Data-Driven Models for eHealth Applications

System Analysis Techniques

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***Abstract*-Mathematical model delivered both from knowledge of a system and from experimental data may provide additional information about the system under consideration. This information may be further exploited for different purposes, such as prediction, diagnosis, decision making and system control. Data-driven models have been found to be particularly useful in assessment of some human abilities in sport and medicine. We demonstrate the usefulness of data-driven models in custom eHealth application.**

Keywords- eHealth; Wireless Sensors; Endurance Training; Estimation; Decision Making Support; Optimization

I. INTRODUCTION

Expansion of wireless measurement devices allows acquiring large volumes of physiological data and monitor physical activity of sportsmen [1]. Moreover, these devices became widely available due to increasing use of smartphones [2]. Typically, smartphones are equipped in accelerometers, optical sensors, GPS. Additional sensors, such as: heart rate sensor, gyroscope, ECG and EMG sensors, glucometer, magnetometer, GSR (Galvanic Skin Response) sensor, strain gauge, may be connected to the smartphone through the Bluetooth protocol. Further on, these data are sent to desired location (e.g. application server of a computer center) to be stored, processed in a real-time and results are sent back to the sportsmen or a trainer access device. This makes measurement data available anytime and anywhere.

Physiological data are used to system identification, which is determining the exact form of a mathematical model describing phenomena of interest. Later on we present mathematical model relating heart rate (HR) signal, running speed and fatigue. The model has few parameters and values of these parameters may be estimated with use of measurements performed by the user. This allows the model to adapt to particular user. Such models are result of both expert knowledge and measurement data and are thus called data-driven models. Analysis performed with use of a data-driven model combines expert's knowledge with measurement data, whereas typical approach to statistical analysis makes use of data only. Mean values and other statistics represent the data, whereas data-driven model is representation of data and expert's knowledge, [3].

Data-driven models are useful in eHealth applications, because they can quantify many aspects of physical activity. There are several examples of application of data-driven models in eHealth literature. Aforementioned model of HR response to training intensity is proposed in [4, 5]. It describes processes that occur in cardiovascular system. In [6]-[8] many models of blood glucose level (BGL) response to meal [7] and physical activity [8] are introduced. Models are used to predict the BGL for particular patient and to control BGL of diabetes. In [9] models are used to analyze energy of sportsmen. An application for swimming techniques analysis is described in [10]. The source of data driven mathematical models for dynamic physiological processes is [11]. The use of mathematical models for performance and fitness assessment with relation to fatigue is treated in [12]. In [13, 14] the training of tennis player is taken into consideration. Data-driven model together with pattern recognition techniques were applied in [15] to generate rehabilitation scenarios for impaired patients. Some artificial intelligence methods for physical activity support were applied in [16].

In general, eHealth applications requirements are: distributed acquisition of measurement data and their processing, availability of data anytime and anywhere [17], availability of decision making support services [18], personalization [19, 20]. Described solutions focus rather on supporting people in their daily activities, not necessarily on professional athletes in preparation for Olympics. Non-professional users prefer mobility over accuracy. Therefore, we assume the use of cheap sensors having moderate accuracy of measurement.

The key points of modeling procedures in eHealth are as follows. At the beginning an appropriate model is worked out for particular task and measurement possibilities. The model should contain some parameters to be set on the basis of measurements taken during experimental trials. Next, system identification techniques are used to estimate values of these unknown parameters. From now on, predictions, conclusions and decisions may be done on the basis of the model parameters, not only the data. Ability of a subject to perform exercise may be assessed on the basis of parameters values or results of model-based simulation.

In Section II data acquisition in eHealth applications are reviewed. In Subsection II. B we present architecture of application to support endurance training, developed by authors. The whole procedure of data-driven model usage is given in Section III. Section IV concludes the work.

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II. DATA ACQUISITION IN EHEALTH APPLICATION

A. Sensors

Wearable sensors to acquire human physiological and kinematic data, together with portable access devices, are offered by many companies [21]. Both commercial and research teams develop solutions for support professional and recreational purposes. In the commercial fields of applications Polar belongs to the most important companies offering wearable devices together with data processing tools [22]. Wrist worn watch and chest worn heart rate sensor are used to measure and present data to the user. Polar provides equipment for fitness improvement and for maximization of performance. These devices are used in motivational feedback i.e. generate beeps every time when certain amount of calories is burnt. It is useful in preventing injuries and overtraining. Moreover the Polar's software provides tools to optimize training intensity. Suunto [23], provides devices that generate personalized training plan. Based on results of user's training monitoring these devices are capable of making recommendations for training volume i.e. the frequency, duration and intensity. Moreover, proposed training plan may be adjusted to the user's current capabilities i.e. when the user's activity level decreases. The miCoach product od Adidas is advanced training tool [24, 25] that can be used to optimize training plan for endurance training, strength and flexibility. Data are measured from stride and heart rate monitor. The website allows the user to manage the training process. Important feature of the system is digital coaching, which serves to motivate user – through feedback – by giving his/her voice notifications such as "speed up" or "slow down" and informing about the workout progress. MOPET is an example of advanced project [26] under development. It uses measurement data to work out the user's mathematical model. The model adapts to the user and is used to predict user's performance. On the basis of the model analysis, advices concerning the user's health state and safety issues are generated. Such a model based prediction plays an important role in element of personalization and context-awareness systems [27, 28].

On the market many commercial equipment for wireless acquisition of physiological and kinematic data are available. We chose devices produced by Zephyr Technology and Shimmer Research. Equipped with these sensors, the user has ability to measure the following physiological signals: heart rate, breath rate, temperature, ECG and others such as acceleration. Shimmer Research offers following sensors: ECG (Electrocardiography), EMG (Electromyography), GSR (Galvanic skin response), Acceleration, Gyroscope, GPS etc. Products of both companies are still under development but many successful applications have been reported by both researchers and engineers' teams [9, 29, 30].

Depending on eHealth area and application type, different configurations of the platform may be set up. For example, requirements of athletes (intensive training) and impaired people (rehabilitation) are different, hence different platform configurations.

B. Architecture of Application

Users may carry these devices easily, hence the term Body Area Network (BAN) or Personal Area Network (PAN) is used. Data acquired by BAN are transferred via the gateway nodes to servers. Servers process data and send results to the user access device (smartphone, laptop). End users may be sportsmen and trainer or patient and physician. All the elements mentioned above, i.e. wireless sensing units, servers and users access devices, constitute distributed computational environment.

We developed eHealth application having three-tier architecture, depicted in Fig. 1. There is a data acquisition tier (BAN, PAN), data processing and decision making support tier and presentation tier.

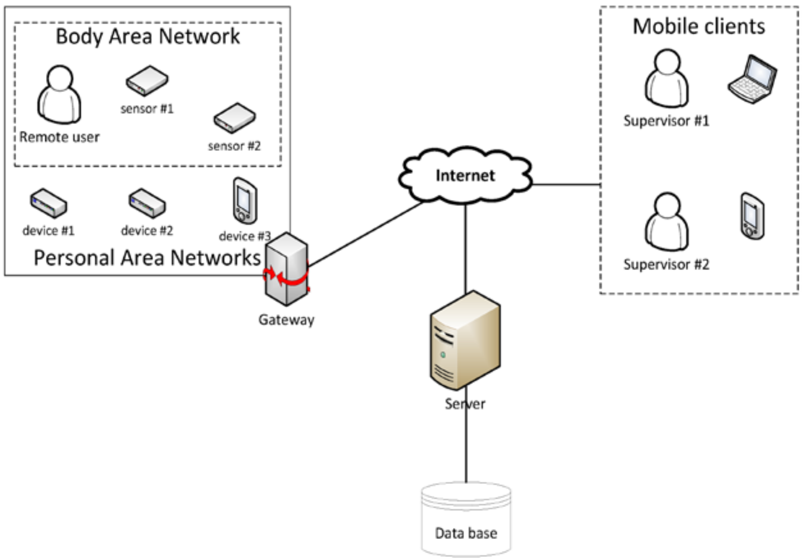

Fig. 1 System architecture for healthcare and wellness

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The first tier is wireless sensor network that is composed of sensing units that are placed on human body and his/her environment. Each user of the system may use several sensing units. Acquired data can be preprocessed on personal server such as smartphone and further transferred to server through Internet connection. It is worth stressing that smartphones usually play double role in the proposed application: simple processing of acquired data and maintaining connection between users wireless sensors and remote server.

The key element of the system is the second tier composed of servers intended for computational purposes. These servers provide functionalities that perform advanced data processing. Architecture of the application allows defining problem-oriented scenarios, meaning that functionalities are delivered in the form of compositions of basic computational services [31, 32]. Some applications use only data filtering and statistics but decision support task usually require data-driven model and advanced algorithms for estimation, optimization, control, and pattern recognition.

Another element of the second tier is data base or streaming data base. They are used to store acquired measurements, to prepare learning sets for classifiers, optimizers and controllers.

The last tier is presentation tier and its main purpose is visualization (e.g. charts) and reporting (e.g. tables) of data processing results. In Fig. 2 architecture of application is illustrated.

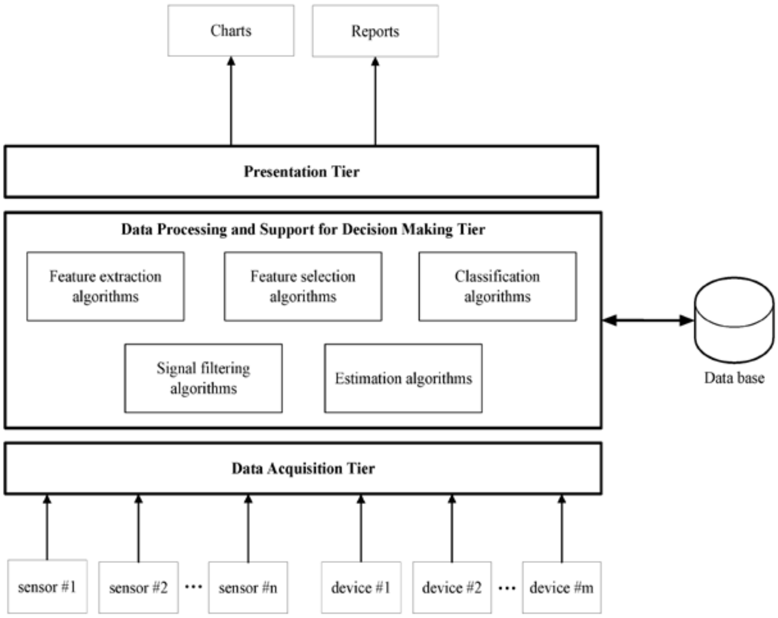

Fig. 2 Architecture of eHealth application

The next section describes custom application that we developed with use of the described architecture.

III. ENDURANCE TRAINING SUPPORT

The main goal of the application is to support endurance training for a runner. We describe how the application works, from the viewpoint of system modeling and analysis techniques.

A. Data-Driven Model of Heart Rate Response

The goal of the footrace is to run a given distance in a shortest time. Two variables are measured by wireless sensors in a real-time: the user speed and the heart rate (HR). The most important issue in this task is to spread the effort of a runner in such a way that the time of the run is the shortest. The application does it for the user. All decisions are worked out on the basis of mathematical model describing cardiovascular system and fatigue during exercise [4, 5]. The model describes relation between the heart rate and exercise intensity. Increasing heart rate allows the cardiovascular system to deliver more blood and oxygen to active muscles. The model takes into account short-term and long-term effects of exercises. It has the form of nonlinear set of differential equations:

$$x_1'(t) = -a_1 x_1(t) + a_2\left[x_2(t) + u^2(t)\right] ,$$
$$x_2'(t) = -a_3 x_2(t) + \frac{a_4 x_1(t)}{1+\exp\left[a_5 - x_1(t)\right]} , \tag{1}$$

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where x_1 is HR change from the rest (resting heart rate), u denotes speed of the user, x_2 may be considered as fatigue. Fatigue is caused by such a factor as: vasodilation in the active muscles leading to low arterial blood pressure, accumulations of metabolic byproducts (e.g. lactic acid), sweeting and hyperventilation. Variable x_2 summarizes all these factors. Parameters $a_1, a_2, ..., a_5$ take nonnegative values. The user performance may be characterized by the set of these five numbers. The model is developed according to physiological phenomena behind the process [4]. Typical model response is depicted in Fig. 3.

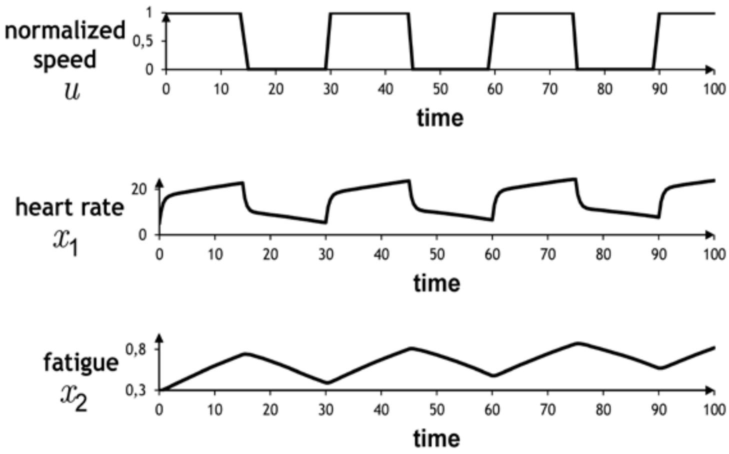

Fig. 3 Typical response of the Model (1)

B. Estimation of the Model Parameters

Values of parameters are determined using input-output time series measured from the user. The input signal is speed $u(t)$ and the output is HR signal $x_1(t)$. HR signal is directly measured by wireless sensor, whereas speed is evaluated as a filtered integral of acceleration measured by the accelerometer. The user performs few training protocols. Typical training protocol involves step-like functions $u(t)$ that determine length of the resting (zero speed), the exercise (high speed) and the recovery (walking or resting) periods (see Fig. 4).

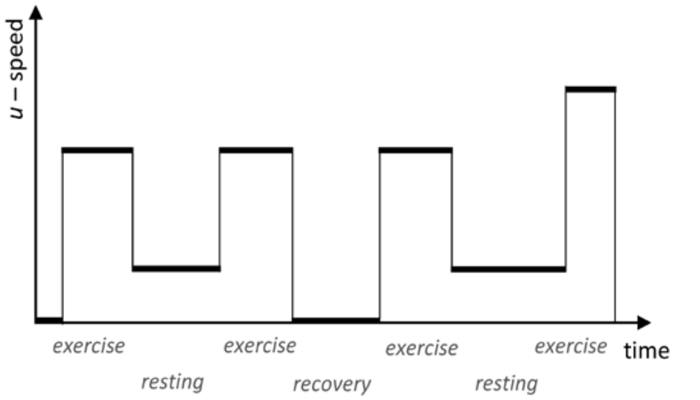

Fig. 4 Typical training protocol

Note, that $x_2(t)$ signal is not measured. It may only be evaluated during simulation. The task of estimation of such a closed-loop nonlinear systems' parameters calls for numerical optimization algorithm. In [4, 5], where the treadmill is used to control speed, authors employ the Levenberg-Marquardt procedure.

The task to be solved is to estimate values of unknown parameters $a_1, a_2, ..., a_5$ in such a way, that model responses x_1 best fit to HR measurements. The sum of squared differences of areas between simulated and measured signals is chosen as a performance index. Estimates minimize performance index. The search for optimal values of parameters in five dimensional spaces is performed in two stages. Simulated annealing [33] gives approximate solution and then BFGS method [34] finds optimum more accurately. The block scheme of estimation procedure is given in Fig. 5.

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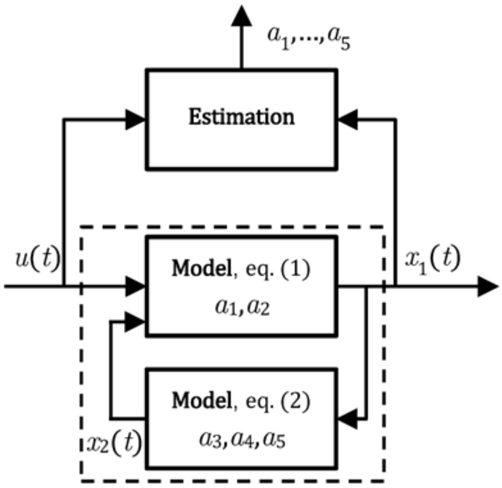

Fig. 5 The model and estimation procedure

C. Decision Support Task – Problem Formulation

The application aims at supporting a runner during a footrace. The goal of the footrace is to run a given distance in a shortest time. The user question is how should I run in order to do my best? She/he needs the optimal training protocol.

If the user model is given and parameters are estimated, the following optimization task is to be solved, [35]. For a given: distance D to run, fatigue and speed limits $x_2^{\max}$ (after this upper bound is exceeded, the user terminates a footrace) and $u^{\max}$ (the user is not capable of running faster, due to the fitness level), find such a training protocol $u^*(t)$, for which a desired distance is completed in a shortest time.

The footrace time T is solution of the equation:

$$D = \int_0^T u(t)dt \tag{2}$$

resulting in performance index:

$$T = Q\big(u(t), D\big) \tag{3}$$

There is a constraint for fatigue:

$$\max_{t\in[0,T]} x_2(t) \le x_2^{\max} \tag{4}$$

and constraint for the user speed:

$$\max_{t\in[0,T]} u(t) \le u^{\max} \tag{5}$$

Note that x_2 in (2) is related to $u(t)$ by the model equations (1).

If we want to force the user to do his best, we may require, that the highest fatigue occurs at least at the end of the race:

$$x_2(T) = x_2^{\max} \tag{6}$$

If needed, we may take into account additional requirements concerning upper bounds for the heart rate:

$$\max_{t\in[0,T]} \frac{d}{dt} x_1(t) \le \Delta x_1^{\max} \tag{7}$$

where $\Delta x_1^{\max}$ stands for maximum allowed heart rate change speed. For people having cardiovascular problems restriction for maximum acceptable level $x_1^{\max}$ of the heart rate is imposed:

$$\max_{t\in[0,T]} x_1(t) \le x_1^{\max} \tag{8}$$

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Another disease is taken into account by defining constraints concerning relevant physiological parameters. For example, diabetic users control blood glucose level (BGL). During exercise, glucose is utilized so BGL decreases. BGL must not fall below certain level $G^{\min}$, determined by a doctor:

$$\min_{t \in [0,T]} G(t) \geq G^{\min} \tag{9}$$

The quantity $G(t)$ in (9) is predicted track of blood glucose level, worked out from the model described in [6]-[8].

D. Optimization of Training Protocol

To sum everything up, for the basic setting that only involves Constraints (4)-(6), optimal training protocol $u^*(t)$ is solution of the following optimization task:

$$u^*(t) = \arg \min_{u(t) \in \Omega} Q(u(t), D) \tag{10}$$

where Ω is the space of all possible protocols $u(t)$. The shortest time for the optimal training protocol $u^*(t)$ is:

$$T^* = Q(u^*(t), D) \tag{11}$$

There are inequality Constraints (4), (5) defining maximum values of functions $x_2(t)$ and $u(t)$ and equality Constraint (6) determining the value of the function $x_2(t)$ at the Point T.

The Space Ω of all possible Protocols $u(t)$ is limited to compositions of step-like functions, as shown in Fig. X. Therefore, the process of training protocol design may be simplified by parameterization of the function $u(t)$. It is represented as a sequence of pairs of numbers, describing the duration and the speed of successive exercise periods. Parameters should determine: length of the periods (resting, exercise and recovery) and associated speeds (recovery period has zero speed by default). It is also possible to assign each period a predefined speed. This stems from the fact, that people typically walk and run with their characteristic speeds. Parameterization reduces the problem to real-valued optimization. Parameterizations make optimization easier, but introduce another problem. Since the footrace is completed after the Distance D is made, the number of parameters describing the solution may vary during the optimization process. Therefore, only optimization methods that are capable of varying number of dimensions during search, may be applied. We chose Simulated Annealing, but evolutionary algorithms should also perform well.

Sometimes training protocols generated by simulated annealing are similar to those obtained by the well-known, in physiological literature, Interval Method, but the most commonly generated type of protocol has different properties. It looks very interesting and an example is depicted in Fig. 6.

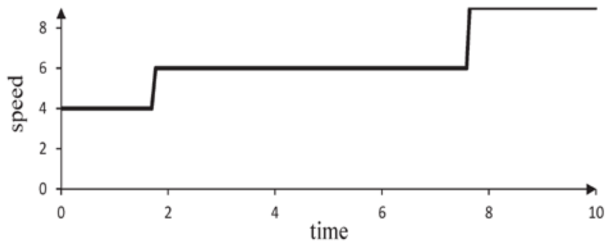

Fig. 6 The training protocol commonly generated by simulated annealing

The general strategy illustrated by this example is to increase the user speed up to the moment of maximum speed, where the user reaches its limits at the end of the route.

E. Control Task

The optimal training protocol is just a reference signal. The next step is to actuate it. The user is expected to follow it as close as possible. The user should be supported in switching between exercise, resting and recovery periods as well as in maintaining the correct speed during these periods. This functionality has been realized using voice commands uttered by the smartphone (“run faster”, “slow down please”). We use the PID controller with hysteresis. Controller takes current value of $u(t)$ signal delivered by the sensor and reference protocol $u^*(t)$ generated by optimization routine before the footrace and produces a voice command $\mu(t)$.

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F. *Adaptation*

With time, the user improves (or decreases) his/her performance and the model updates are necessary. This may also happen due to: worse or better, compared to average, user condition (e. g. after the party). When the user does not follow the reference trajectory, values of the user model (1) parameters need to be updated and the training protocol should be recalculated. Therefore, from time to time the application checks the user model validity and - if necessary – it updates the user model parameters using measurement data that have been stored in a database.

The application provides adaptive control system supporting the user in a real-time (see Fig. 7). Adaptation takes place in response to events occurring during the single training as well as reaction to long term effects caused by systematic training. With use of the model adjusted to the exerciser, optimal training protocols are generated and actuated.

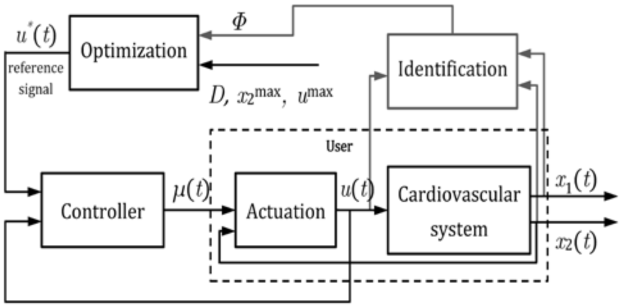

Fig. 7 Adaptive control system for endurance training support

The user story is the following. Before the application is used to support physical activity, the user is asked to perform few predefined training protocols. This is the first adjustment of the model to the user. Typical usage scenario starts from typing: - the footrace distance, - maximum speed, - the limit of fatigue (maximum speed and fatigue limit are learned by the application later on). Optimal training protocol is worked out using the user model simulations. In the background, comparison of the model responses to the measured signals is performed. If the difference becomes significant, the user model is updated and a new training protocol for the rest part of the route is generated.

IV. CONCLUSIONS

Since large volume of measurement data may be sent to computer centers and processed in a real-time, advanced processing algorithms may be performed on the data. The eHealth system is employed to acquire and deliver data and signals for system identification, optimization and control. Among many functionalities, one of its role is to support management of dynamic exercise intensity. Typically, for such applications, the user data undergo the following processing stages:

- data acquisition,
- estimation of the model parameters,
- model based optimization of the training protocol (planning),
- training support by the control algorithm.

The proposed application is just an example of personalization scheme which relies on composition of new services on the basis of predefined services. Configuration of services depends on the sport discipline practiced by user (context awareness). The system reacts to long term effects caused by systematic training by adjusting the user model and the choice of services he/she needs (user awareness).

The following computational services should be available in order to support physical activity of the user:

- the system identifier that makes use of some machine learning techniques to adjust the user model to measurement data,
- system simulator that may predict the user state for different training protocols,
- training protocol optimizer that works out the best training protocol,
- the controller that supports the user in performing optimal training protocol.

Further works focus on development of advanced functionalities that make use of pattern recognition methods.

The proposed research has some practical implications. It provides a way of designing advanced functionalities to eHealth systems. The direct application of proposed solution is the support of the anaerobic threshold training. From a long-term perspective, it may serve to support decisions concerning the training workload in order to achieve desired training goals. Our proposal makes it possible to design the training routine for an athlete in a safety way. Other examples are injury prediction and movement disorders detection. However, some pattern recognition routines should have been included into the scheme.

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