t) and fatigue h(t).

$$g(t) = w(t) * e^{\frac{-t}{\tau_1}} = \int_0^t w(t') \cdot e^{\frac{-(t-t')}{\tau_1}} dt'$$
$$h(t) = w(t) * e^{\frac{-t}{\tau_2}} = \int_0^t w(t') \cdot e^{\frac{-(t-t')}{\tau_2}} dt' \qquad (2)$$

Hence, the FF-Model is re-oriented daily, for which the following discretization holds.

$$g(n) = \sum_{i=1}^{n-1} w(i) \cdot e^{\frac{-(n-i)}{\tau_1}}$$
$$h(n) = \sum_{i=1}^{n-1} w(i) \cdot e^{\frac{-(n-i)}{\tau_2}} \qquad (3)$$

For the time continuous performance-output an antagonistic of fitness and fatigue is proposed. Furthermore it assumes an initial value p* of performance.

$$p(t) = p^* + k_1 \cdot g(t) - k_2 \cdot h(t) \qquad (4)$$

Thus, the discretizised model provides:

$$p(n) = p^* + k_1 \cdot \sum_{i=1}^{n-1} w(i) \cdot e^{\frac{-(n-i)}{\tau_1}} - k_2 \cdot \sum_{i=1}^{n-1} w(i) \cdot e^{\frac{-(n-i)}{\tau_2}} \tag{5}$$

The set of model parameters (τ1, τ2, κ1 and κ2) was determined by minimizing residual sum squares (RSS) between predicted and real performances. Computations were completed using MatLab 2008 (version R2008a, The MathWorks™).

PerPot: The subsequent formal description refers to the basic PerPot version drafted in figure 2 with the following definition of variables and parameters (Perl, 2001).

LR	(external) Load Rate
SP, *RP*, *PP*	Strain, Response and Performance Potential
SR, *RR*, *OR*	Strain, Response and Overflow Rate
DS, *DR*, *DSO*	Delay of Strain Rate, Response Rate and Strain Overflow Rate

The main equations of the complete PerPot meta-model are as follows, where all upper limits (i.e. potential capacities) are normalised to "1" and all lower limits are normalised to "0":

Raising Potentials *SP* and *RP*

$$\begin{aligned} SP &:= SP + LR \\ RP &:= RP + LR \end{aligned} \tag{6}$$

Computing rates

$$\begin{aligned} SR &:= \frac{min(min(1, SP), max(0, PP))}{DS} \\ RR &:= \frac{min(min(1, RP), min(1, 1 - PP))}{DR} \\ OR &:= \frac{max(0, SP - 1)}{DSO} \end{aligned} \tag{7}$$

Updating potentials *SP*, *RP* and *PP*

$$\begin{aligned} SP &:= SP - SR - OR \\ RP &:= RP - RR \\ PP &:= PP + RR - SR - OR \end{aligned} \tag{8}$$

The PerPot model parameters (starting capacity of SP and RP as well as DS, DR, DSO) were estimated from the pool of real performances by minimizing residual sum squares (RSS) between predicted and real performances. In the present analysis the PerPot software version 10-4 was used. For both studies, a time scale of approximately equidistant intervals of 1 or 2 days between the sessions (training and testing) was chosen.

Statistical analysis

The statistical parameter mostly used to determine the model-fit is the “Coefficient of Determination” (R^2) as described above. The problem is that there is no consensus on the exact definition of R^2. Only in the case of linear regression - were R^2 is simply the square of a correlation coefficient - are all definitions equivalent. By reason that in most contributions no detailed explanation of the applied equations can be found and the coefficient of correlation comprised no information about the level of the analysed variables, we determined two different values to test the models´ validity.

The mean relative deviation (rel.dev.) between the modelled and actual performances (PP, MP and FI) gives practical information about how accurately and close to the real data the model is able to describe the value series. Complementary to this, the Intraclass Correlation Coefficient (ICC; one-way random, single measure) was calculated to test the basal course.
Based on the individual model parameters and the real training loads, the performances of the last two weeks (one wk training and testing, one wk testing only) were estimated by extrapolation. The quality of the prediction was determined by the relative deviation (rel.dev.) between predicted and real performances.

Results

First it had to be determined, to what extent the two studies succeeded in provoking development in mechanical performance output, conforming to the theory, with their varying endurance-oriented training programmes. With Study 1, it can be shown that with TP-A (M1), after an initial improvement in performance, a progressive increase in intensity led to a reduction in performance. In the regressive training phase, and especially one week after the end of training, a gain in performance beyond the starting level could be observed (Fig.3, upper diagram). For subject M2 (TP-B), a clear though irregular gain in performance in the period of study was shown as predicted (see above). Subject F1 (TP-C) was able to improve her performance over the first 12 days, and plateaued at this level for the remainder of the programme. The collapse in performance on day 38 can be attributed to minor health complaints, which were reported by the subject in advance of the test (Fig.3, upper diagram).
In Study 2 for subject M3 (TP-A) a similar picture to that of M1 (TP-A) developed with regard to the progress of PP and MP (Fig.4, upper diagram). Contradicting this is the curve of the Fatigue-Index (FI) (Fig.4, lower diagram, top). The theoretically assumed progress for the TP-B of subject F2 can only be observed for the MP. In contrast, the TP-C of subject F3 leads in FI to a predicted continual increase in performance up to a limit value (Fig.4, lower diagram, top).

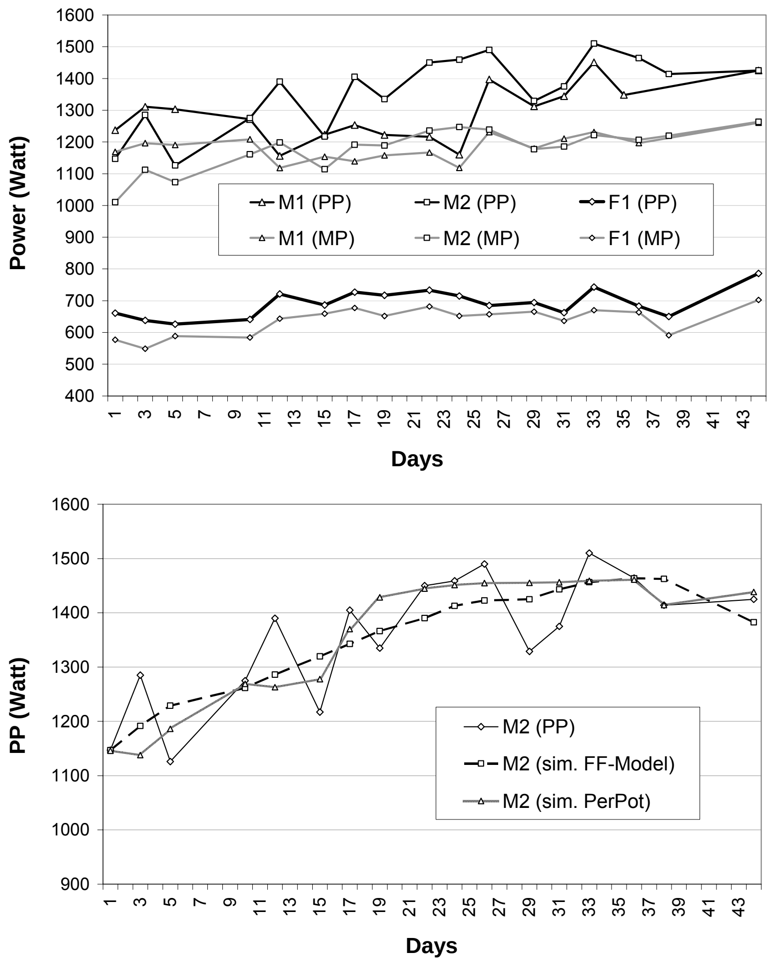

Figure 3. Progression of performances of the mechanical parameters Peak Performance (PP) and Mean Performance (MP) of all subjects of Study 1 (left); comparison to demonstrate the differences in dynamic between the FF-Model and PerPot simulation using subject M2 as example.

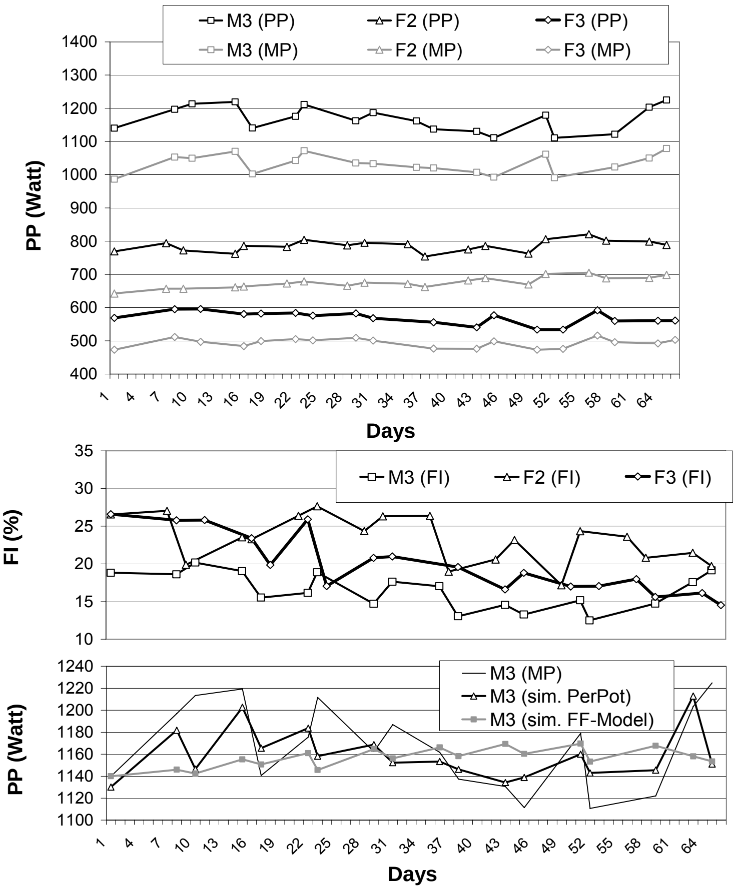

Figure 4. Progression of performances of the mechanical parameters Peak Performance (PP), Mean Performance (MP) and Fatigue-Index (FI) of all subjects of Study 2 (left and right top); comparison to demonstrate the differences in dynamic between the FF-Model and PerPot simulation using subject M3 as example (below bottom).

With the two antagonistic models, the real performance values can be simulated on average to a mean relative deviation of 2.78% (FF-Model) and 2.48% (PerPot) respectively (Table 2). The differences between the two studies (FF-Model 3.52% and 2.04%, and PerPot 2.9% and 1.98% respectively) can be explained by the lesser dynamics in performance progression in Study 2. The twice-weekly training led to a lesser performance adaptation. Model fit is evident to varying degrees according to the study, subject and training programme. Whereas in Study 1, satisfactory model fit could be achieved for both models, with r_{ICC} values exceeding .60 (with one exception), this was not achieved in Study 2, except for the parameters with performance adaptation conforming to theory, as described above (Table 2).
A comparison of the two models shows that in nine out of fifteen cases, better model fit to real performance data is achieved with PerPot, which can be attributed to the more adaptive internal model dynamics of that model (see Fig.3, lower diagram and Fig.4, lower diagram, bottom). The prediction of the performance values for the final two weeks of the training experiment were, indeed, on average of higher quality for PerPot, i.e. showing smaller deviation from the original values. However, it also became evident here, that measured against rel.dev., a satisfactory prediction could only be achieved with sufficient model fit (r_{ICC}). As demonstrated by the individual values, the simulated values in the week without training deviate clearly from the original values, especially with PerPot. With the FF-Model, prediction of values succeeds to a smaller middle percentage deviation in eight of the fifteen subjects.

Table 2. Model parameters for the test data of all subjects of both studies (rel.dev.: mean relative deviation between the modeled and actual performances; r_{ICC}: Intraclass Correlation Coefficient; τ_1 and τ_2: decay time constants of fitness and fatigue; κ_1 and κ_2: magnitude factors of fitness and fatigue; DS and DR: delay values of strain and response; Pred.: relative differences between the performances of the last two weeks (one wk training and testing, one wk testing only).

Study 1		**FF-Model**								**PerPot**					
Subj. (TP)	Perf.	rel. dev.	r_{ICC}	τ_1	τ_2	κ_1	κ_2	κ_1/κ_2 ratio	Pred.	rel. dev.	r_{ICC}	DS	DR	DS/ DR	Pred.
M1	PP	3,90	.642	45,2	11,3	0,242	0,372	0,65	3,12	3,36	.770	6,8	6,3	1,08	4,33
(A)	MP	2,12	.603	31,0	11,2	0,166	0,269	0,62	1,62	2,11	.360	1,5	1,5	1,00	4,16
M2	PP	4,36	.804	10,0	6,0	0,150	0,130	1,15	3,32	3,78	.824	3,0	2,5	1,20	3,50
(B)	MP	3,04	.803	9,0	4,0	0,090	0,070	1,29	7,06	2,31	.848	2,4	1,9	1,26	2,03
F1	PP	3,99	.560	9,0	5,0	0,834	1,291	0,65	8,14	3,72	.600	2,0	2,0	1,00	3,08
(C)	MP	3,70	.688	6,0	3,5	1,286	1,780	0,72	8,43	2,66	.793	2,5	2,0	1,25	4,12
	Mean	*3,52*	*.715**	*18,4*	*6,8*	*0,461*	*0,652*	*0,85*	*5,28*	*2,99*	*.730**	*3,0*	*2,7*	*1,13*	*3,54*
Study 2															
M3	PP	3,00	-.160	4,0	3,0	0,090	0,110	0,82	11,65	2,08	.491	1,6	1,1	1,45	2,69
(A)	MP	2,82	-.085	5,0	4,0	0,170	0,190	0,89	12,35	1,85	.511	1,9	1,2	1,58	2,79
	FI	1,54	.653	10,0	1,0	0,000	0,000	1,29	3,84	1,43	.798	2,0	2,0	1,00	4,20
F2	PP	1,42	.445	13,0	13,0	0,092	0,033	2,82	5,47	1,55	.219	4,3	3,7	1,16	11,03
(B)	MP	1,06	.921	29,0	27,0	0,070	0,008	8,95	3,00	1,28	.714	4,3	3,8	1,13	5,00
	FI	2,68	.610	41,0	41,0	0,000	0,000	2,78	6,21	2,83	.382	2,0	2,0	1,00	3,97
F3	PP	2,12	.545	10,7	20,8	0,476	0,275	1,73	3,56	2,36	.257	2,5	1,1	2,27	3,72
(C)	MP	2,00	.354	9,6	22,7	0,320	0,092	3,46	3,26	1,89	.490	3,3	2,8	1,18	2,44
	FI	1,67	.894	45,0	1,0	0,000	0,00	0,27	0,99	2,52	.748	2,0	1,5	1,33	6,35
	Mean	*2,04*	*.600**	*18,6*	*14,8*	*0,135*	*0,079*	*2,50*	*5,59*	*1,98*	*.550**	*2,7*	*2,1*	*1,35*	*4,69*
Total	Mean	**2,78**		**18,5**	**10,8**			**1,67**	**5,44**	**2,48**		**2,8**	**2,4**	**1,24**	**4,11**

* Before calculating the average correlation coefficients the values were transformed into Fishers Z-Values (Bortz & Döring, 1995).

The model parameters (τ_1, τ_2, κ_1, κ_2, DS and DR) display a broad distribution in both studies, meaning a physiological interpretation of the parameters is only possible to a limited degree (Table 2).

A further evaluatory step investigated whether the criticism of ill-conditioning made by Hellard et al. (2006) applied to our data. To this end the determined model parameters were correlated to one another (Table 3).

Table 3. Correlation between estimated model parameters.

Model parameter	**N**	**Model**	**Correlation coefficient**
τ_1 - τ_2	15	FF-Model	.388
τ_1 - κ_1	15	FF-Model	-.362
τ_1 - κ_2	15	FF-Model	-.274
τ_1 - κ_1/κ_2	15	FF-Model	.091
τ_2 - κ_1	15	FF-Model	-.185
τ_2 - κ_2	15	FF-Model	-.278
τ_2 - κ_1/κ_2	15	FF-Model	.633*
κ_1 - κ_2	15	FF-Model	.964**
DR - DS	15	PerPot	.967**
DR - DS/DR	15	PerPot	-.400
DS - DS/DR	15	PerPot	-.161

The only significant relationships arising for the FF model were between the two magnitude factors of fitness and fatigue, as well as the decay time constant for fatigue (τ_2) and the magnitude factors ratio (Table 3). In PerPot, there was statistical interdependence between the two flow delays DS and DR.

Discussion

FF-Model

Comparing the parameters determined by the FF model with the details of previous studies, the large distribution of the decay time constants (τ_1, τ_2) as well as that of the magnitude factors (κ_1, κ_2) is immediately obvious. Busso et al. (1991) reports τ_1 values for eight untrained men of between 5 and 30 days (mean = 38; SD = 9) and τ_2 values of 1 to 5 days (mean = 1.9; SD = 1.5). Reviewing all the previous experiences with the FF model, one finds values, with τ_1 = 38 - 60 and τ_2 = 4 - 15 (Taha & Thomas, 2003). In reference to this critical overview Hellard et al. (2006) were interested in (1) assessing the appropriateness of fit, (2) the accuracy of the model, (3) ill-conditioning and (4) the stability of the Banister model. Over and above that, a review and suggestion of alternative methods to model the training-performance relationship is given. They conclude that the FF-Model showed substantial variability in the determined parameters (decay time constants, magnitude factors and time to peak performance after the end of the training period), making it imprecise. Furthermore, fitness decay time constants up to 65 days (range = 13 - 65; mean = 38; SD = 16) do not confirm training experience and are undesirable from a practical point of view. Nevertheless, it could be demonstrated that “the variability in modelled performances was reasonably small and the Banister model was stable” (Hellard et al., 2006, 519). So the disappointing results could be ascribed to the improper parameters used to indicate training strain and performance.

The here presented values for τ_1 (range = 4 - 45.2; mean = 18.5; SD = 15.2) and τ_2 (range = 3 - 41; mean = 10.8; SD = 11.5) deviate considerably from those previously published. Especially in comparison to Busso et al. (1991), where endurance training in untrained subjects was also investigated, we arrive at considerably larger τ_2 values. The broad spread, even within similar performance levels among the subjects and under similar training methods (eg. endurance training), lead to the assumption that the delay parameters are intrinsically dependent on study design and on the quantification of the training as well as that of performance. In summary, it must be supposed that the original physiological interpretation of the decay time constants, with a range of up to 39 days for τ_1 and 38 days for τ_2 must be judged critically (Taha & Thomas, 203; Hellard et al., 2006).

As already detailed in the introduction, the absolute values for the factors κ_1 and κ_2 are exclusively dependent on training load unit, and do not admit any other physiological interpretation. Only the relationship of both values to one another, the κ_1/κ_2 ratio, can be compared to other studies (Busso et al, 1997). In a study of elite swimmers by Mujika, Busso, Lacoste, Barale, Geyssant and Chatard (1996), the κ_1/κ_2 ratio ranged from 0 to 13.34, while Ganter et al. (2006) derived significantly lower values between 0 and 2.43 in a bicycle study with untrained subjects. The findings made here, as well as the data referred to in the literature, point to an enormous distribution of the κ_1/κ_2 ratio parameter. The ratio of 1(κ_1) to 2 (κ_2) propagated in earlier work can thus not be assumed in general (Morton et al., 1990; Fitz-Clarke et al., 1991).

PerPot

For the parameters of PerPot, comparable data is only available from the field of weight training (gymnastics) (Torrents et al., 2006) and endurance training (cycling) (Ganter et al., 2006). By means of multiplying the delay values DS and DR by factor 3, as well as a subsequent adaptation to the chosen time-scale, the decay time of the positive and negative training effect for PerPot can be expressed in days, analagous to the parameters τ_1 and τ_2 in the FF-Model. According to this, temporal delay values for DS resulted of between 10 and 47 days (mean = 16.9; SD = 9.8) and for DR of between 8 and 44 days (mean = 19.9; SD = 9.6). While Ganter et al. (2006) came up with similar values, which because of identical time scales are directly comparable, in Torrents et al. (2007) (weekly performance measurement), DR values lay above those of DS, ie. while the negative influence decays in comparison to the positive during endurance training with untrained subjects, in weight-lifting with female gymnasts of national standard, the opposite effect is in evidence.

Comparison of FF-Model and PerPot

Although the FF-Model (mathematics) and PerPot (informatics) differ intrinsically in their model structures, both claim to represent the interaction between training and performance. Moreover, in both models a time-delayed, positive and negative influence of training on performance (antagonistic concept) is pre-supposed. Hence, the two models can be compared in terms of their model fit, ie. how well they can be aligned to actual data, and of their prognostic accuracy. Furthermore, the temporal delay in the decay of the positive and negative training effect can be represented in days in both models, meaning the temporal parameters are also formally comparable. Interpretation, nonetheless, requires reference to the respective model structure.

In the comparative study by Ganter, Witte & Edelmann-Nusser (2006) both, the FF-Model and PerPot were used to model the performance responses to training in cycling. The coefficients of determination ranged between r^2=.000 and r^2=.833 for the FF-Model and r^2=.134 and r^2=.928 for the PerPot, but the differences were not statistical tested. For the majority of the subjects at least one of the constants of the FF-Model is equal to the upper or lower limit used according to Busso et al. (1997). Hence, the interpretation of the model parameter values is questionable. Even though the FF-Model offers a higher quality of prediction on average, it is assumed that the FF-Model "will not be preferred" because of the inexplicable values of the decay time (Ganter, Witte & Edelmann-Nusser (2006, 59). Also the general applicability of PerPot can not be supported by the authors. The dissatisfying results are due to unstable performance levels of the athletes, a too short training period and the variability in the measured performance. Another reason for the inconsistent findings could be assumed in the research method (field study), or more precisely in the uncontrolled training on personal bicycles on the road (field study). Furthermore results in the 30-seconds-all-out test are largely determined by the motivation of the subjects, particularly in light of the three testing sessions per week.

Comparing the two models in regard to the results of our studies, it becomes clear that a better model fit as well as the average of prediction accuracy was able to be achieved with PerPot. But with the FF-Model, prediction of values succeeds to a smaller middle percentage deviation in eight of the fifteen subjects.

Comparing the time constants (τ_1, τ_2 and DS, DR) determined by the two models, the inverse relationship of the value pairs becomes obvious. While in the FF-Model the negative influence decas more quickly than the positive, PerPot produces the opposite relationship. It is necessary, however, to consider the strengthening factors κ_1 and κ_2 in the FF-Model, whose relationship indirectly influences the temporal effect delay. In seven of eleven cases

with $\tau_1 > \tau_2$, κ_2 was also $> \kappa_1$. The results indicate that time parameters merely represent inner-model factors, and that any interpretation with regard to phsiological mechanisms is misplaced given the current state of understanding.
Finally, the ill-conditioning problem, which means any model parameters were highly correlated, has to be discussed. Our findings were not in line with Hellard et al. (2006), who estimated high correlations within the two decay time constants (τ_1 - τ_2 = .99 ± .01) and the two magnitude factors (κ_1 - κ_2 = .91 ± .13) just as between these parameters (κ_1 - τ_1 = .69 ± .26; κ_1 - τ_2 = .69 ± .26; κ_2 - τ_1 = .75 ± .30; κ_2 - τ_2 = .76 ± .27;). In the present research only the magnitude factors of fitness (κ_1) and fatigue (κ_2) were excessively highly correlated, what however is caused in the mathematical framework of the FF-Model. That applies to the high correlation of the PerPot parameters DS and DR.
Comparing the results of the two studies regarding to the used research method and design, it could be assesses, that endurance training of 45 minutes twice weekly is not enough to provoke sufficient changes in performances over a period of eight weeks. Furthermore, in both models a better model-fit and prediction accuracy was achieved by equidistant time interval between the training and testing sessions as arranged in Study 1. On the other hand the 15-s-Wingate-Test in Study 2 offers a more differentiated analysis of the progression of anaerobic power output. On the basis of two none correlated performance factors (PP/MP and FI) individual differences in the adaptation characteristic founded in different training programs could be measured and simulated.

Conclusion

The aim of the two studies was to compare the FF-Model and the PerPot regarding to model the relationship between training and performance. In detail the model-fit and the accuracy to predict future performances were analysed. Both models showed substantial variability in the estimated model parameters, so that a physiological interpretation of theses parameters is critical. Further research should be conducted to determine substantial differences between both models in the quality of modelling the effect of training on performance. Therefore long term studies with standardized conditions have to be carried out.

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Application of Service Oriented Software Architectures in Sports: Team Training Optimization in Cycling

Thomas Jaitner, Marcus Trapp

University of Kaiserslautern

Abstract

Advances in information technologies and microelectronics provide a huge potential for performance monitoring and feedback training in sports. The high dynamics of innovations on one hand as well as constitutional or situational changes of constellations and objectives in many sports disciplines on the other support the notion of more flexible and adaptive systems. In this paper a software approach based on a service oriented architecture is presented that supports dynamic integration of heterogeneous devices in a sports-specific environment. A first application has been established to improve team training in cycling. The objective of the team cycling training system (TCTS) is to improve the training of a whole group of cyclists in a way that each cyclist should meet his predefined exercise intensity as close as possible.

KEYWORDS: SOFTWARE ENGINEERING, ADAPTIVE SOFTWARE ARCHITECTURE, FEEDBACK, ENDURANCE

Introduction

During the last decade, information technologies have gained particular importance for the control of training and the development of performance in elite sports (Liebermann et al., 2002). Miniature sensors and microcomputers embedded in the sports equipment or attached at the athletes allow the acquisition of performance related data of with high accuracy and without any interference on the movement execution. Small devices such as PDAs, UMPC and smartphones can be used to provide real-time feedback. Hence, athletes are enabled to adapt their training load accurately to their actual physical disposition during training and competition. Additionally, wireless transmission of status data and visualization to the trainer support external intervention if a non optimal performance can be observed.

Typically, feedback systems in sports are tailored solutions for a narrow and explicit defined range of application (e.g. Smith & Loschner, 2002; Baca, 2003; Baca & Kornfeind, 2006; Wagner, 2006). Therefore, a limited set of sensors are integrated in a specific software application. Major advantages of such a proceeding are an optimal fitting for a specified demand of a sports discipline or even of an individual athlete as well as technical aspects as optimal exploitation of memory, low energy consumption and reliable data transmission. On the other hand, any changes of the systems such as the integration of different sensors, altering specifications or modes of information (e.g. acoustic instead of visual feedback) require more or less massive modifications of the basic structure of the system. However, if technical aspects such as power consumption, processing power or memory requirements are not limiting factors more flexible, adaptive systems offer a wide range of application. In general, these systems provide simple integration of different sensors and devices and adapt automatically to altering specifications.

Dynamically changing conditions and objectives are inherite characteristics of biological systems as well as in sports. As example, athletes on advancing level of performance may achieve greater benefit from feedback information of different kind and quality. Individual skills and abilities of different subjects may result in varying demands on feedback training and performance monitoring. Moreover, a change-over between diverse activities is a constitutive component of sports disciplines such as Biathlon and Triathlon. Biathletes perform alternating sequences of skiing and shooting, whereas triathletes consecutively compete in three different events. Quite often, such transitions are accompanied by a change of sports equipment. Whereas for the first examples information technologies can be adapted without pressure of time before the training or competition starts, fluent transitions between events require the integration new sensors in runtime. As example, during the transition from cycling to running in Triathlon, sensor data from the bicycle are not further available and sensors attached at the running shoes must be implemented at once.

Particularly in team events, constellations may occur that are not clearly determined in advance or even emerge spontaneously. As example, road cyclists join together to breakaway from the field. Cycling groups in Triathlon are formed depending on the swimming performance. Cyclists even train in groups with a varying number of participants, especially for long lasting training sessions (Gregor & Conconi, 2000). For cycling training, technological system help the cyclists to maintain their predefined exercise intensity, or to change regularly the formation of the group. Therefore, a contribution to an ideal development of performance as well as for the prevention of overtraining can be expected. But even in a competitive situation, technological support that aims on performance optimization of the whole group would pay off for the individual, as example by keeping other cyclists on distance or getting an ideal position for the running event in Triathlon.

Existing commercial solutions as the Ergomo™ or SRM™-system focus on the performance of the single athlete. Hence, benefits for team training can be obtained only indirectly based on subjective interpretation of individual status data, e.g. when the leading cyclist changes to a subsequent position in the slipstream if his heart rate exceeds a certain limit. Meanwhile, a few approaches exist that consider team training as a complex system in which the performance of all cyclists at any time depending on their position within the group as well as the formation of the group should be considered (Le et al., 2008a; Le et al., 2008b; Fliege et al., 2006; Jaitner et al., 2006). From a computer and software engineering point of view team training optimization im-poses two major challenges:

1. Cyclists with different sets of sensors (e.g. heart rate, cadence, velocity or power sensors) or measure devices from different manufacturers (SRM™, Polar™ etc) should be integrated within one system. Additionally, sensors and devices might also differ in kind and quality of service.
2. Teams will consist of a varying number of participants. This includes two aspects. First, teams are initially established by several cyclists. Secondly, subjects might join or leave the team during runtime. Group splitting, as example, can occur dur-ing training due to fatigue reasons.

In this paper we present a software approach that supports dynamic integration of heterogeneous devices in a sports-specific environment. The software architecture described in the following is based on the principles of service oriented architectures (Krafzig et al., 2004). As first application, team cycling training system (TCTS) has been established. The objective of the TCTS is to improve the training of a whole group of cyclist in a way that each cyclist should meet his predefined exercise intensity as close as possible.

Principles of Service Oriented Architectures

Service oriented architectures (SOA) consist basically of a collection of services that communicate with each other. An automatic orchestration of all services offered by the participant components provides a high flexibility and adaptability during runtime (Erl, 2006, Bartelt et al., 2005). Components may be hardware components (sensors, e.g.) as well as software components (training algorithms, e.g.). Thus, a service may simply deliver sensor values or perform complex computing routines as the calculation of training parameters. Each component offers at least one service but may offer a large number of services. To be able to offer a service, a component may need several other services offered by different components.

Each service is identified by its software interface only. An interface describes what kind of service it represents and how to use this service. Thus, it is not necessary to know the exact type or vendor of a specific service to use it. This allows a flexible usage of several hardware configurations.

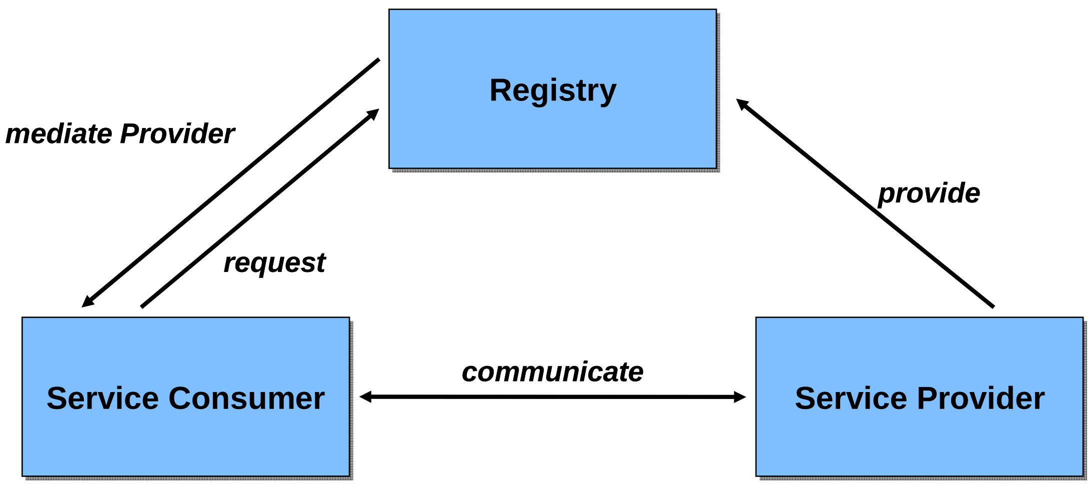

Figure 1: Structure diagram of a service oriented architecture

A configuration service or registry manages and orchestrates all services within the system automatically (fig. 1). The extent of this automation depends on the implementation of the service oriented architecture (e.g. web services, CORBA, JINI, DaiSY, OSGi). Every component registers services it offers and services it needs at the configuration service. As soon as a service consumer requires a service offered by a service provider, the registry automatically connects the services accordingly. These services then communicate directly without further support of the registry. Additionally, components can use several services with the same interface in parallel.

Services can differ not only in type (e.g. delivery of specific sensor data) but also in quality (e.g. sampling rate). Accordingly, a service consumer can request the best service available. The Configuration Service determines automatically the best set of services (if there are several services with the same interface) and connects them. As example, a consumer service may initially use a service of low quality. As soon as a service of higher quality is available, the configuration service arranges the change to the new service to improve the quality of the system. Different configuration sets allow the components, and thus the system, to be more flexible. For example a training control algorithm component could offer a very simple control based on a basic set with only the pulse sensor as needed service and the more advanced control set, containing the power sensor as well as a needed service. This enables a flexible configuration at runtime since the configuration service checks for better configurations and notifies the application if applicable. Therefore it is possible to change the configuration (for example, introducing a new sensor) without changing the software or restarting the system.

Team Cycling Training System

Basic Considerations

Determining the optimal exercise intensity is a crucial factor in cycling to improve performance. Low intensities will not result in the desired training effect, but too high intensities may cause overtraining or illness (Kuipers & Keizer, 1988). Typically, biomechanical parameters such as power, cadence and speed are used to quantify the external load. Among these parameters, the power exerted on the pedal can be considered as a direct and objective indicator of the external load (Coyle et al., 1991; MacIntosh et al., 2000; Stapelfeldt et al., 2007; Stapelfeldt et al., 2006). To estimate the internal load or physical stress that results from an external load the heart rate is the widely chosen parameter, especially under conditions of training (Achten & Jeukendrup, 2003; Faria et al., 2005; Gilman, 1996). The heart rate is subject to considerable fluctuations that might be caused by external conditions (temperature, height, e.g.), physical abilities and dispositions (fatigue, nutrition, health, e.g.) or technical skills (seating position, e.g.) (Gregor & Conconi, 2000; Jeukendrup & Van Diemen, 1998; Jeukendrup & Van Diemen, 1998; Too, 1990). Further, a cardiovascular drift of up to 15 beats per minute has been observed during long lasting aerobic exercises with constant load (Mognoni et al., 1990). However, the study of Lucía et al., 2000) has confirmed that the values of the target heart rate generally remain stable in professional cyclists during the course of the season.

Besides the physiological and biomechanical measures subjective sensations are considered as a reliable and highly relevant indicator for the determination of the appropriate exercise intensity (Gregor & Conconi, 2000). Over years of training, athletes (as well as trainers) on a high level of expertise have developed a distinct perception of one's own body (or the body of athletes they are responsible for, respectively). Therefore, they are able to regulate the physical stress according to their actual physical disposition or state by adapting the external load in an optimal way. To develop this perception skills in young and less experienced athletes it the application of self evaluation techniques during training seems promising. However, subject's sensations are not monitored by powermeters or other technological systems in cycling up to now. A well known and easy-to-use method for the evaluation of physical exertion is the RPE scale (Borg, 1998), which consist of a rating scale that is also applicable for exercise and training.

In typical group training, cyclists ride in a single or double row, covering a distance of up to 200km. For best training effects, each cyclist should ride with an individual exercise intensity that depends on various factors such as physical capabilities and skills of the cyclist, bike aerodynamics, road surface and incline, head wind and temperature (Atkinson et al., 2003; Too, 1990). Due to the headwind effect the leading cyclist must exert greater power to maintain the same speed as subsequent cyclists. Draft effects can reduce the energy expendure up to 40% (Neumann, 2000). In consequence, a cyclist being pulled by the leader may achieve the adequate speed, but cardiocirculatory and metabolic effort will be lower. To improve team training the cyclists might regularly change positions, adjust the speed of the whole group or arrange their positions according to individual differences in exercise intensities (Lindner, 2005; Schmidt, 2001).

Based on these considerations the objectives of the TCTS can be specified:

1. The TCTS should improve the training of the single athlete considering physiological and biomechanical data as well as subjective sensations
2. Team training should be improved in a way that each cyclist is as close to his individual predetermined exercise intensity as possible.

Software architecture

A service oriented architecture implemented on an OSGi platform forms the basis of the TCTS. Each service provided by the system components can be assigned to one of the following categories (Bartelt et al., 2005):

- Technical services provide application independent basic middleware functionality, e.g. lookup service for registering and discovering other services or a security service.
- Functional input services collect data from the environment (e.g. heart rate) and make them available for further processing.
- Functional output services pass data to the user, like a device for a visual or acoustic output of the heart rate.
- Functional application services use input and output services and realize morecomplex applications, e.g. a trainings control algorithm.

These services are offered by hardware and software components each bicycle (or cyclist) must provide. Essential components of the TCTS are a graphical user interface (GUI), a single training component, a group training component and a set of senors (e.g. pulse belt, power sensor). Except for the group training component, all components must be present on each bicycle.

The principal functioning of the TCTS is shown exemplarily in Figures 2 to 5. Here, components are coloured blue whereas the yellow bars indicate the services offered by the components. Communication between two services is illustrated by a connecting line. The minimum set of sensors consists of a pulse sensor and a power sensor. As soon as heart rate and power values are provided, single training can start (fig. 2). If thecyclists installs a more sophisticated meausure device (e.g. Ergomo™ or SRM™ system), additionally sensor data such as cadence can be derived and the TCTS switches automatically without any intervention by the user to a more complex configuration that provides a higher quality of service (fig. 3).

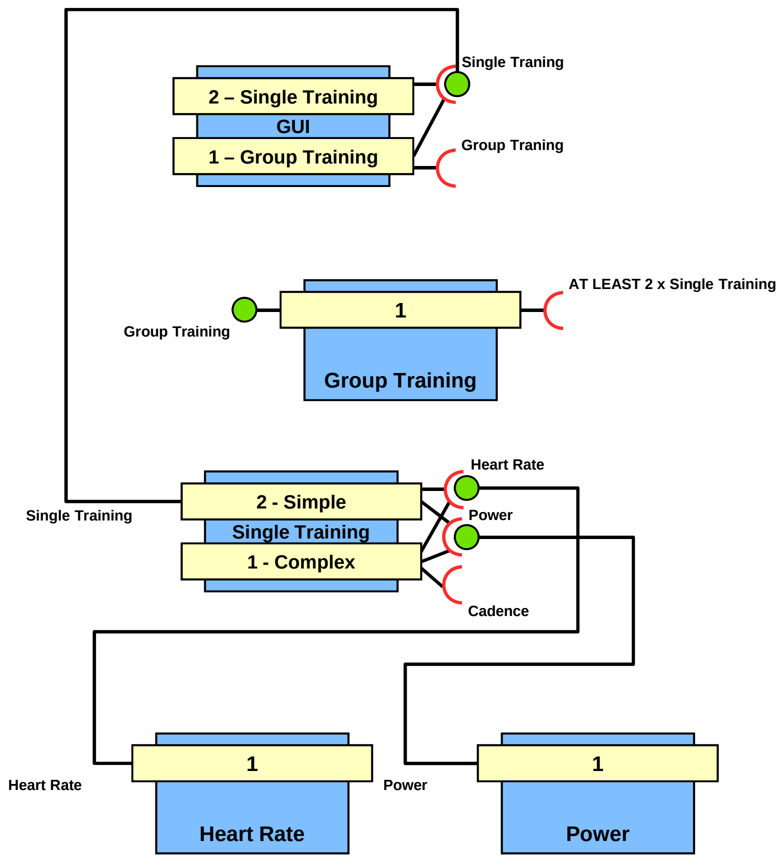

Figure 2: Service configuration for a simple single training

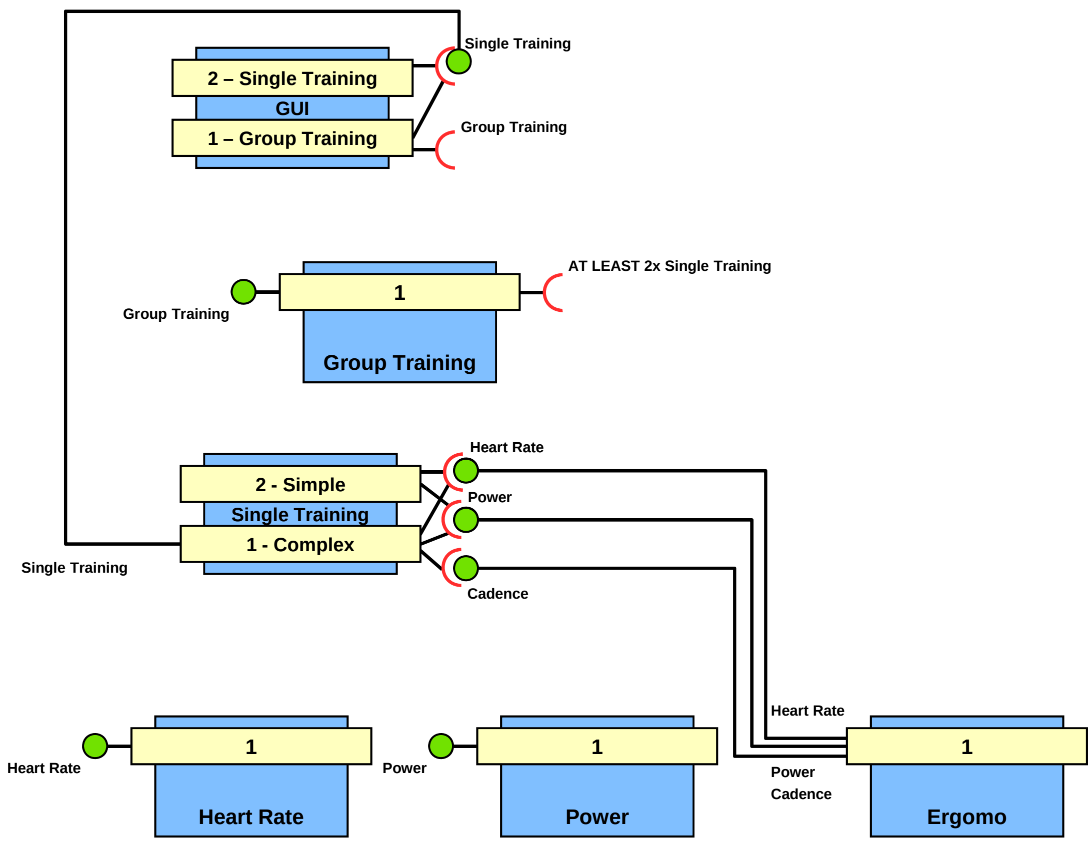

Figure 3: Service configuration for a complex single training

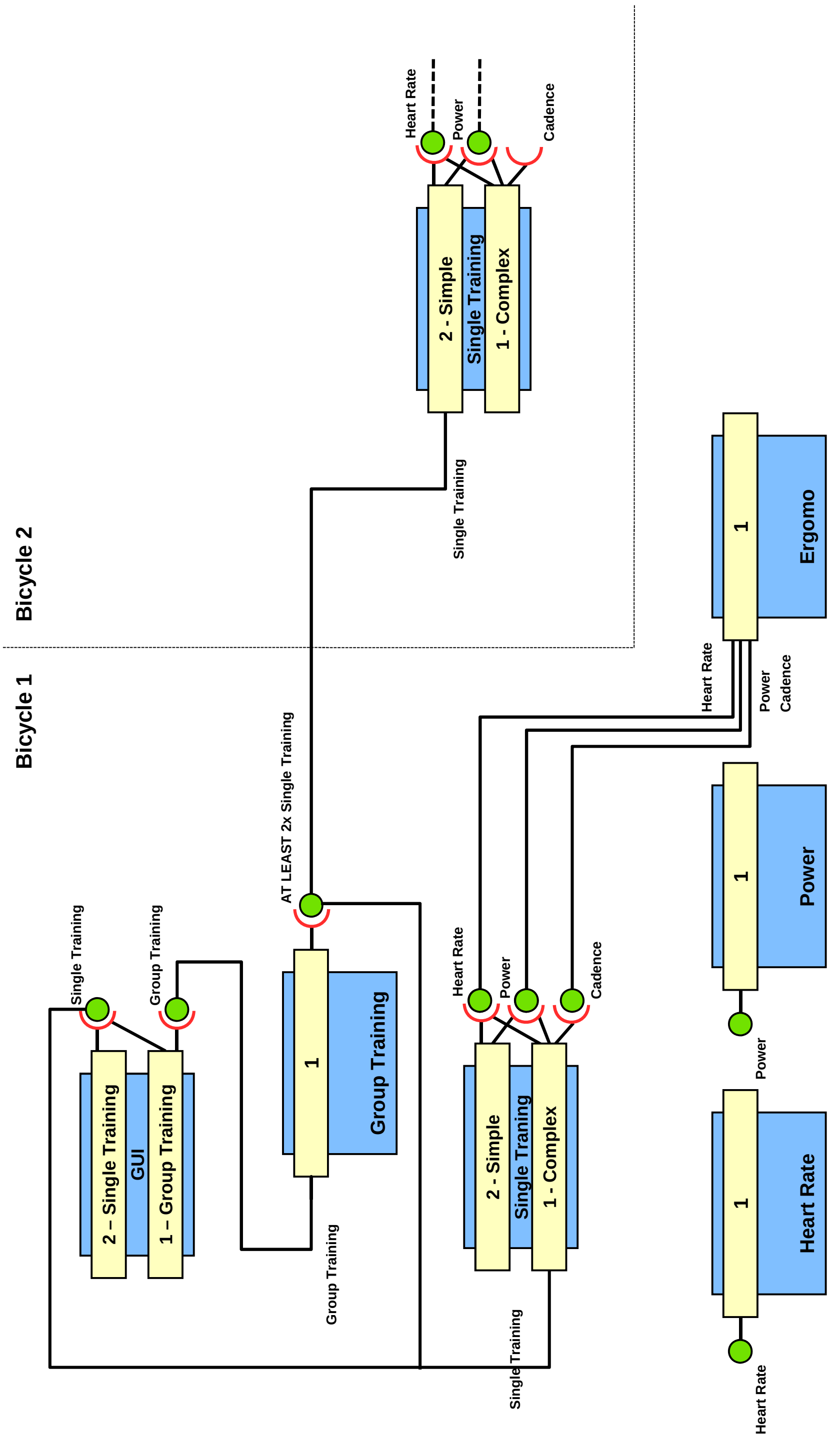

Figure 4: Service configuration for group training

To establish group training at least two bicycles (or single training services, respectivly) are necessary. Two or more cyclists with TCTS may meet at the beginning or later during training. The TCTS then automatically recognizes that multiple single training services are available and activates the group training service (fig. 4). Group training starts after the cyclists gave their content.

In general, the same flexibility and adaptability described above for sensor components can be provided for all system components. Therefore, different trainings algorithms for single or group training as well as various user interfaces can be integrated in the same manner.

Practical application

A prototype has been established that allows control of a group training of up to four cyclists. Each bicycle is equipped with a powermeter (Ergomo™) and an Ultra Mobile Personal Computer (UMPC). The cable connection between the Ergomo™-System and the UMPC has been established via serial port (RS232). All UMPCs are connected among each other using Wi-Fi technology forming an ad-hoc network.

Figure 5: UMPC attached at the handlebar of a bicycle

A cyclist mainly interacts with the TCTS via a graphical user interface that is able to display all currently available sensor values (as heart rate, power, speed, etc.) and training parameters (recommended position within a group, target pulse corridor). Crucial parameters such as heart rate and power are highlighted by colour if a predefined treshold is exceeded (fig. 6). Messages, as example training advices, are displayed on a status bar and additionally supported by an audio signal. Typical advices are "Go faster!", "Slow down!" or "Take the lead!".

Subjective sensations are also considered for the control of training. After starting the training this will be the main manual input. Cyclist can use the large arrow buttons on the lower left and lower right of the GUI to easily adjust their current rating of perceived exertion.

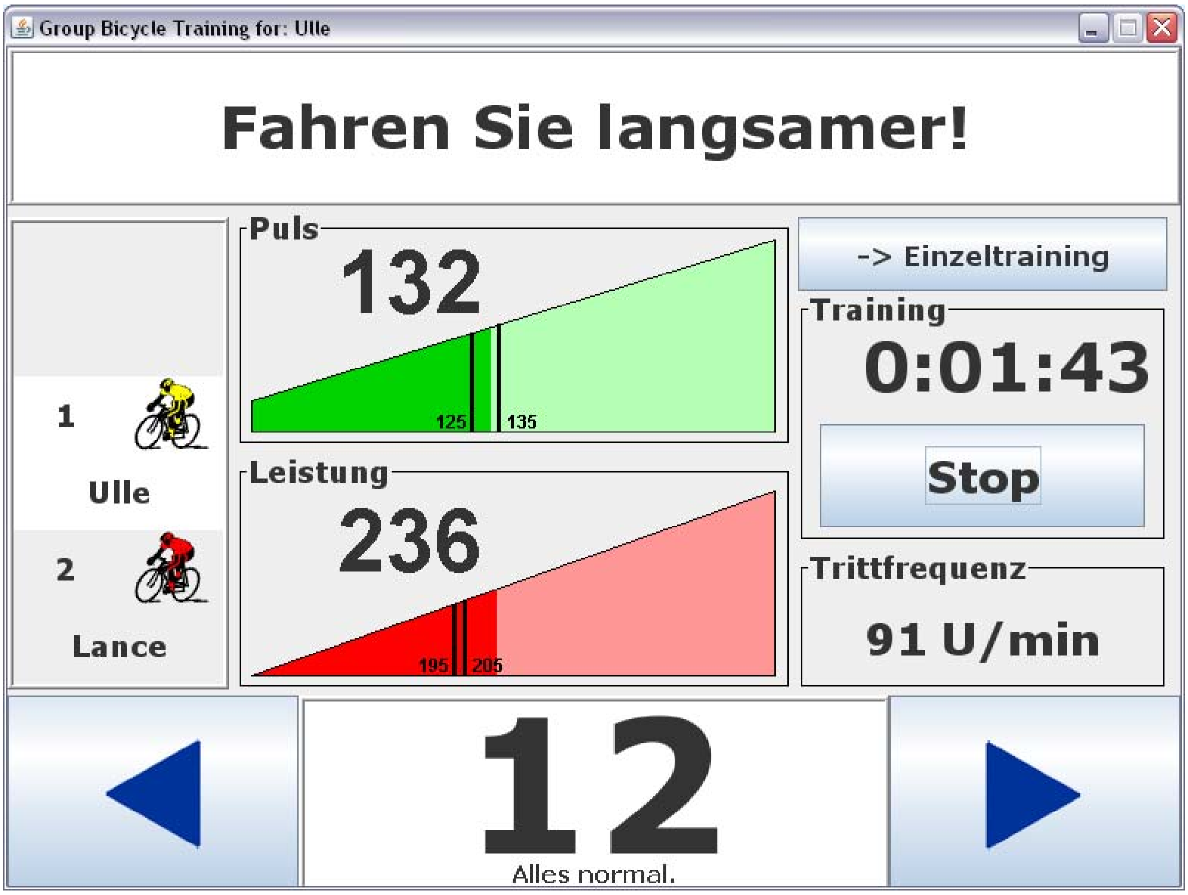

Figure 6: For each cyclist, heart rate ("Puls"), power ("Leistung"), cadence ("Trittfrequenz") and time as well as the position are monitored on the touch screen of the UMPC. On top, feedback as well as advice from the TCTS is displayed (e.g. "Drive slowly"/"Fahren Sie langsamer"). The bottom line shows the current rate of perceived exhaustion on the Borg scale. With the two buttons on the left and the right, cyclists can adjust their rating.

A single control algorithm has been implemented which primarily focusses on the control of the cyclist's heart rate by regulating the power. An individual training plan composed of training phases serves as initial input. Every phase is described by its duration as well as the cadence the cyclist should pedal, the power exerted on the pedal and the expected heart rate during this phase. The target values that define the exercise intensity can be derived from a lactate performance curve that results of a graduated exercise test, e.g.. A range of tolerance for each parameter is defined in advance, as example a range of +/- 3 bpm for the heart rate. If the difference between actual and target values exceeds the range of tolerance for a given time, the exercise intensity will be decreased or increased, respectively, by adjusting the target values. The range of tolerance, latencies as well as the gradient for the adaptation of exercise intensity can be easily adjusted according to the individual or a whole group of cyclists.

The effect of the training control algorithm might be easily explained by two examples. If a cyclist is above the upper bound of the heart rate tolerance corridor for the current training phase for a period of 30 seconds, e.g., the recommended target power will be decreased by 10 Watt (example 1). Now, the cyclist has a lower power to reach which should also lower her/his heart rate. If the cyclist stays above the upper bound of the heart rate tolerance corridor, nevertheless, the system lowers the value again. This procedure will be repeated until the adjusted target value is 20% below the recommended value taken from the initial training plan. If the lowest allowed recommended target power is set, the TCTS will not

lower this value even if the heart rate is still too high. The system reacts in the opposite way every time the cyclist stays 30 seconds below the lower bound of the heart rate corridor. Then the athlete will be advised to cycle at a higher speed by increasing the target value for the power (example 2).
The group training control is based on the single training control as described above. Two or more cyclist can form a training group. If a cyclist decides to stop training, he has to be split from the group. During the training the group control application improves the training effect of every single cyclist while keeping the group together. Therefore, the optimal group speed is calculated in a way, minimizing the sum of differences for all cyclists between the target values of their initial training plans and the new target values of the group. Moreover a formation is calculated which determines the position of each cyclist and whether the cyclists drive in one or two lines.
If the cyclist's sensor values are not within the tolerance corridor, the following rules are taken for optimization in the given order:

1. Change the cyclist's position: the new position is determined in a way that the cyclist's heart rate will move towards the tolerance corridor. The cyclist will be sent to front when his values are lower than the tolerance corridor and vice versa.
2. Change the formation: If at least two cyclists are overstrained for a longer period of time and even after change of position, and at least two cyclists are unchallenged for a longer period the formation should be changed ordering the cyclists in two lines for minimizing the load difference between front row and back row cyclists
3. Adapt the group speed: If either all cyclists are overstrained or all cyclists are unchallenged for a longer period of time and the previous rules did not help, the group speed has to be adapted accordingly.

All data gathered during the single or group training are stored persistently and can be used for evaluations afterwards.
Based on the examples for the single training control described above the control algorithm for the group training will be explained in the following. The cyclist in example 1 might cycle in leading position whereas the cyclist in example 2 follows in second position. Then the leading cyclist will be advised to change in a rearmost position to exploit the slipstream and the second cyclist will take the lead. If for all cyclists the actual values exceed the range of tolerance (example 1) and the positions are changed permanently, the speed of the whole group will be adapted.
Subjective sensations are implemented as a further control parameter of the TCTS. During the whole training the system asks the cyclist frequently to enter her/his current rating of perceived exertion (RPE) as feedback about her/his current physical condition using the RPE scale, also known as Borg scale (Borg, 1998). The Borg scales ranges from 6 to 20. The lower the value the better the cyclist evaluates her/his current physical condition. Low values are chosen, if the physical stress that results from the applied training load is perceived as low. High values (<14) stand for a high or very high amount of perceived exertion and indicate that the athletes is exhausted or overstrained.
Every time a new value is entered the range of tolerance of the cyclist's heart rate will be adjusted as described below (fig. 7).Each stored training plan assumes a RPE value of 12. A different value affects the range of tolerance for the heart rate set point values taken from the stored plan. If the cyclist enters a value between 6 and 9, which means she/he is today in good shape, the upper bound of the tolerance corridor will be increased one point for every value lower than 10 (see Figure 7b). If the cyclist enters a value between 14 and 17, which means she/he is today in a bad shape, the lower bound of the tolerance corridor will be

increased one point for every value greater than 13 (see Figure 7c). A value between 10 and 13 does not affect the tolerance corridor. If the cyclist enters a value of 18 or greater, the system recommends stopping the training. In addition the recommended target power will be immediately set to a value that corresponds to 120 bpm according to the cyclist's personal profile. The cyclist then is in the cool down phase of the training. The recommendation to stop the training will only be given if the RPE value is too high, not if the expected target power will not be reached.

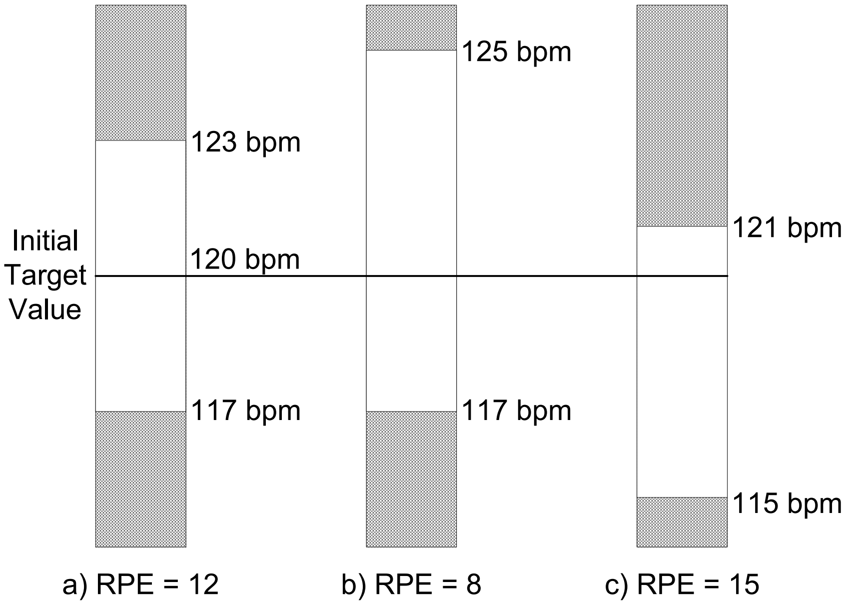

Figure 7: Influence of the rating on the Borg scale on the target values and the range of tolerance of the heart rate: (a) initial state, (b) a rating ≤ 9 increases the upper boundary, (c) a rating ≥ 14 leads to a downwards shift of the range of tolerance.

Discussion and conclusions

In this paper, a new approach for performance monitoring and feedback training systems is presented. Its core item is a service oriented software architecture that supports the integration of different hardware (sensors, output peripherals, e.g.) and software components (training routines, e.g.) during runtime. Hence, a high adaptatibility and flexibility can be achievde that facilitates the application of the same system with various configirations in different situationes or under variable conditions.

A first prototype has been established to improve team training in cycling. So far, monitoring and feedback training systems in cycling had a major focus on the single athlete. The team cycling training systems also considers the complex interaction between individuals as well. The high flexibility offers a wide range of applications not only in cycling. As example, cyclists with different powermeters are enabled to train in one team. Further, athletes might change their sensors and peripherals as for the transitions from swimming to cycling or from cycling to running in triathlon. In this case, data collection will proceed without interruption or restart of the system. Even the spontaneous formation or splitting of cycling groups can be supported.

However, there are several technical limitations. Compared to commercial cycling computers, the UMPCs are quite large. The duration of training is limited by battery capacity as well as weather conditions. Moreover, test runs have shown that the advice on the display might be hard to read, especially if the sun is shining. A voice output has been implemented alternatively. Therefore, future work will be on more adequate output devices as well as on

the integration of new sensors (GPS, inclination sensors, e.g.). Further, the developement of more sophisticated training algorithms will be on focus. In a next step, a model predictive controller will be implemented, that considers the influence of cardiovascular drift and fatigue (Le et al., 2007).
According to the preliminary experiences in youth training, the TCTS supports a more effective cycling training. Beyond, further empirical evidence from training experiments is needed.

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Training and Competition Analysis in Olympic Archery

Nico Ganter, Kerstin Witte, Synke Giggel, Jürgen Edelmann-Nusser

Department of Sport Science, Otto-von-Guericke-University Magdeburg

Abstract

In order to analyze the interaction between training and performance in Olympic archery an antagonistic model (PerPot) and neural networks were used to model individual performances of seven archers on the basis of training and competition documentations. The modeling resulted in moderate model fits for the PerPot-model, suggesting the use of the model for the rough planning of overall training load. The rather poor model-fits for the neural networks may arise from methodological problems of the approach as well as limitations in the quantification of training and performance in archery.

KEYWORDS: ARCHERY, TRAINING, MODELING, NEURAL NETWORKS, PERPOT

Introduction

The understanding of training processes and the underlying adaptation mechanisms is a central issue in training science. Since the behavior of the athlete in response to training is known to be of complex nature, views have changed to a nonlinear systems perspective in the more recent past. In order to analyze athletic behavior, the interacting time series of training load and performance output can be utilized. Antagonistic concepts like the PerPot-model introduced by Perl (2001) and nonlinear mathematical methods like artificial neural networks appear useful for this purpose. A recent study dealing with the analysis of training and performance interaction in cycling by using the PerPot-model is known from Ganter et al. (2006). Applications for modeling competition performances in swimming by means of neural networks are described by Hohmann et al. (2000) and Edelmann-Nusser et al. (2002; 2006).

The aim of the study was the modeling of performances in Olympic archery on the basis of the archers' training and competition documentations with the aid of an antagonistic model (PerPot) and neural networks.

Methods

The performances of seven national top-level archers (A- and B-level) were modeled. Training and performance data were monitored over a period of more than two years. The training documentations consisted of training loads in seven different categories. Shooting categories and quantification units were: TT5 (technical training – 5 m distance; number of arrows), TTC (technical training – competition distance; number of arrows), STC (score training - competition distance; number of arrows) and CT (competitions and training competitions; number of arrows). General training categories included: ST (strength training; duration in minutes), ET (general endurance training; duration in minutes) and MT (mental training; number of sessions).

The performances were quantified using the competition results or the results of performance measures in training. Archery competitions are composed of shooting at various distances and at various targets with various numbers of arrows under different conditions (e.g. indoor and outdoor season). So comparing archery performances between different competitions is complicated. In this study archery performances were transformed to a point scale with a reference value of 1000 points (similar to the LEN point scale in swimming), where the reference value is related to the national record shot under the specific conditions of the event:

$$\text{performance points} = 1000 * \left(\frac{\text{rings}}{\text{rings (German record)}} \right)^3$$

In order to model the individual performances of the archers, an antagonistic model (PerPot, Perl, 2001) and neural networks were used. By using the PerPot model, the input component resulted from the overall training load of the shooting categories per week, according to the total number of arrows shot. The output component was set as the performance achieved during the week in either a competition or a training competition, transformed to the performance points scale. In the next step, the intraindividual model calibration was performed using time-variant model parameters, which were re-estimated for each seasonal period, corresponding to the indoor and outdoor seasons. Model validation was performed upon the comparison between estimated and real performance profile of the archer.
For the modeling by means of neural networks, a feed forward network (Multilayer Perceptron - MLP) was used. In order to analyze the influence of the amount of training in the six documented categories (except category MT) on performance three models were computed for each archer. The first model incorporates the training in the weeks 4 and 3 preceding the competition and training competition performance, respectively. Within the second model, the training in the weeks 2 and 1 preceding the performance is taken into account. Each of the two MLP consisted of three layers. In the first layer, 12 input neurons are located, each representing the weekly amount of training performed in the six categories for the two consecutive weeks. The output layer is represented by one neuron that corresponds to the respective performance value. For the hidden layer, two neurons were chosen in order to minimize the degrees of freedom of the MLP, which then results in 26 (according to the number of connections between the neurons). The third model takes the outputs of the first two models (week 4/3 and week 2/1) into account by calculating the average of the respective performance outputs.
Evaluation of the models was performed using the leave-one-out cross validation method, where all datasets are presented to train the MLP, except one dataset, which is then used to test the trained model and to compare the network output with the real performance and thus calculate the model error. So, during leave-one-out cross validation, one model error is calculated for each dataset, once used for testing, leading to a mean error for each of the three models.
After the leave-one-out cross validation, the general model validity can be identified by calculating the determination coefficient r^2 between estimated and real performances, which describes the variance in real performance values explained by the model.

Results

PerPot

The modeled performances of archer S3 are illustrated in Figure 1. The mean difference of the model is 40.3 points or 4.6 % (see Table 1). With respect to the average performance of this archer, this would correspond to a deviation of 19 rings in the FITA round (144 arrows) or 5 rings for 36 arrows shot at 18 m indoor distance.

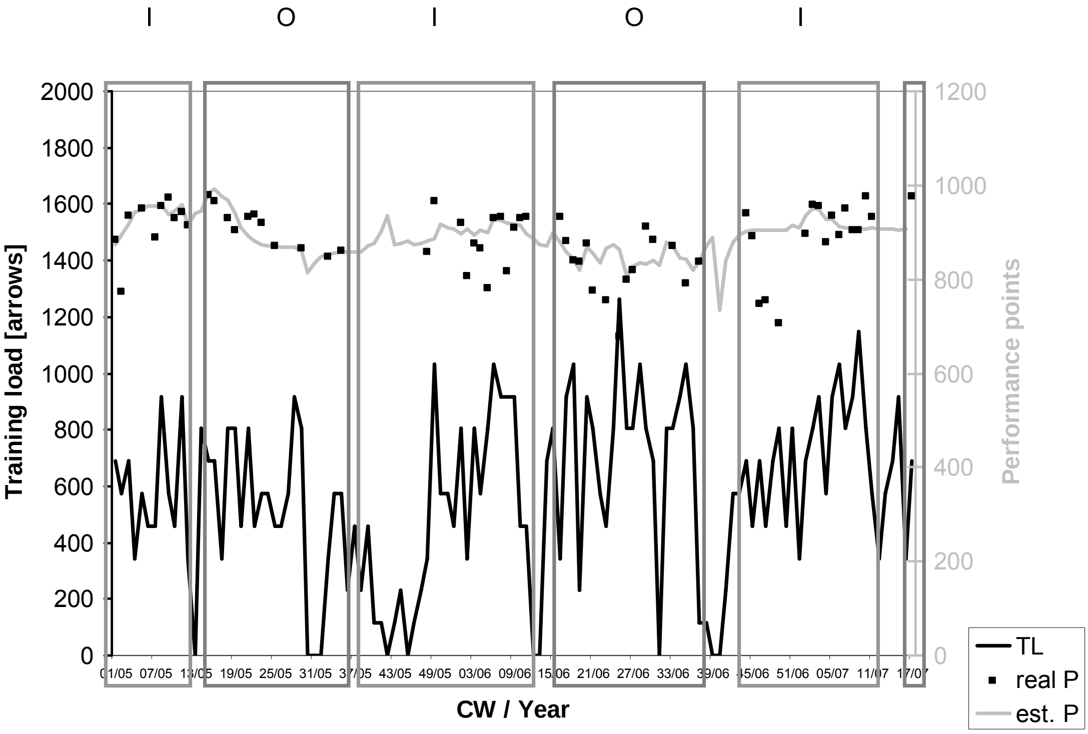

Figure 1. Modeling of performances with the PerPot model for archer S3: Illustration of the real performances (real P) and the estimated performances (est. P) and the training load (TL) for the calendar weeks (CW) since 01/2005. The seasonal periods indoor season (I) and outdoor season (O) are separated by gray frames.

Table 1. PerPot: Mean deviations (Dev.) of the intra-individually calibrated models for the archers S1 to S7 to the real performances (given in points and percent). Coefficient of determination r^2 indicates the validity of the model (n: number of performance values).

	n	Dev. [points]	Dev. [%]	r^2
S1	72	27.7	3.0	0.19
S2	56	27.5	3.0	0.46
S3	66	40.3	4.6	0.25
S4	61	24.9	2.7	0.50
S5	64	23.2	2.6	0.26
S6	65	22.1	2.5	0.41
S7	56	25.0	2.8	0.63

For the remaining archers the model deviations are given in a range between 22 and 27 points (2.5 to 3.0 %) and result in coefficients of determination between 0.19 and 0.63 (see Table 1).

Neural Networks

The results of the overall model for archer S1 are illustrated in Figure 2. Obviously, single data sets give model errors up to 150 points. The mean difference for this archer is 36.7 points or 4.0 % (see Table 2). This would correspond to a deviation of 17 rings in the FITA round (144 arrows) or 4 rings for 36 arrows shot at 18 m indoor distance. For the remaining archers the model deviations are given in a range between 29 and 47 points (3.3 to 5.3 %) and result in coefficients of determination between 0.10 and 0.21 (see Table 2).

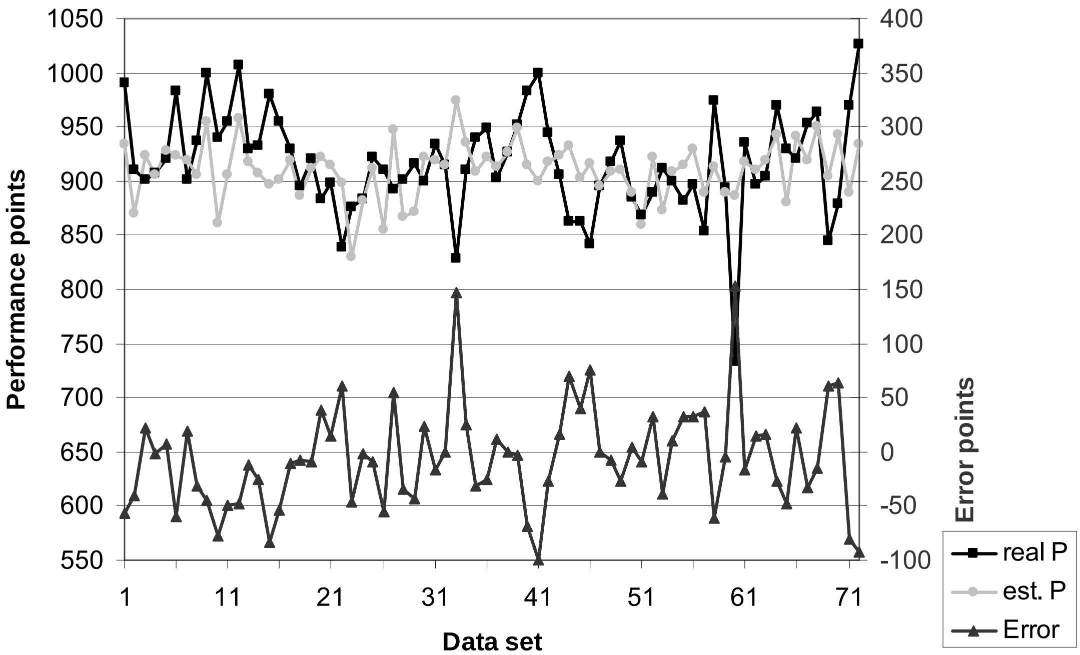

Figure 2. Modeling of performances with the neural network for archer S1: Illustration of the real performances (real P) and the estimated performances (est. P) and the resulting error of the overall model (as the average of the first and second model).

Table 2. Neural networks: Mean deviations (Dev.) of the intra-individually calibrated models for the archers S1 to S7 to the real performances (given in points and percent). Coefficient of determination r^2 indicates the validity of the model (n: number of performance values).

	n	Dev. [points]	Dev. [%]	r^2
S1	72	36.7	4.0	0.10
S2	50	43.8	4.9	0.13
S3	63	47.4	5.3	0.10
S4	58	39.4	4.3	0.16
S5	62	29.2	3.3	0.10
S6	69	34.3	3.9	0.10
S7	50	42.8	4.8	0.21

Discussion

Training analyses in Olympic archery were performed using the training and competition documentations of seven national top-level archers. Limitations of the proposed approach arise from the difficulty in adequately assessing the training content in archery as well as the sufficient quantification of the actual performance on the basis of competition and training competition results. The proposed training categories involve the arrows shot during the specific technical and competition training as well as the amounts of general training. Consequently, the overall training load of the archer can be estimated, but the quality of

single training contents (in particular the quality of the technical training) can not be taken into consideration for the model. In order to assess the performance in archery, which can be quantified using the mean shooting score, and make it comparable between different shooting events (characterized by different distances, target face diameters, number of arrows and indoor/outdoor-shooting), the score was transformed to a point scale in relation to the national record particular for the event. However, such a transformation can not take the influence of external conditions (for instance wind and weather during the outdoor events) on the shooting score into account.
The utilized PerPot-model was designed for analyzing physiological adaptation processes and allows the consideration of only one input parameter, corresponding to the global training load. In this case global training load was defined as the overall sum of arrows shot during training and competition. This, however, does not allow to discriminate between the quality and quantity of specific training contents. The results indicate model fits with moderate quality, and in particular the short-term performance changes can rarely be modeled. Therefore, the PerPot-model seems rather suitable for the rough planning of the overall specific training load in high-level archery. Additionally, the stability and variability of the model parameters in the long-term (for instance over several training years) may provide information on the individual progress of the training process.
By utilizing neural networks for training analysis, it is possible to consider the effects of training amounts in the different categories on performance. From a methodological point of view, however, large amounts of data sets are required for an adequate training of the neural network, which are often limited in high-level sports. Therefore, in the presented approach only the training performed in the four weeks preceding the performance was considered. The individual model fits give larger errors and poor model validity compared to the PerPot-model. Besides methodological aspects of the neural networks (amounts of data sets for training, configuration of the network and the training) the above mentioned limitations in assessing training contents and actual performance might be possible reasons. Furthermore, a relatively high variability can be attributed to the quantified archery performances, where besides external conditions affecting performance during shooting, further determinants like experience and mental strength are important in the competition situation and can not be assessed with the proposed models.

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Interactivity and interactions in e-learning – Implementation within a blended-learning scenario

Nina Roznawski, Josef Wiemeyer

Institute of Sport-Science, Darmstadt University of Technology

Abstract

Interactive features denote one of the most important surplus values of e-learning. In the scientific discussion interaction and interactivity are distinguished. Numerous options are available to enhance interaction and interactivity in e-learning. In this contribution we report on an e-learning project that tries to implement interaction and interactivity using a blended-learning scenario which is based on a specific didactical approach. Online and offline phases as well as single and team work are merged. First results of formative evaluations are promising. The students appreciate the course and particularly the interactive features. In the future, summative evaluations will show whether the interactive blended-learning scenario is superior or not.

KEYWORDS: INTERACTIVITY, INTERACTION, BLENDED-LEARNING, EVALUATION

Introduction

When addressing the surplus value of e-learning the buzzword "interactive" is one of the most important features that come up almost immediately (Roblyer & Ekhaml, 2000). In general, the term means that there is a reciprocal effect of actions between two or more entities. In the simplest case, one entity acts and the other entity reacts. In the scientific discussion the terms "interactivity" and "interaction" are differentiated, but there is no generally accepted definition of these terms. Whereas literature shows a large number of taxonomies for classifying interactions within e-learning systems, the meaning of the term "interactivity" is varying, depending on the context and the perception of the respective author. According to Wagner (1997, p.21) we define "interactivity" as the capability of technology to enable and enhance reciprocal effects of actions, whereas "interaction" denotes "behaviors where individual and groups directly influence one another". The following section shows where interactivity and interaction appear within e-learning systems, how they are implemented and why they are important for e-learning.

First of all there are at least four different parts within an e-learning system that have to be considered (Wiemeyer, 2008). On the one hand there is the technical system (computer, network etc.) that establishes connections, processes information and presents the learning content and on the other hand there is the learning content. Two kinds of persons are acting within the complex scenario: learners and teachers. According to Wiemeyer (2008), there is a complex interaction of these four parts. In order to enable interactions between these parts within e-learning environments, specific technologies are needed. These technologies offer a number of interactive options. One option is the support of computer mediated synchronous communication (online-chats, video conferencing) or asynchronous communication (e-mailing, discussion forum, mailing-lists, and wikis) between teachers and learners and among

learners. Another option is the delivery of interactive learning objects like animations, simulations, questions, and tasks.
Considering the numerous interactive options the question arises why and how these options enhance learning. One way to answer this question is to consider theories and models of human learning. The e-learning discussion refers to numerous (more than 50) models being based on three main learning theories (Kearsley, 2008; Kettanurak, Ramamurthy & William, 2001; Thompson & Jorgensen, 1989; Wiemeyer, 2008): behaviorism, cognitivism, and constructivism. These learning theories emphasize different options for designing appropriate e-learning like reinforcement, repetitions, cognitive elaboration, examples, questions and tasks for transfer, authentic, situated and discovery-based learning environments and social interaction. Another way is to focus on outcomes of interaction and interactivity like participation, motivation, elaboration, exploration, discovery and clarification (Wagner, 1997).
Due to the fact that interactivity and interaction have a specific importance in e-learning, one subproject "Functional movement analysis in practice" of the HeLPS project[4], a cooperative project of the five Hessian Institutes of Sport Science, was particularly dedicated to the goal of designing interactive e-learning units. The aim was to impart knowledge of three different movement analysis concepts (Meinel & Schnabel, 1998; Göhner, 1979; Kassat, 1995) in an interactive way and moreover to exercise the use of these concepts based on different movements in practice.

Didactic Concept

A specific didactic concept and design for the e-learning units and the course-structure was implemented to enhance active involvement by the learners and to use the full potential of interactivity and interaction. Interactivity was mainly realized within the e-learning units by implementing features like support, useful hints and cues, feedback, questions and exercises. Interaction (communication) was supported by a specific course structure based on a blended-learning concept (merging single and cooperative online-working phases and phases of personal attendance, respectively). The course also offers synchronous and asynchronous communication (chat, e-mail, discussion forum) and options for collaborative online and offline work.

E-learning units

For the e-learning units the following didactic design was used. Learners alternately were given text, picture or video information, tasks and questions (drag & drop, cloze, multiple-choice). The specific characteristic of the didactic design is the sequence of information, questions and tasks (interactions with the learners). After a few pages of information learners get the possibility to interact with the system at regular intervals. The chapters are constructed as follows: Each chapter starts with a short introduction, which explains the content by means of an example. First a starting question concerning the following content initiates a deeper understanding of the topic. Thought-provoking impulses, e.g., useful hints, help students to answer the question. The main part of the chapter contains a mixture of textual information and varying media like video-clips, animations, pictures and charts. After having completed the main part students can check their knowledge by means of different types of exercises (drag & drop, cloze, multiple-choice, free answer). During the exercises support by different interactive features like hints, partial solutions and feedback is available

[4] HeLPS is the acronym for Hessian e-Learning Projects in Sport Science (URL: http://www.helps-hessen.de).

to the students (figure 1). If students have difficulties to answer a question immediately, they can use graded help functions (hint, partial solution, feedback, solution) to get further information. Figure 2 shows an example of the partial solution of an exercise. While answering the questions the students get concurrent feedback (correct/ incorrect). Every chapter ends with a short summary of the essential facts of the topic.

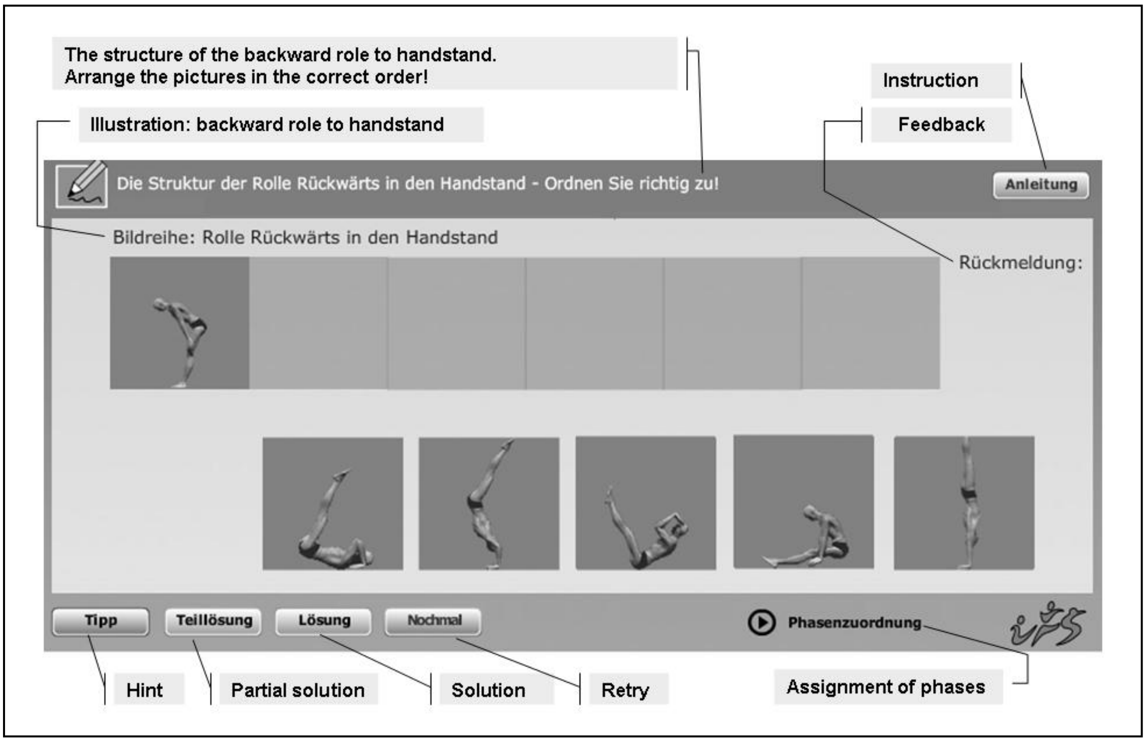

Figure 1. Example for a picture-assignment exercise with interactive features (startscreen).

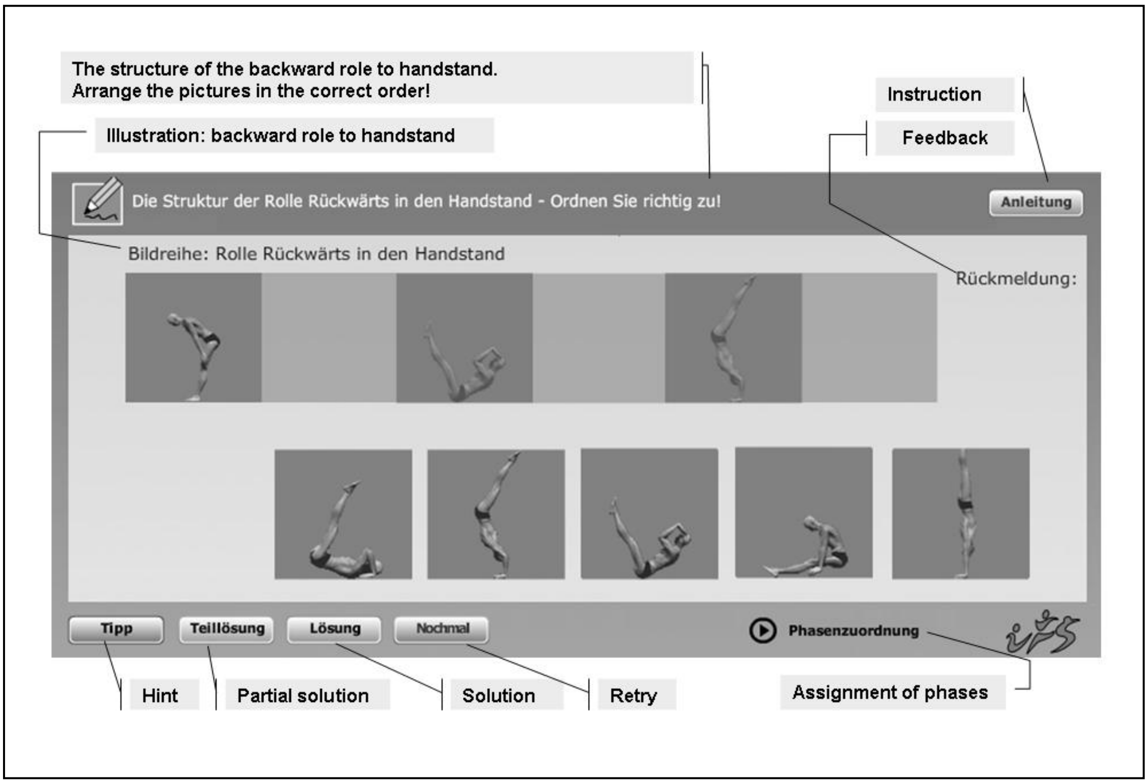

Figure 2. Example for a picture-assignment exercise with interactive features (partial solution)

Course structure

In order to apply the communication and collaboration functions more effectively, the course "How do movements work?" received a new structure. In the winter term 2007/08 the course started using a blended-learning concept. The course was supported by the learning management system ILIAS. Figure 3 shows the structure of the course in summer term 2008. 11 phases of personal attendance and 4 online working phases were offered.

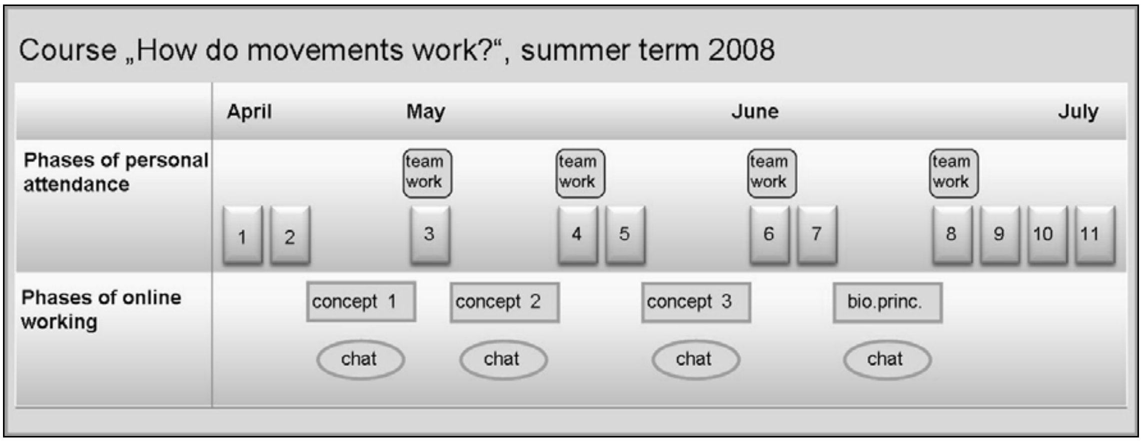

Figure 3. Structure of the seminar „How do movements work?“, summer term 2008 (see text for details)

During the online phases students worked on the e-learning units, dealing with the movement concepts of Meinel and Schnabel (concept 1), Göhner (concept 2) and Kassat (concept 3) and finally the biomechanical principles (bio.princ.). During the online phase a chat lesson was offered. In this chat lesson, students had the opportunity to ask questions about the different concepts of movement analysis to the teacher. Furthermore, the practical application of the concepts to selected sport movements was supervised by the teacher. The learning management system offers also a discussion forum which students mostly used for providing feedback about the e-learning units.

After every online phase one or two lessons with personal attendance followed. In these lessons, the major task was to apply the movement concepts to selected sport movements. This was done in three phases: First a checklist was established and distributed to the students in order to structure the application process. Second, a team phase was performed where three to five students discussed the respective movement. This discussion was moderated and recorded by 'experts', i.e., students who had prepared well for the particular sport movements. Third, the results of the group discussions were presented by the teams in the following plenary session. In summary the following table shows the typical learner activities and the schedule for these activities.

Table 1. Typical learning schedule

Phase	Type	Time slot	Activities
Online	Self-learning	for 1 week	▪ Acquiring the concept at ILIAS ▪ Interacting with teachers, students, using the features of ILIAS (mailing, discussion-forum)
Online	Chat	1 session	▪ Interacting in a moderated chat session, applying the concept to an example ▪ Asking questions about the concept to the teacher
Online	Self-learning	for 1 week	▪ Repeating the concept at ILIAS ▪ Interacting with teachers, students, using the features of ILIAS (mailing, discussion-forum)
Group	Team work	1 session	▪ Applying the movement concepts ▪ Group discussion based on the checklist
Plenary	Discussion	1 session	▪ Presentation and discussion of the teamwork results

Technical implementation

The process of technical implementation comprised three steps:

1. Programming the e-learning objects
2. Building the three e-learning units
3. Building the complete e-learning course

Different software tools were used for the technical implementation. The interactive e-learning objects, videos, pictures, charts, exercises and questions were programmed using Adobe Flash CS3, because this tool offers a number of options for interactive web content design.

The e-learning units were developed in the ResourceCenter, a web-based authoring tool hosted by the httc[5] from the University of Technology, Darmstadt. Besides a text-editor for writing, it allows to upload different multimedia objects (pictures, flash-files, videos etc.) into an online database. These media objects can be used for designing e-learning units. There are also additional functions like an editor for creating test-questions (multiple-choice or cloze-

[5] httc (Hessian Telemedia Technology Competence Center)

questions). Moreover some special technical features like the LOM[6] standard and SCORM[7] or HTML[8] export supported the easy use of the objects and the units.
In addition to the ResourceCenter the technical implementation of the complete course included the learning management system. It is used for the every day working process and based on the open source platform ILIAS. It offers the typical functions of these systems like course management, chat, discussion forum, tests and assessment.

Evaluation - procedure

The course has been realised twice (winter term 2007/08 and summer term 2008). In order to detect strengths and weaknesses of the e-learning units, to improve them and to gain further knowledge about the interactive design, a formative evaluation was carried out during the design and development phases. According to the EPL (enhanced checklist for learning-systems) proposed by Benkert (2001) an interview guideline was created. The guideline focused the following topics: general questions about the e-learning units, working with the e-learning units, structure and navigation, learning content, screen layout, text layout and structure, graphic design, colouring, videos, animations, layout of exercises and solutions, possibilities to interact and adaptability, learning expected learning outcome and learning success.
Interviews with open-end questions and group discussions were applied. The interviews and discussions were conducted in one-to-one conversations or in groups of two or three learners, respectively, and lasted approximately 45 minutes. During every online phase 6 to 10 students were surveyed, all together 24 students participated.

Evaluation - results

Generally, the students appreciated the e-learning units. They particularly emphasized the following positive features: motivating and varied work, greater efficiency as compared to book, clear structure of the e-learning units, well-arranged order of textual information, pictures, videos, questions and exercises, presentation of the learning content (numerous examples), helpful video examples (because of more detailed illustration), good merge of textual information, exercises and questions, comprehension tests immediately after reading the text, questions at the end of the chapters (knowledge examination), feedback and well formulated hints.
After the first evaluation turn numerous suggestions for improvement were put forward as well: option to print the content of the e-learning units, electronic notepad, larger video size, slow motion function for video, further summaries for the remaining chapters, and more questions and exercises for testing within and at the end of the units.

Summary and conclusion

Interaction and interactivity are two important features of e-learning indicating the surplus value of this learning technology. There are numerous options to support and enhance interaction and interactivity. In this contribution we proposed a specific approach to exploit the potentials of interactive e-learning based on a blended-learning approach. Single and team work on the one hand and online and offline work on the other hand were merged to an e-

[6] LOM (Learning Object Metadata)
[7] SCORM (Sharable Content Object Reference Model)
[8] HTML (Hypertext Markup Language)

learning course dealing with functional movement analysis. The results are promising. The students liked and appreciated the interactive features. Furthermore they demanded more interactive support.

On the other hand, some limitations of the approach are clearly visible: There was no control group and no knowledge assessment was performed. This step is planned for the next application of the course in the winter term 2008/09. For this term, a randomized experimental control design will be performed in order to test the differences between different degrees of interactivity.

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An analysis of performance in long-distance rowing by means of global positioning system technology.

Roberto Cejuela, José A. Pérez-Turpin, Juan M. Cortell, Juan Llopis, Juan J. Chinchilla

Laboratory science of physical activity and sport, University of Alicante, Spain

Abstract

The analysis of sports performance by means of technological advances has often been used to calculate the routes of sportsmen in the distances covered, or to calculate speed in orienteering. However, there is still little information on data for Global Position System (GPS) use in long-distance elite rowers. The purpose of this study was to analyze rowers' performance in a long distance fixed-seat rowing competition (14816 meters, Santa Pola, March 2007, Spain). Five boats, with eight rowers each, were used for this analysis, all with GPS technology (FRWD outdoor sports computer series W 600, 2007). Anthropometric measurements were taken and the somatotype was calculated (3.3-3.9-2.2). The calculations included the total time for the race, distance covered by each boat, speeds, route profile, altimeter, temperature and heart rate (9,95±1,35 km×h^{-1}, 91,53±14,13 minutes, 170±4,69 bpm). These results, added to their higher average speed, resulted in a better time in the race, and a shorter distance rowed. The coxswain's skill and experience shows itself as a performance factor in this type of event. The GPS is a suitable tool for recording data in long-distance rowing events.

KEYWORDS: GPS TECHNOLOGY, ROWING, HEART RATE, COMPETITIVE EFFORT, ANTHROPOMETRY.

Introduction

Global positioning system (GPS) technology has often been used in the literature on orienteering (Larsson et al., 2002). This was a turning point in the study of this sport, since one of the main performance factors leading to success is, finding the most suitable route between the control points, and GPS is the tool that makes it possible to store and offer this information.

Competition in rowing events present significant differences compared to orienteering races. The main difference lies in the fact that, in rowing, the position of the control points is known beforehand, although in long-distance races they cannot be seen at first sight. There are different event formats, mainly differing in the distance to be covered (long or short distance), and the movement of the rower, whether on a fixed or a sliding seat.

This study attempts to provide new information on long-distance fixed seat rowing events, based on the usage of GPS technology. There is little information collected in competition situations on the variables determining performance in this category. By obtaining this information, the training programmes can be optimized and greater success in competition can be achieved.

Methods

Five boats, with eight rowers each, were used for this analysis the favourites for the final victory. The event was the long-distance regional championship in the Valencian Community, in the "Falucho o Mediterranean Llaüt" category (Characteristics, figure 1) (Santa Pola, March 2007, Spain). All rowers were amateur, since there are no professional rowers in this category. The coxswain in each boat wore (in his arm) a GPS recording unit (outdoor sports computer series W 600), and each rower wore a Polar S625X pulsometer, which registered his heart rate.
The software used in order to analyze the data was FRWD outdoor sports computer series for the GPS data, and Polar Precision Performance 5.0 for the analysis of the heart rate data.

The calculations included the total time for the race, distance covered by each boat, speeds, route profile, altimeter, temperature and heart rate. Each GPS was calibrated before the start of the event in order to collect data, together with a recording unit and a computer containing the software required. After the event, the statistical analysis was performed by means of the SPSS 14.0 package, in order to compare the data for the various times obtained, speed, route profile and heart rate.

Figure 1. Characteristics of "Falucho o Mediterranean Llaüt": Total length 812 m; mast bow 99m; mast stern 83m; midship section mast, 81m; midship section tug .237m and midship water line tug. 173m. 8 rowers plus a coxswain, having five fixed seats to double rowers except the coxswain.

Anthropometric Measurements

Anthropometric measurements followed protocols of Heath-Carter anthropometric protocol (Carter, 2002), and Marfell-Jones (1991). All the measurements were taken three times for each subject. The equipment used included a Holtain skinfold calliper (Holtain Ltd. U.K), a Holtain bone breadth calliper (Holtain Ltd. U.K), scales, stadiometer and anthropometric tape (SECA LTD., Germany). The physical characteristics were measured in the following order: age, weight, stature, arm span. The following measurements were also taken: sitting height, acromial height, radial height, dactylion height, tibial height, leg length, arm length, biacromial diameter, bicrystal diameter, humerus and femur width; biceps, upper arm, forearm, triceps, subscapular, and suprailiac skinfolds.

Muscle mass was calculated by using for the Lee equation (Lee, Wang, Heo, Ross, Janssen, & Heymsfield, 2000), fat mass was calculated by using for the Withers equation for body density (Withers, Norton, Craig, Hartland, & Venables, 1987), bone mass was calculated by using for the Döbeln equation, modified by Rocha (as cited in Carter & Yuhasz, 1984). The somatype was also estimated using the Heath-Carter anthropometric protocol (Carter, 2002).

All the data gathered was entered into SPSS 14.0 software package. The results were presented with signification as ± standard deviation (±SD). T *Student* tests were used to extract the measurements for the descriptive analysis of the anthropometric values.

Results

The first descriptive results of the comparison referred to the average values of the subjects for age weight and height, and were as follows. The mean values of age (±SD) were analysis 22.8±5.3 years of age. Mean weight values were also analysed 81±7.5 kilogrammes. The average height values were 182.1±5.6 centimetres (Table 1).

Table 1. Anthropometric profile of male amateur rowing competing at the 2007 *Valencian Community, in the "Falucho" category* Championship.

	Rowers (*n=40*)	
Dimension	**Mean±SD**	**Range**
Age (year)	22.8±5,3	17-36
Body mass Index (kg)	24.4±1.4	22.3-27.5
Height (cm)	182.1±5.6	170.0-191.0
Weight (Kg)	81±7.5	67.5-94
Muscle percentage (%)	43.5±2.0	40.6-47.2
Muscle mass (kg)	35.0±2.1	31.0-38.7
Fat percentage (%)	14.7±2.7	9.3-20.3
Fat mass (kg)	12.0±2.8	7.1-17.9
Bone percentage (%)	16.1±0.9	14.3-17.4
Bone mass (kg)	13.0±0.9	11.6-14.5
Arm span (m)	1.8±0.1	1.7-2

The somatype was also estimated using the Heath-Carter anthropometric protocol (Carter, 2002). The mean somatotype for rowers of fixed seat (3.3-3.9-2.2) demonstrate that these athletes are best described as endomorphic mesomorph. In figured n°2, graphical representation is expressed in the average somatopoint of the group in two dimensions in comparison with a reference population.

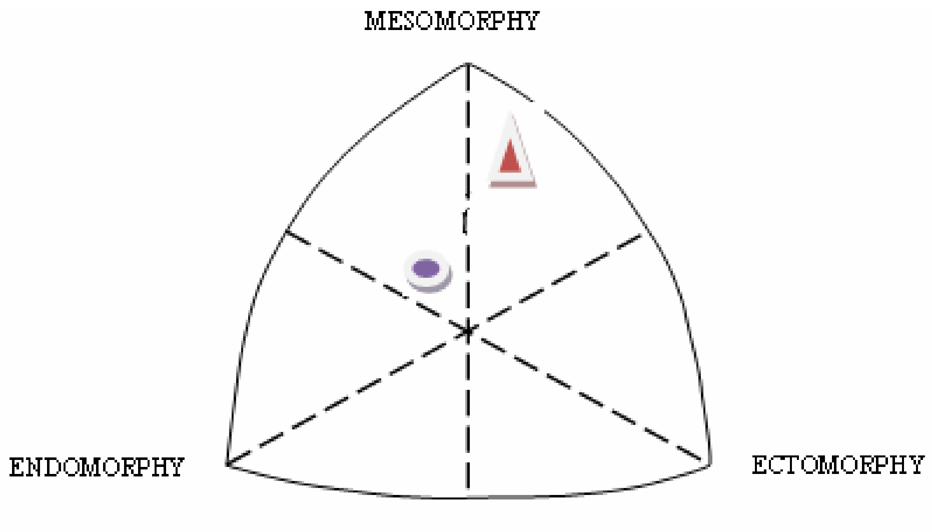

Figure 2. Male rowers of fixed seat (Santa Pola, 2007). The mean Somatotype: 3.3- 3.9- 2.2.

Male Paddlers JJ.OO Sidney 2000. (Ackland, Ong, Kerr & Ridge, 2003). The mean somatotype: 1.6-5.7-2.2

SAD: 2.5

The official distance for this event is 14816 meters, and in that edition the average temperature outdoor was 28,8±2,23 degrees centigrades. Table 2.

Table 2. Data obtained in competition (2007 *Valencian Community, in the "Falucho" category* Championship)

Boat Names	Ranking	Total Time (minutes)	Distance Covered (metres)	Average Speed (kilometres per hour)	Maximum Speed (kilometres per hour)	Average Hearbeat Rate (per minute)	Maximum Heart Rate (per minute)	Total Heartbeat Number	Average Temperature (degrees centigrades)	Maximum Temperature (degrees centigrades)
Real Club de Regatas	2º	76.05	14460	11.45	13.4	171	193	13922	28.6	31.2
Universidad Politécnica de Valencia	3º	76.15	14480	11.4	13.3	173	191	13990	28.8	31.4
Universidad de Alicante	8º	100.38	15086	9.1	13.6	175	192	14175	29.1	31.1
Oliva Regatas	9º	101.53	15315	9.1	13.3	168	188	14574	25.6	27.1
Denia Remeros	14º	103.54	14874	8.7	12.1	163	183	15159	31.9	35.7
Average Datas		*91.53+-14.13*		*9.95+-1.35*		*170+-4.69*			*28.8+-2.23*	

The first significant result of the comparison showed that the average speed of the boats in the event was 9,95±1,35 km/h. There is a statistically significant difference (p<0.05) between the first two boats analyzed (ranking 2nd and 3rd in the event) and the other three which reached intermediate positions in the final standings. There were no significant differences in the maximum speeds; there were, of course, in the final timing, where there is a clear difference between the first two boats and the others.

Discussion

The rowers in our study are amateur, have a different Anthropometric Measurements than elite rowers in the other studies. Two main differences are presented. Firstly, higher body fat percentage (14.7±2.7% vs 10.49±2.3%) versus elite rowers sliding seat (Jürimäe, Mäestu, Jürimäe & Pihl, 1999).
Secondly, a somatotype categorie Endomorphic mesomorph (3.3- 3.9- 2.2). If it is compared this somatotype with Olympics paddlers. (Ackland, Ong, Kerr & Ridge, 2003) Meaningful differences are found (2.5) in the Somatotype attitudinal distance (SAD), the distance in three dimensions between any two somatopoint (S), calculated in component units (Carter, 2002), (figure 1). As a result being the Olympic paddlers ectomorphic mesomorph (1.6-5.7-2.2).

This differences can be found due to the kind and time of the subjects training and the differences in the race requirements. The type of training done is different as the race distance is much higher, the effort time is much longer as the way it is rowed in fixed seat that leads to a lower workload in the legs and hips. Although the main factor seems to be the amateur rowers, versus the two other reference populations which are professionals. This could be reassured comparing the kind of trainings done and the competition performance factors.

In the date of competition (table 2), It is important to highlight the different distance covered by the various boats because, although the official distance was the same for all entrants, the second and the third boat chose optimal routes, which allowed them to cover a shorter distance than the other boats, ranking 8th, 9th and 14th. This result, added to their higher average speed, resulted in a better time in the race, and also a shorter distance rowed. The coxswain's skill and experience shows itself as a performance factor in this type of event.

The comparison between these data and the heart rate does not yield any significant statistic correlation. The heart rate depends on intrinsic individual parameters (age, training level, rest…) and on extrinsic ones (temperature, humidity…) (Russell, Rossignol, & Sparrow, 1998). These heart rate data are determining factors in quantifying how intense the event has been, and the individual effort it has entailed for each rower.
By obtaining these data and determining the anaerobic and aerobic thresholds, by means of an effort test on an ergometer, the intensity of competition may determined, and therefore, optimized training programmes can be scheduled in order to obtain better results in events.
Lakomy & Lakomy (1993) Differences were determined in behave of the heart rate in rowers and non-rowers at submaximal and a maximal rowing test. Showed that rowers were more efficient on the ergometer than non-rowers. The rowers of this study are amateur, and most of them do not follow adjust parameters to the control in training intensity. Taking advantage of the obtained data in competition. (table 2), and also test data in ergometer, training process can be optimize determining different intensity zones in relation to the performance factors that competition offers and the thresholds determined for each rower. (Cosgrove, Wilson, Watt & Grant, 1999).

Table 3. Comparation results the % heart rate maximun in competition of Long Distance (Santa Pola, march 2007) than 2000m competition (Jürimäe, Mäestu, Jürimäe, & Pihl, 1999)

14816m competition	Age (year) **Mean±SD**	Average Hearbeat Rate (per minute)	% Heart Rate Maximal	2000m competition	Age (year)	Average Hearbeat Rate (per minute)	% Heart Rate Maximal
Real Club de Regatas	22.2	171	86.45	10 rowers (4.7±1.83 years experience training)	18.9±1.66	179.9±4.9	89.45
Universidad Politécnica de Valencia	21.5	173	87.15				
Universidad de Alicante	21.9	175	88.33				
Oliva Regatas	28.7	168	87.82				
Denia Remeros	27.1	163	84.49				

From maximal heart rate average of the rowers in each boat, it is determined the % of maximal HR that has been obtained during the competition (table 3). The mean of the boats were 86.5±1.49. In addition comparing this data above with Jürimäe, Mäestu, Jürimäe, & Pihl (1999) in one competition of 2000m, a lower % maximal HR is obtained (86.5±1.49 versus 89.45±4.92) in the rowers of long distance. Effort average intensity is lower, this can be due to a greater time of the effort apart from other parameters (91.53+-14.13 min Vs 7 min 28 sec), the rowers category or level (amateur vs elite), and the performance factors.

If it is compared % HRmax in each boat, no meaningful differences are observed. Although getting a lower performance in the competition, the two last boats do not represent lower values of the effort intensity. It is important to highlight that in case intensity competition would be evaluated by the average HR, this would be a mistake, due to this two boats with higher age average, have a lower Hr average, how ever their %HRmax is similar to the others rowers.

Conclusions

The GPS is a suitable tool for recording data in long-distance rowing events. The data obtained make it possible to analyze and describe intrinsic and extrinsic data on the rowers and the whole boat. Such data, together with the individual heart rate recorded, yield actual information on how intense the competition has been for each rower and for all the boats.

This result, added to their higher average speed, resulted in a better time in the race, y shorter distance rowed. The coxswain's skill and experience shows itself as a performance factor in this type of event.

The %HRmax is a great intensity indicator of the effort that competition offers, but the main performance factor in this kind of competitions is to get the excellent trajectory (route profile) to row the shorter distance possible and get the higher average velocity.

More research is needed about long-distance rowing in competition conditions to compare this data above with new studies.

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TOWARDS THE SPORT AND WELLNESS ECOSYSTEM

Daidi Zhong

Nokia Research Center, Helsinki, Finland

Abstract

This paper describes the Sport and Wellness Ecosystem, which is a comprehensive environment including many traditional sport-related researchers, manufacturers and service providers, as well as many new players from other ecosystems, such as personal wellness, fitness and healthcare. This ecosystem uses a seamless data chain to link all the participants. The overall target is to create many new technologies, applications and markets with the joint efforts by multiple different societies. The standardization bodies, Bluetooth SIG and Continua Health Alliance, are used as examples to describe SWE. And two commercialized products, Nokia Sports Tracker and Nokia Wellness Diary, are used as examples to show how SWE can be utilized.

KEYWORDS: SPORT, WELLNESS, STANDARD, WIRELESS, SENSOR

Introduction

After more than 30 years' development, nowadays, the sport science has become a truly multidisciplinary research area. The hot topics in this area include, but not limited to, the following key domains:

- Physiology
- Psychology
- Physics
- Sport Medicine
- Biomechanics
- Information and Communication Technology (ICT)
- Sport Education or Coaching
- Industrial Design

Researchers from this society have created a lot of useful applications for the purposes of professional sport activities. They have been widely adopted by professional sport market, thus dramatically changed the way that traditional sport was doing [Baca, 2006 & Perl, 2006]. However, after entering 21st century, the scope of sport science has been gradually extended. Those professional applications were shipped towards consumer market, which enables various new opportunities. This article is particularly interested in the topics related to such "technology transferring and migration" activity, which is illustrated in Figure 1.
In the past decade, we have already observed a lot of professional technologies achieved great success after transferring to consumer market. The classic examples are the Global Positioning System (GPS) [Daly, 1993], and the Code Division Multiple Access (CDMA) [Dubendorf, 2003]. Originally, they were both created for military purpose; but in the recent

years, they have been successfully equipped by the consumer electronic devices, and adopted by consumer market.

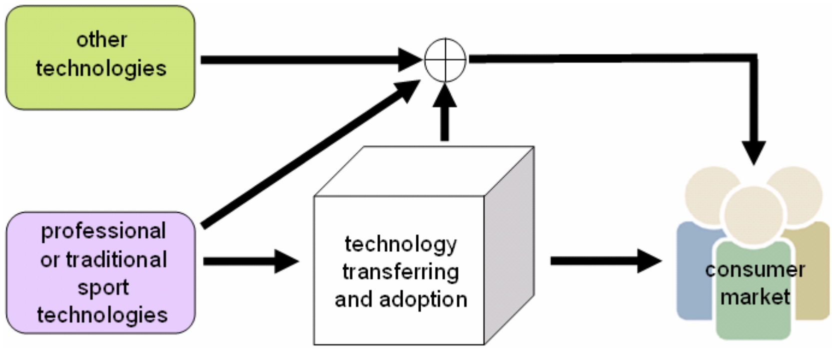


Figure 1. The technology transferring and migration towards consumer market.

Similar things happen in the sport domain as well. One of the typical examples is the Wii™ Sports manufactured by Nintendo©, which is a successful product focusing on the market of sport gaming. Wii™ is the 5th home video game console released by Nintendo. Compared to traditional video gaming system, it efficiently utilizes the wireless radio technology and accelerometer sensor, which enables brand new user experiences.

Another example is the ICT-based sport educational (or coaching) system [Lames, 2006], which leverages the start-of-art information and communication technology, and significantly enhanced the traditional educational (or coaching) system based on text, picture, and video recording.

Although such new opportunity looks promising to both the academic and industrial societies, but "how to leverage the existing technologies" and "how to establish good collaboration between academic and industrial societies, in order to proceed together along this direction" are big challenges for us. Only after we could together come up with a suitable solution for these obstacles, and carry it on with joint effort, the massive consumers could start to enjoy the real benefits brought by our innovations.

The essential motivation of this paper is to describe a possible solution, from the industrial perspective, to build the Sport and Wellness Ecosystem (SWE). The motivation of this presentation is to clarify the relationship between existing traditional sport-related technology and new ICT-enabled technologies. By understanding this relationship, folks could acquire a bigger picture of the entire SWE. Under this framework, many new interesting sub-topics could be studied, such as:

- How to transfer professional sport-related technologies into consumer markets
- How can such technologies be successfully integrated into our daily life?
- What kind of new opportunities do we have there?
- Where is the gateway towards consumer?
- What kind of new research topics could we identify from the feedback from consumer markets?
- What benefit can sport research society and industrial society gain respectively from the SWE?
- What responsibility shall be taken by each stakeholder of SWE?
- What is the relationship between SWE and other neighboring ecosystems?

The Key To Sport And Wellness Ecosystem

All the aforementioned research areas, under the context of sport science, are working together towards the same ultimate goal – To improve the quality, safety and performance of human sport activities. However, these research areas, by nature, concentrate on completely different contents. In order to better understand the SWE, the first question we need to answer is ---- What is the key element which links them together?

To further understand this question, we shall take a closer look at all the researches that are carried in these areas. One general observation is: most of them are based on certain raw data, which is collected during human sport activities.

- Such collected data, can be physiological data, physical data or peripheral multimedia data.
- The same data, can be interpreted in different ways, with different perspectives and focuses.

This is why so many researchers with different background could work together towards the same objective. They are basically working over the same raw data. By jointly considering various aspects of the same sport activity, multi-modal analysis can be easily carried out, which leads to a comprehensive understanding of the sport activity. Therefore, to build the SWE, is equivalent to

- build a worldwide unified “toolbox” which allows researchers and users to easily collect raw data.
- enable a unified way to share sport-related information and work with each other about it.

Another interesting observation is: all these raw data are captured by certain devices. Generally, they can be regarded as “sensor”. Typical examples are thermometer, accelerometer, speedometer, etc. Even the video camera can also be seen as a “video sensor”. Sensor is the heart of the entire SWE. Without sensor data, the space for our innovation will be quite limited. Therefore, to properly manipulate the sensors, and to smoothly connect them to any other elements within SWE, become the key to open the door of SWE.

The Responsibility of Academy and Industry within SWE

As the stakeholders of this ecosystem, the academic researchers, sensor vendors, data collector manufactures and service providers shall closely work together, to ensure the proper operation of the entire ecosystem. Each of them could contribute to SWE with its own professional knowledge. Their works are supplemental to each other, which ensure the multidisciplinary nature of SWE. To make this happen, everyone shall take its own responsibility.

Responsibility 1: Model the sensor devices

Sensor device is the source of the raw data. It is very important that all the data collectors could access any sensor device with a generic way. This requires folks work together to produce a general model for sensor device, which contains basic and common features of all the sensor devices.

Responsibility 2: Transmit the collected data

At the initial stage of some investigations, researchers tend to use proprietary solution to transmit the data. This simplifies the designing procedure, but introduce big interoperability problem when transferring technology from laboratory to market. In addition, the lack of multi-vendor availability will often leads to poor cost safety of the final products. In order to connect all the elements of SWE, defining a standardized way to transmit sensor data is necessary. Industry folks definitely shall take this responsibility, to define suitable fundamental standards to serve this purpose. Through these standards, the raw data can be smoothly and seamlessly transmitted from sensor device to ordinary data collectors, such as PC, mobile phone, watch and room hub.

Responsibility 3: Transmit the collected data to internet

Internet has already entered into the stage of web 2.0 [Hinchcliffe, 2006]. Nowadays it has already become an indispensable element of our daily life. Especially for young people, the "internet" means a lot: daily life, leisure, entertainment, shopping, communication, etc. Many web services have been created to satisfy the dynamic user demands over internet. Similar rule applies to sport domain too, where users have strong desire to upload their personal sport data to internet, e.g., personal blog, web service, user community, etc. They have various motivations to share, compare and exchange such data over internet, possibly together with peripheral information such as personal multimedia data. Therefore, it is very important that data collector vendors and service providers could work together to establish a standardized and secured interface for this purpose. After that, sport will not only mean "sport", but also means: entertainment, gaming, leisure, shopping, personal health, etc.

Responsibility 4: Transmit the collected data to other professional ecosystems

The sport medicine [Bamberg, 2008] applications rely on the physical and physiological data collected from the user or patient. On the other hand, the telemedicine [Galarraga, 2007] technology has been significantly developed recently, which allows patient's data be transmitted seamlessly towards hospital system. Therefore, there is a great opportunity here to extend the scope of traditional sport medicine, by combining medical theories with modern ICT technologies. It would be ideal if there is a standardized and secured way to exchange such medical information between related entities. This requires a joint effort from academic researchers, medical industry, hospitals and ICT engineers. Neighbouring domains, such as occupational healthcare, epidemiology and public health, could also gain benefits from this interface.

Responsibility 5: Insurance and social welfare system

In modern society, nowadays the obesity and hypochondria have already become "popular" terms in our daily life. An efficient and cheap way to overcome them is to encourage people to actively participate into more sport activities. Better technologies and new services can be utilized by sport applications to make them more attractive to the massive users. If the penetration of this idea is deep enough, we can expect a significant improvement of the life quality and wellness status of civilian. Subsequently, the burden of social welfare system will be dramatically reduced. This may also bring side benefit towards insurance companies. On the other hand, by extending the scope of sport industry, more companies working in the new market can be created; thus more job opportunities can be expected. The entire human society will gain huge benefit from this. Therefore, the government and insurance companies shall take the responsibility to assist the development of SWE. We are happy to see that such idea have already gone beyond the documents. Some pilots [HealthSpace, NUADU] have already been conducted in different places, which resulted in many useful experiences.

Responsibility 6: Academic researchers

Academic society can leverage such infrastructure (which is built by industrial society), to identify new research problems and to create new concepts with minimal configuration. With the existing infrastructure, the cost and resource consumption is expected to be lower than the traditional researches. Furthermore, the delay caused by technology transferring to market can be shorter. The entire research and development procedure will be dramatically accelerated.

Exemplar Infrastructure for Establishing the SWE

As examples of the aforementioned infrastructure, the Bluetooth Special Interest Group (SIG)® and Continua Health Alliance® will be introduced here. These two organizations are closely working together, to provide a seamless data chain from sensor devices to web services and hospitals.

Bluetooth Technology

Wireless communication has been widely adopted by various application domains. Compared to the wired communication technologies, it brings people with excellent mobility and new capability. One of the most successful wireless technologies in Personal Area Network (PAN) is the Bluetooth radio technology. In fact, the PAN is actually the most interested domain for many sport-related applications.

Bluetooth SIG®, founded in September 1998, is a privately held, not-for-profit trade association. The SIG has more than 10,000 member companies that are leaders in the telecommunications, computing, automotive, music, apparel, industrial automation, and network industries. So far, more than 2 billions Bluetooth devices have been shipped to market. Bluetooth SIG grants its members with the access to the Bluetooth specifications. The SIG also specifies a qualification process that products must be tested in accordance with before they may be branded with the Bluetooth trademarks and sold to consumers. It also markets the Bluetooth brand and technology and owns the trademarks and standardization documents.

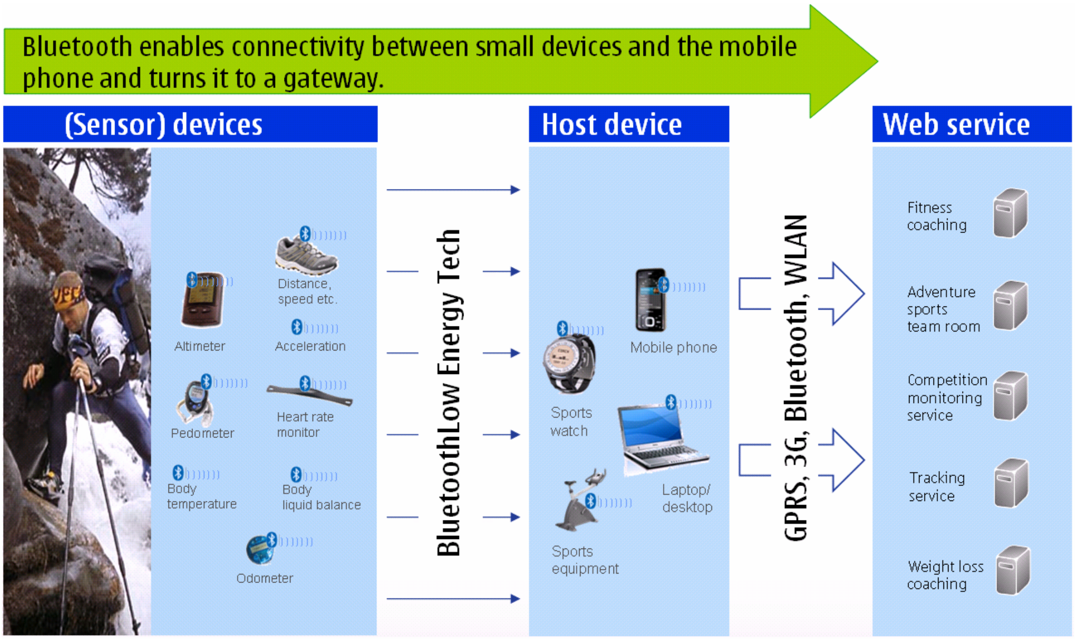


Figure 2. The working flow of Bluetooth Low Energy Technology.

Generally, the sport-related sensor devices are regarded to have only limited resource and capability. They usually are powered by button-cell battery, e.g., wearable sensors. On the other hand, due to the requirements on mobility, cost and size, even the data collector devices are often quite simple, compared to desktop or laptop system. A typical example is the sport watch, which has limited resources. Thus, the classic Bluetooth radio technology cannot satisfy such stringent requirement of power consumption. In addition, the limitation of the number of device within one piconet in classic Bluetooth cannot meet the requirements set by some wearable sensor applications [Armstrong, 2007]. Therefore, the Bluetooth Low Energy

Technology (BLET) is developed and utilized by Bluetooth SIG® as the major wireless radio for data transmission under such situation. Figure 2 shows a working flow of this system.
One significant benefit for manufactures to adopt BLET is the minimal added-cost over existing classic Bluetooth radio. Both technologies can be implemented with the same radio chip, and common Host Controller Interface (HCI). This means: with zero added cost, a device will be equipped with two radios, which are capable to serve different application scenarios. Thus, the additional cost is mainly caused by the development of protocol and profile stack. More comprehensive discussions about this technology can be found in [Special Bluetooth Edition, 2008].
The BLET system contains a Sensor Framework to ensure wide interoperability between different sensor devices and data collector devices. The targeted application domains are not only limited to sport and wellness, but also include personal healthcare, aging independence, home automation, industrial automation, etc. The common features and functionalities of all the sensor devices are extracted and formulated as a profile -- Sensor Profile. This profile ensures a basic level interoperability, and provides the basic functionalities of sensor devices.
On top of this profile, multiple public Service Classes can be created to serve for different dedicated purposes. Compared to Sensor Profile, these Service Classes can provide additional useful functionality and certain added-value, which can significantly increase user experience. Furthermore, vendor could also create private Service Classes to protect their own core technology, but in the meanwhile, still maximally utilize the BLET radio. This gracefully reduces the investment of manufactures, and speeds up the research & development procedure.
In order to integrate the sensor devices with the web service, the BLET system defines the so-called "gateway" functionality. It allows the measured data to be transmitted to remote data collectors via backbone network or internet, enabling the remote access to the sensor devices. While in the same time, the simplicity and low power consumption of sensor device remain the same. This is achieved by allowing remote device to access the proximity device which is near the sensor device, and such proximity devices are generally have more capability and resource than sensor devices. Figure 3 shows a simple example of it.

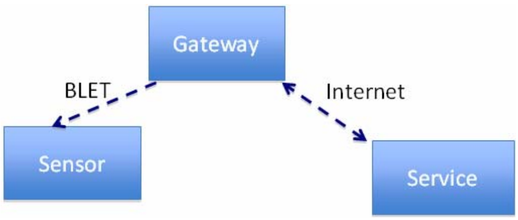


Figure 3. The example of gateway device enables the remote access from web service to sensor device. The complexity and power consumption of sensor device remains in a low level.

Continua Health Alliance

The Continua Health Alliance® (Continua) is an open industry group of healthcare, technology and fitness companies establishing a system of connected personal telehealth solutions that fosters independence and empowers people and organizations to better manage health and wellness. Its key objectives include:

- Empower individuals and patients to better manage their health by providing them with information regarding their fitness and health through personal medical devices and services.
- Allow loved ones and professional care givers to more accurately monitor and coach chronic disease patients and elderly individuals living independently.

- Enable medical and fitness device manufacturers to rapidly develop interoperable devices and services using industry developed connectivity standards.
- Enable health care providers to offer better quality care through personalized health solutions assembled from a rich marketplace of interoperable health care devices and services.

So far, Continua has already attracted nearly 200 member companies, including many big players in medicine, sport and technology markets; and it is still growing.

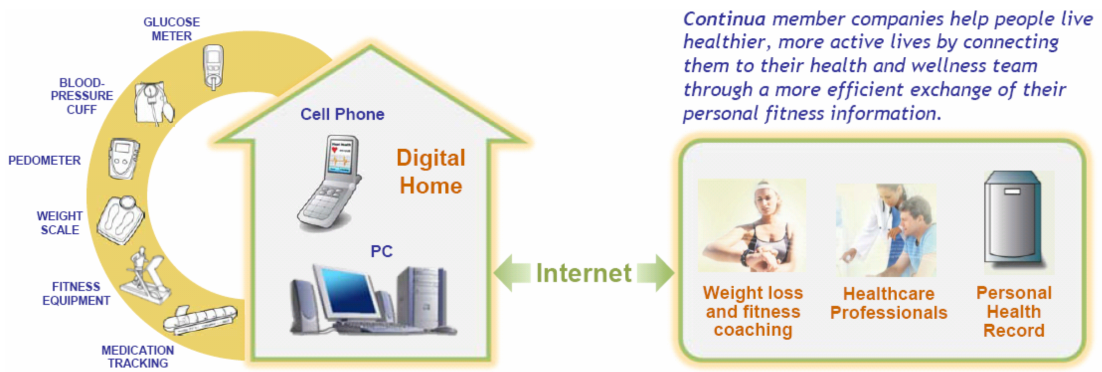


Figure 4. The vision of Continua's targeting use case in Health and Fitness domain.

The Continua system can be roughly described by several interfaces, which is shown in the Figure 4. Continua regards the PAN-interface (which the Bluetooth and BLET are mainly working on) as one of the entries of the entire Continua Health Alliance ecosystem. On top of that interface, the WAN-interface supports the data exchange between personal proximity devices (e.g., phone and PC) and web services. When the data enter into medical and clinical ecosystem, the related xHR-interface is defined by Continua to ensure the data conform to the format that are widely used in health record system.

Continua are actively working with many related standardization bodies to ensure the best interoperability. The principle collaborators include: Bluetooth SIG, USB, HL7, IHE, IEEE. In principal, the Continua is not intended to create its own standard. Instead, it usually chooses some major standards from different domains, and leverage their existing market, users and stakeholders. As a result, Continua produces documents called Interoperability Guideline, to describe the standardized way of how to multiple external technologies, and enforce the usage of these guidelines among its members. As an example, Figure 5 shows the PAN-interface that has been implemented in Continua Interoperability Guideline v1.0.

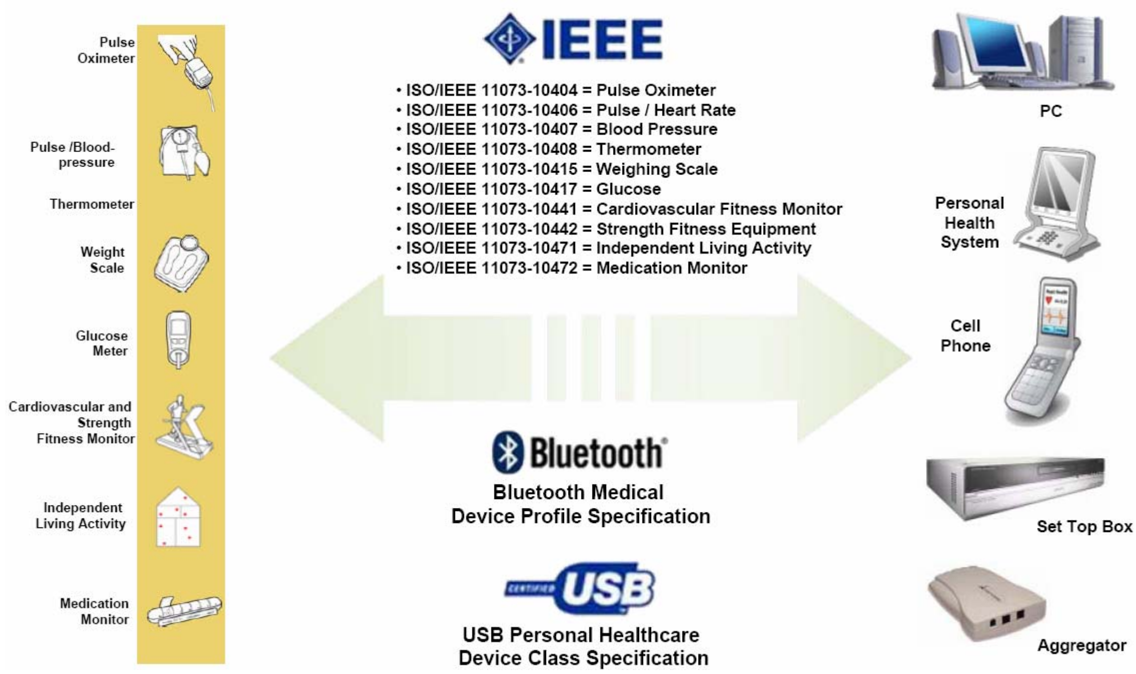


Figure 5. The PAN-interface that has been implemented in Continua Interoperability Guideline v1.0.

Aforementioned interfaces describe the hierarchical system of Continua ecosystem along a vertical direction. On the other hand, horizontally, Continua is working on three major domains; Disease Management (DM), Aging Independence (AI) and Health and Fitness (HF). Among them, the HF domain has direct connection towards sport science. However, this does not mean the sport-related devices and data can only work within HF domain; they also have plenty of opportunities to serve other two domains. This is exactly the very place where many scientific researchers could work on, to create many innovative user applications.

Seamless Data Chain and New Opportunities

What links the sport devices into Continua ecosystem is the PAN-interface. Both the classic Bluetooth and BLET are suitable radio technologies for such purpose. In fact, Continua has already adopted Bluetooth technology as the wireless PAN-interface in Version 1.0 of Continua; while the BLET has already been chosen as one of the candidates during the development of Version 2.0 of Continua. Such kind of close collaboration produces a seamless data chain from sensor to internet, which is the key to enter into consumer market or any other new landscape.

By jointly using Bluetooth and Continua ecosystem, the sport-related devices can be utilized in many conventional application domains, as well as to some new domains. The same sensor data can be transmitted to different destinations, which allows numerous new applications to be developed for various purposes. In addition, the traditional professional sport services can also be smoothly transferred into consumer market, which may lead to huge profit. Based on this, different web service and user community could be created, to satisfy different user demands. User interaction is also enabled with low complexity and low power consumption in the actuator devices. Such scenario is illustrated in Figure 6.

From the academic perspective, such movement is considered to be profitable too. New domain leads to new research opportunity. “How to adopt to the consumer market” and “How to create consumer applications with sport specialty” will become hot topics in the sport academic society. Furthermore, this will also stimulate the peripheral researches such as:

- user experience study

- personal daily health and fitness
- epidemiological impact of personal sport activity
- relationship between sport activity and nutrition
- remote sport education and coaching
- ICT-based rehabilitation technology
- new sport-related business model
- regulatory issues caused by new technology

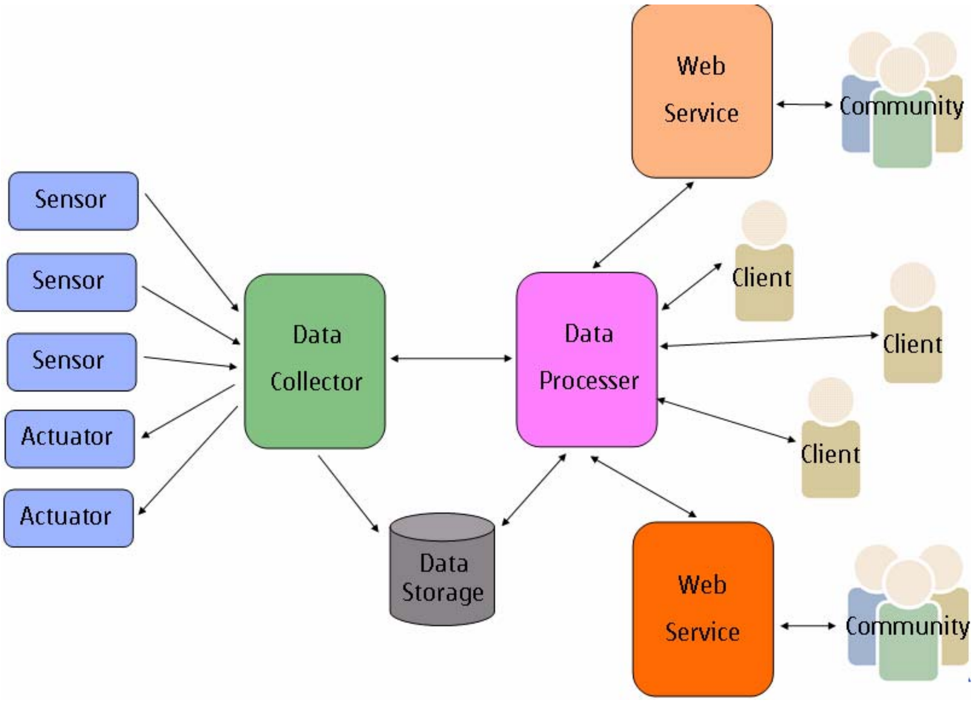


Figure 6. From Sensor to web service.

In addition, by entering into new market, the sport manufacturers and service providers can gain more revenue. Part of it will be rewarded to research society to promote the following research activities along this direction. Therefore, once such positive iteration circle is established, a Win-Win situation can be expected.
From engineering perspective, designing sport devices based on standardized technologies will largely reduce the burden of implementation. Engineers can concentrate on the functional features, rather than lower-level technical details. In practice, they may choose to buy existing modules from module vendors, and then, to create user application based on a set of simple API. Thus, the overall development procedure is minimized, and the products can easily be shipped to existing market. Compared to the proprietary solution, the standardized modules provide better user adaptation and long-term market penetration.

Exemplar Applications Based On Aforementioned Infrastructure

The Bluetooth and Continua ecosystem, together, can be regarded as a good example of how traditional sport applications and vendors could smoothly enter into SWE. The following text will describe two examples which turn this concept into reality.

Nokia Sports Tracker

The importance of outdoor personal sport activity in our daily life has been increased recently. The related market has become quite promising in past years, especially in Europe and Northern America. To satisfy such requirements from consumer market, Nokia® Corporation has launched the Nokia Sports Tracker, which is a GPS based sport activity tracker that runs on smartphones. User can download it from internet with zero cost. This application runs as a “client-server” manner. Figure 7-9 show the screenshot of client-side, server-side and user community respectively.

The data chain of Nokia Sports Tracker starts from sensor devices, through the mobile phone, and finally reaches the web service and web community. Many sensor devices can be integrated into this system, such as heart rate belt, speedometer, pedometer, hygrometer, thermometer, etc. In addition, the mobile phone itself also provides certain sensor-like data, such as GPS information. Usually, these sensor data are transmitted within the PAN. Multiple wireless radio technologies are available for such purpose. Due to the world-wide coverage of the personal consumer market and proven robustness, the Bluetooth technology is utilized as the major transport tool for Nokia Sports Tracker.

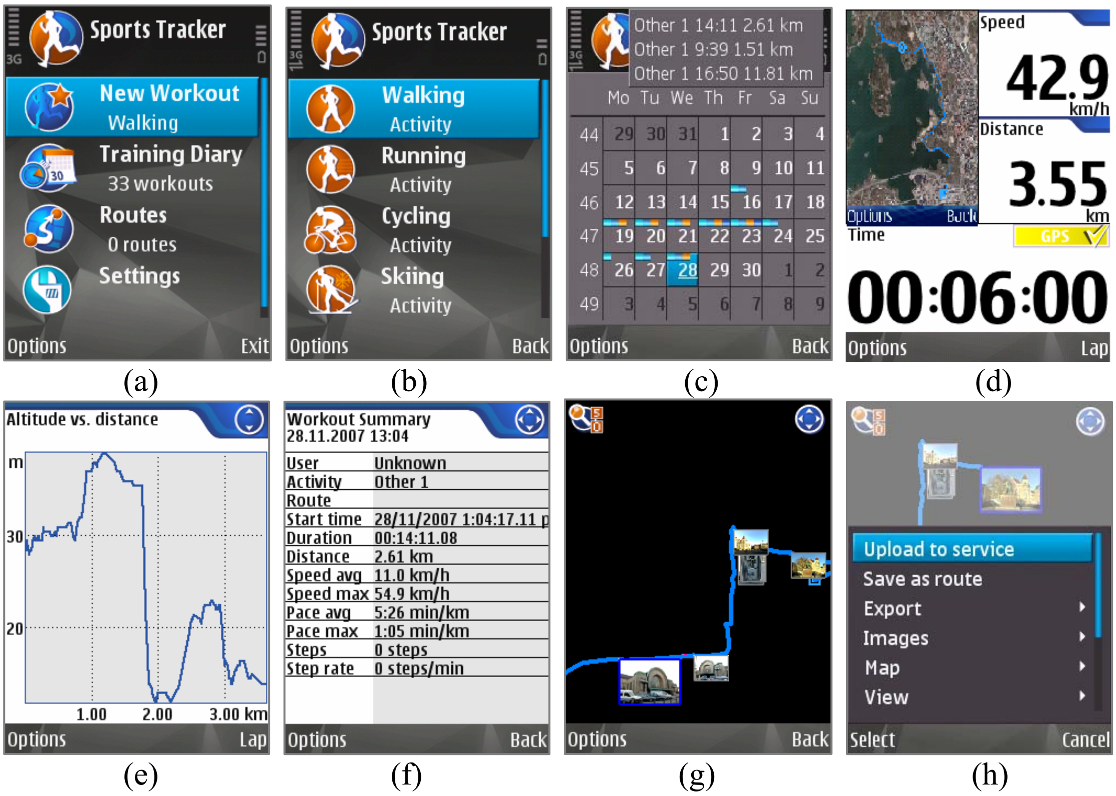


Figure 7. Screenshots of the client-side software of Nokia Sports Tracker. This example runs over Nokia N95 model, Symbian S60 3rd version. (a)1st-level menu. (b) 2nd-level menu. (c) The amount of personal sport activity can be overviewed in phone calendar. (d) The speed and distance can be shown in realtime during the sport activity. (e) Visual illustration is also available. (f) The workout is summarized at the end of each training. The corresponding result can be uploaded to corresponding web service. (g) User may take pictures along the route. (h) The route tracked by GPS, together with the captured pictures, can be uploaded to web service.

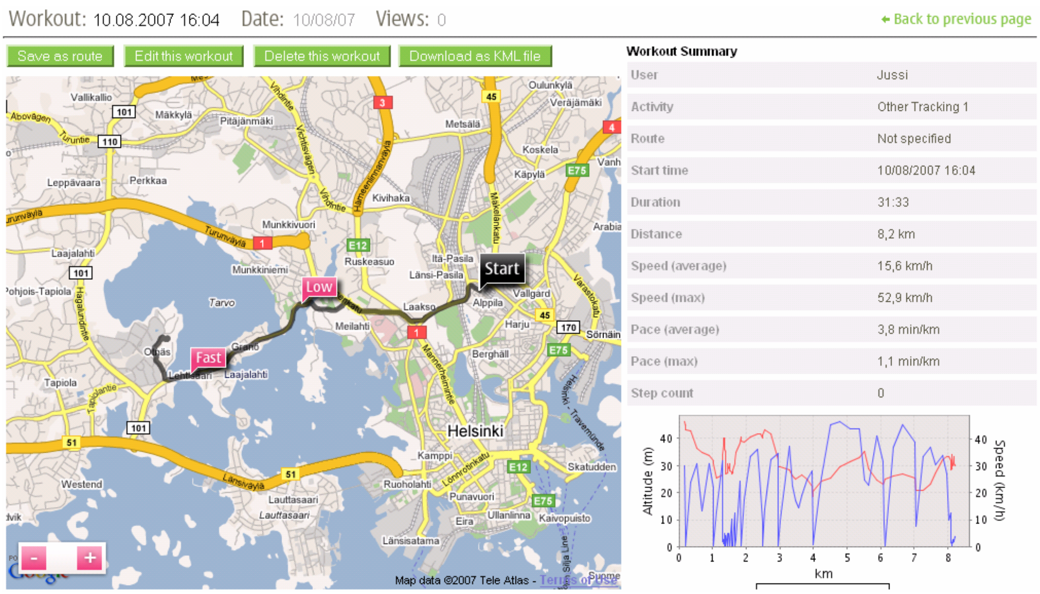


Figure 8. Screenshots of the server-side software of Nokia Sports Tracker.

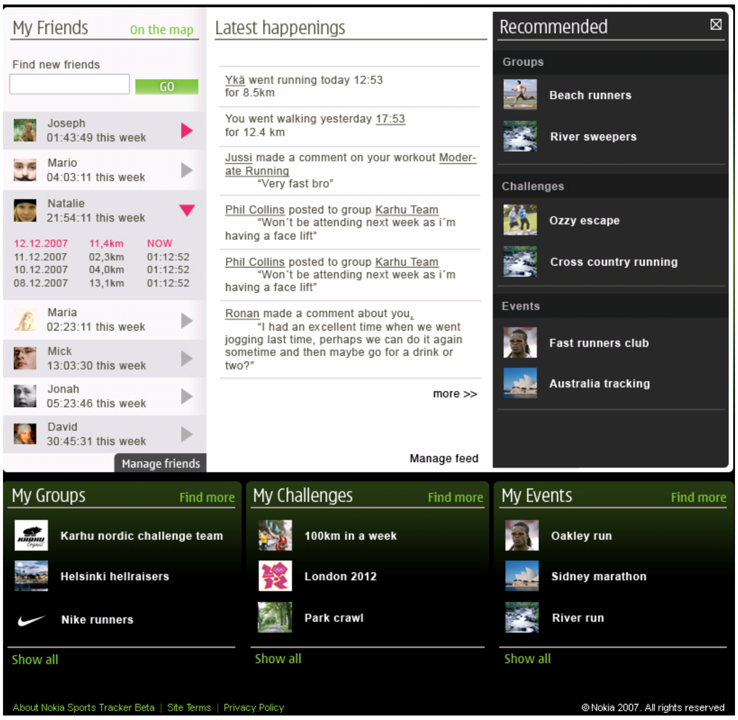


Figure 9. Screenshots of the web user community of Nokia Sports Tracker.

In the next step, these sensor data are efficiently combined with the personal information and multimedia data stored in the phone, to form an integrated data package. Such data package can be uploaded to web service through various data links like: WLAN, 3G or USB. The entire transmission procedure is transparent to the users. All that a user needs to do is just to press one button --- "Synchronization", which is provided by the client software application installed in mobile phone.

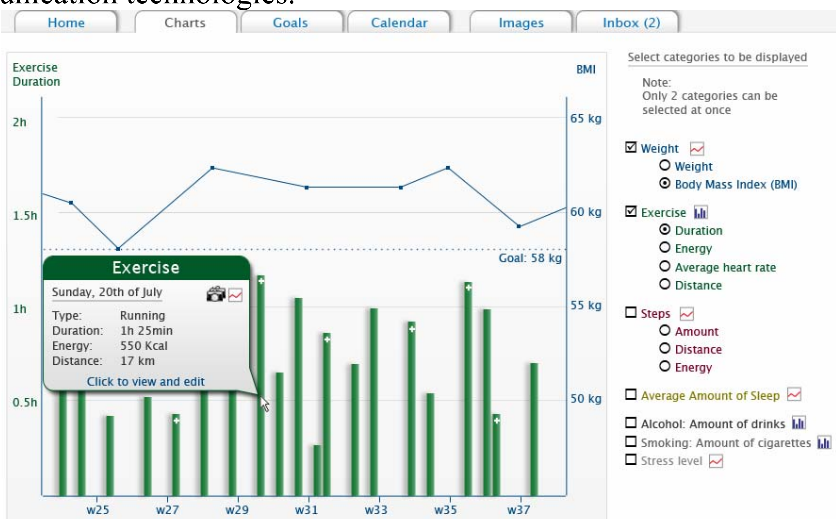
Once such data reached the web server, service providers can build their own web service and user communities. Nokia has already implemented a web user interface, where people can manage and share their own personal sport-related data. The interesting point of Sport Tracker is, it seamlessly links the sport sensor, GPS data, internet map service, multimedia data and web community. Such infrastructure shows strong attraction towards many manufactures who traditionally were working in different domains. Such environment provides plenty of new business opportunities for all the participants who were not capable to cover so many different domains previously.

Nokia Wellness Diary

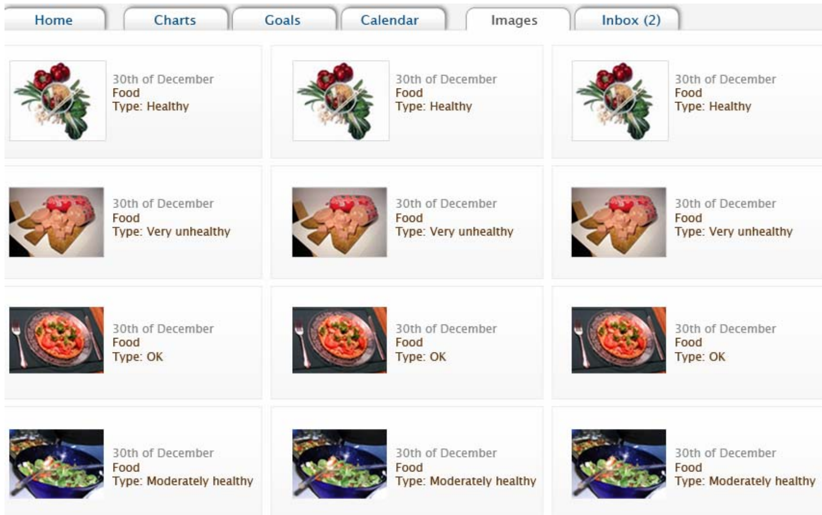
Accompany with the rapid development of personal electronic consumer devices, the personal wellness and healthcare has become a hot topic in recently years. ICT significantly improved the quality of service in related domains like: home healthcare, personal wellness and personal fitness. Such fact allows the personal sport data to be a valuable input of the personal wellness ecosystem. The similar sensor data as listed above, combined with the information of daily nutrition intake, daily calorie consumption, physical movement and basic physiological parameters, can provide comprehensive information and long-term monitoring capability for personal healthcare providers and hospital systems.

To build widely applicable consumer systems on top of these sensor data, again, we need a standardized and seamless data chain. In fact, this data chain covers bigger cope than the above data chain, because these collected sensor data may finally be sent to hospital system or personal healthcare providers. More interfaces will be involved in this data chain; more companies will participate; more new opportunities will be crated. This is actually what Continua is working for.

To prove and solidify such concept, Nokia® Corporation launched the Nokia Wellness Diary, a personal wellness service based on mobile client and web server. Users use mobile phone and PAN-interface to collect data from many sensors. Such data is stored in the mobile phone, and later is uploaded to dedicated web services. Similar to Nokia Sports Tracker, the data is presented in the server side with well-managed visualizations. The personal healthcare providers, who have been granted permissions, as well as the users themselves, can log into the web service to browse the collected data. Based on this infrastructure, users and healthcare providers are able to communicate with each other directly. The healthcare providers can provide healthcare-related consultation, or sport training program, through various communication technologies.



(a)



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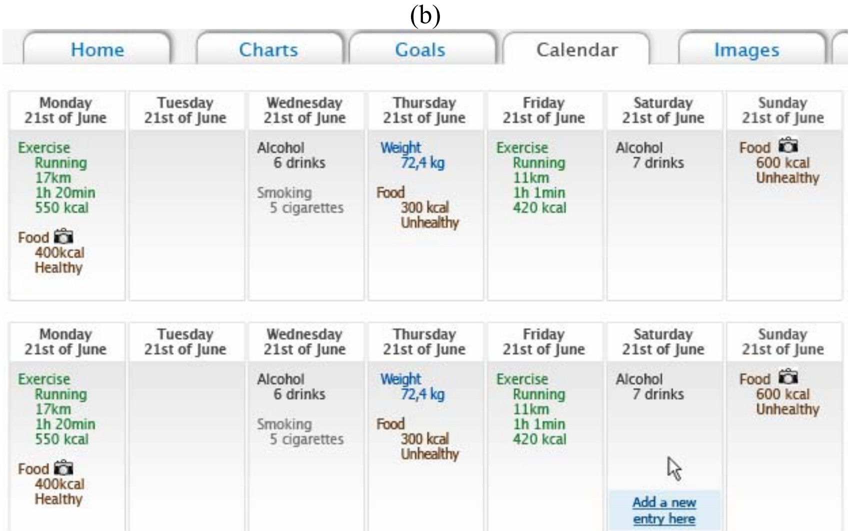

(c)

Figure 10. Screenshots of the server-side of Nokia Wellness Diary. (a) Visualization of the data of body weight, exercise and daily steps. (b) Daily food intake is linked to calendar. (c) Personal info (alcohol, weight, smoking, food, exercise, etc.) are overviewed in calendar.

Although the architecture of Nokia Wellness Diary is similar to Nokia Sports Tracker, and the sensor data they are utilizing has overlapping, but their purposes are completely different. The Nokia Wellness Diary is meant for personal wellness management, while Nokia Sports Tracker is meant for personal sport management. This is, in fact, an advantage for traditional sport equipment manufactures when entering into personal wellness market; because this helps them to avoid redundant works. The same equipment can be utilized by two different ecosystems, which means the market space can be increased without increasing the cost of implementation. Furthermore, the Nokia Wellness Diary can directly import the data produced by Nokia Sports Tracker, which means less amount of user input. This can be considered as a great benefit from the usability perspective. Figure 10 and 11 present the screenshot of client-side and server-side respectively.

Nokia is actively working with Continua, to make sure the Nokia Wellness Diary matches the Continua ecosystem, in terms of interoperability and quality of service. On the other hand, by leveraging the Continua, Nokia Wellness Diary achieves direct contact to healthcare providers, end users and device manufactures. It is such kind of mutual interaction between multiple entities visa standardized interfaces which actually build the Win-Win situation, as well as the Sport and Wellness Ecosystem. This fact can be easily observed by the rapid increasing number of downloading of Nokia Wellness Diary, or the increasing number of participants in Continua.

Figure 11. Screenshots of the client-side of Nokia Wellness Diary.

Conclusions

This paper describes the Sport and Wellness Ecosystem. It heavily relies on a seamless and interoperable data chain from sensor device to various destinations. Such data chain can be regarded as the essential skeleton of the entire ecosystem. The continuous development of ICT is the guarantee of this data chain, as well as the driving force of the SWE to move forward.

By leveraging the ICT, academic and industrial folks from traditional sport application domain can smoothly step into new ecosystem, and to create new markets. The collaboration between Bluetooth SIG and Continua Health Alliance is a typical example to prove the feasibility of SWE. Bluetooth provides the means to allow data collectors to collect data from sport sensors; after that, the data are transmitted within Continua system, to reach different destinations, such as web services and hospital system. The publicly-defined standards ensure the worldwide interoperability between different manufacturers.

Based on that, the Nokia Sports Tracker and Nokia Wellness Diary are presented as productized examples to show how this data chain can be utilized for different purposes. Many interesting sport-related consumer applications can be easily established within the SWE.

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