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Digital Twin in Sport: From an Idea to Realization

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Abstract: A digital twin is a virtual model to reflect a physical object and helps it by making proper decisions. The decision-making process is based on the same input data that the simulated physical object has access to. Due to exploiting artificial intelligence, the decision-making process of the digital twin is more sophisticated than that of the physical object. In this study, the digital twin is applied to the sports training domain, where it addresses those questions that have arisen during the implementation of interval cycling training sessions. Thus, the digital twin runs on a mobile device (i.e., the Raspberry Pi platform), with which a cycle is equipped and demonstrates user-friendliness, robustness, reliability, and accuracy. The interval training sessions are transferred to the mobile device in the form of the domain-specific language EasyTrain, ensuring higher expressive power and ease of use. During the implementation, the digital twin advises the athlete with predicted information obtained by a sophisticated prediction model via a screen. The results of a huge experimental work showed that the difference in the average efficiency of the interval training implementation between the two cyclists that performed the experiments is prominent, as the efficiency of the professional training surpassed 90%, while the amateur training efficiency barely achieved 70%.

Keywords: digital twin; interval sports training; domain-specific language; cycling

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1. Introduction

Nowadays, sport is one of the most important activities in the world. In particular, team sport disciplines, such as football, volleyball, and basketball, attract a lot of people [1,2]. Moreover, people also identify with their idols playing the roles of holders in team games. Obviously, a similar situation is not far away in individual sport disciplines. Additionally, in these disciplines, winners enjoy huge attention from their fans. Take, for example, sport disciplines such as cycling, running, and tennis, where successful athletes can normally survive with the fruits of their labor.

The big change in sport has arisen with the emerging multi-sport disciplines, such as triathlons and duathlons, where athletes undergo more sport disciplines sequentially one after another, while the total time is the sum of the times achieved in particular disciplines, to which their times for preparing for the next discipline are also added (i.e., so-called transition times). Interestingly, in these disciplines, amateur competitors compete together with professional ones at the same time [3]. Consequently, the wall between the amateur and professional sports has started to be knocked down, while amateur athletes are additionally stimulated to train more in order to draw nearer to the results of their idols.

Normally, amateur athletes cannot hire the support of professional sports trainers due to their great cost. Consequently, they choose the help of modern sport technologies, such as Garmin, Polar, Suunto, and Coros mobile sport watches [4,5]. Besides measuring the load indicators during the implementation of training sessions, these also offer advice on how to train (i.e., training plans), archiving of already implemented training sessions, and miscellaneous analysis of an athlete's progress in training [6]. Artificial Sport Trainer (AST) [7] presents complete help for an athlete in individual sport disciplines in all phases of sport training, where all these phases are covered using computational intelligence (CI) algorithms [8,9].

Although sports watches allow most functionalities necessary for monitoring the implementation of the sport training sessions, and are small and simple for wearing during the implementation, the huge development of the Internet of Things (IoT) devices demands a universal mobile device capable of connecting the huge range of sensors simply and reliably [10–13]. One such kind of device is most certainly the Raspberry Pi, i.e., a low-cost mobile computer with solid hardware as well as software equipment [14].

A digital twin is a virtual model to mimic a physical object [15]. It is connected to the same input stream as the corresponding physical object, and it is capable of predicting the decisions based on this input more reliably and accurately that the controlled object [16]. The idea behind using the digital twin in sport is to advise athletes (i.e., physical objects) during the implementation of sport training sessions how to overcome different situations during the implementation, in order to achieve the performance as demanded in the proposed training plan.

In our study, interval cycling sessions are taken into consideration, where the heart rate is imposed as a measure of intensity. Obviously, the digital twin is put onto the Raspberry Pi mobile device capable of controlling different IoT sensors and a global positioning system (GPS) receiver, and, finally, installed on the cycle. Indeed, the digital twin is not simply a simulation that controls one particular process, but it is a study of a virtual environment capable of running more simulations of multiple processes simultaneously [17]. Here, the virtual environment is perceived by the heart rate (HR) monitor and GPS receiver, while a planned interval cycling session presents the framework of the digital twin model. The interval cycling session can be created either by the real sports trainer manually, or by the AST automatically. Then, it is transmitted to the mobile device in the form of domain-specific language (DSL) that is simple to use and ensures enough expressive power [18] to describe the sport training domain efficiently.

Two scenarios were tested using the proposed solution, in which amateur and professional cyclists implemented the same training plan. The performances of both athletes were recorded carefully by the digital twin, while the differences were identified and analyzed in detail. The results of the experimental work were promising and showed that the proposed digital twin can be applied successfully in practice.

The main contributions of the paper are as follows:

- introducing the concept of the digital twin in sport;
- design and implementation of the digital twin for controlling the implementation of the interval training in cycling;
- proposing the mobile device platform for running the digital twin on Raspberry Pi;
- design and implementation of the DSL EasyTrain for transmitting the training plans to the digital twin;
- testing and evaluating the digital twin on two case studies, i.e., by controlling the implementation of the interval training for professional and amateur cyclist training.

2. Basic Information

2.1. The Basics of the Sport Training

Although human physiology is more or less the same for all human beings, the response of humans' bodies is different for the same training program [19]. This means that each athlete in training has unique personal characteristics. A cyclist with more fast-twitch muscles, for instance, needs more workouts for improving endurance and vice versa, the cyclist with more slow-twitch muscles must perform more workouts for improving speed in order to become an all-round cyclist [20].

Despite the differences in the athletes' physiology, four common principles of the training process can be identified as follows [21]:

- progressive overload;
- specificity;
- reversibility;
- individuality.

Progressive overload considers that an athlete needs to increase the amount of training for increasing fitness gradually and steadily. Thus, workouts cause physical stress on an athlete's body. This stress can be either positive, when the overload causes only fatigue, or negative, when injuries emerge because of too great of an overload. Sport training affects, specifically, two physiological categories of changes in fitness that are both critical for high-performance athletes: central and peripheral. The former refers to the heart, lungs, and blood, while the latter to muscles. Reversibility deals with the problem of losing fitness. It is well-known that fitness cannot be regained with resting. Individuality means that each athlete's body imposes its own physiological characteristics. Consequently, as each athlete is unique, his or her training plan must be unique.

In general, a sport training session is expressed mathematically as a quadruple:

$$TS = \langle Type, Duration, Intensity, Frequency \rangle, \tag{1}$$

where *Type* refers to the type of training session (e.g., for improving speed, power, or strength), *Duration* prescribes an endurance of a particular training session, *Intensity* determines how intensively the workout needs to be performed, and *Frequency* identifies how often should the athlete train. In line with this, duration is more important for specifying the amount of training than the distance. Interestingly, intensity is inversely related to duration in the following sense: The higher the intensity, the shorter the duration of the stress that can be overcome by the athlete's body. It can be measured in more ways, while the heart rate (HR) and power (PWR) meters remain the most important intensity measures in cycling.

Considering HR, the intensity of a workout is prescribed using the so-called HR-zones that are based on a percentage of the athlete's maximum HR, i.e., functional threshold HR (FTHR). The FTHR is an athlete's bio-marker, and denotes the highest numbers of beats per minute (bpm). Normally, this value is approximated by subtracting the athlete's age from the number 220. The example of five HR zones according to Coggan [20] is illustrated in Table 1, from which it can be seen that the first two (i.e., 'Active recreation' and 'Endurance') are of low intensity, the third (i.e., 'Tempo') is of moderate intensity, while the last two (i.e., 'Lactate threshold' and 'VO_2max') are of high intensity.

The HR-zones are determined according to percent of FTHR ('% FTHR' column). The table also contains a recommended duration of workouts in minutes for continuous and interval sport training sessions, and the border values of HR-zones for a 40-year-old athlete (with FTHR = 180 bpm). The continuous training session refers to a workout that is performed only once (i.e., $Frequency = 1$), while the interval training session consists of a sequence of speed and recovery intervals (i.e., $Frequency > 1$), where both the intervals are determined by their intensity and duration. Typically, speed intervals need to be performed at a higher intensity and shorter duration, while the recovery intervals are usually of lower intensity, but longer duration.

Table 1. HR-based training zones.

HR-Zone	% FTHR	Continuous	Interval	FTHR = 180
Active rec.	<68	30–90 min	n/a	122
Endurance	69–83	60–300 min	n/a	123–149
Tempo	84–94	60–180 min	n/a	150–169
Lactate th.	95–105	n/a	8–30 min	170–189
VO_2max	>106	n/a	3–8 min	>190

A sport trainer quantifies the volume of training using a training load. Mathematically, the training load is expressed according to Banister [22]:

$$TRIMP = Intensity \cdot Duration, \tag{2}$$

where training impulse ($TRIMP$) also presents the primary measure of the performed training.

2.2. The Digital Twin Concept

A digital twin represents a digital replica of a physical entity [15] and belongs to the top 10 strategic technology trends for 2019 as proposed by the Gartner group [23]. The founder of this technology was the National Aeronautics and Space Administration (NASA) during the rescue mission of Apollo 13 in 1970. According to Gene Kreuz, NASA chief flight director for Apollo 13, the simulators, supplementing the first digital twin were some of the most complex technology of the entire space program [24]. These simulators, running simultaneously with the damaged spacecraft, helped to bring the crew back to Earth alive. In particular, an analog simulation of the conditions in space and a virtual assembly enabled scientists on Earth to advise the crew by solving the problems in space.

Digital twin technology has proven to be indispensable nowadays. IoT sensors enabled digital twins to become cost-effective, so they could become imperative to Industry 5.0 and play the main role in understanding, analyzing, and optimizing physical objects. In line with this, the digital twin integrates technologies such as artificial intelligence (AI) and machine learning (ML) [25]. The main domains of their applicability are forecasting problems, i.e., problems where one monitors changes in virtual models or predicts potential risks before applying new plans, which are necessary for Industry 5.0. Nowadays, digital twins solve various problems in medicine and sports.

A scheme of the proposed digital twin is illustrated in Figure 1, from which it can be seen that this joins three different worlds, i.e., physical, analog, and digital, into a whole. The physical world (the environment) is sensed by the humans and their replicas (i.e., the digital twins) by sensors.

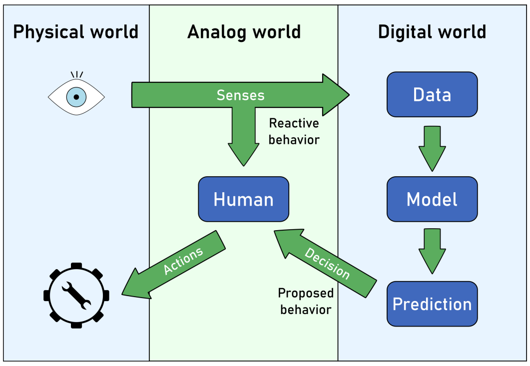

Figure 1. Scheme of the proposed digital twin model.

Although a human senses the environment using five sensory organs (i.e., eye, ear, skin, nose, and mouth), a digital twin is capable of sensing only digital data acquired from digital sensors. Here, we are interested in digital sensors whose results are presented to humans in a user-friendly form (e.g., a display). Such senses can be processed by human brains and transmitted as data to the digital twin simultaneously.

The human reacts to the senses with action, the selection of which is a consequence of the decision-making process in the mind (reactive behavior). On the other hand, digitalized data are processed by the digital twin's model that makes decisions on the basis of predictive analysis. This decision prescribes the so-called predicted behavior by the digital twin and is transmitted to the human. At the end, the human alone decides how to react to the sense: reactively or predictively.

3. The Digital Twin in Cycling

The digital twin plays the role of personal assistant, and helps the athlete in the implementation phase of the sport training by advising how to react in some situations appearing during the training session at each moment. Consequently, it demands some kind of mobile device capable of hosting the applications on limited hardware. Nowadays, there are a lot of mobile devices offering these characteristics, from general to special purposes. These devices can either be worn by an athlete or mounted on the cycle. It must be connected to the Internet and be wearable with many IoT sensors for monitoring the behavior of the athlete and the cycle.

3.1. Design of the Digital Twin in Cycling

Indeed, the proposed digital twin in cycling consists of the following three components (Figure 2):

- network connection;
- a feedback system;
- predicting model.

Each athlete in the implementation of a sport training session follows the demands of a training plan that determines a framework for a digital twin model.

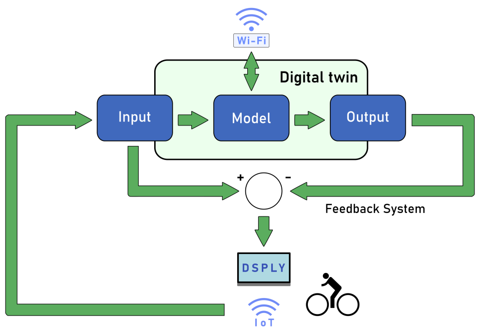

Figure 2. Scheme of the proposed digital twin model for cycling.

The training plan can be transferred to the mobile device using a network connection through a wireless Internet, such as WiMAX, 4G, 5G, or Wi-Fi. Although many formats exist for data transfer, a special DSL EasyTrain is applied in [26] in order to enable real, as well as artificial sport trainers (such as AST [27]) to transfer training plans in an easy to use and universal way. The detailed description of the DSL is omitted due to the paper length limitation.

A feedback system has a closed-loop characteristic [28]. This means that the output affects the control on the one hand and induces sequence of cause-and-effects that exist between the input and output variables, on the other. Data (the input for the model) are obtained from the IoT sensors, with which a cycle or an athlete is equipped. The model transforms raw data into training load indicators, on which basis new predictions are made. The results of the prediction are presented on the display of the mobile device together with the sensed data, and both are subjects of the athlete's final decision making.

Many modern ML methods could be used for predicting the digital twin's decision. However, the selection of the proper one relies on the speed of the digital twin's response. Obviously, the speed is connected strongly to the limited hardware on mobile devices.

3.2. Implementation of the Digital Twin

An interval training session is defined formally as a tuple:

$$TS^{(Int)} = \langle Int\_type, t_{spe}, \overline{HR}_{spe}, t_{rec}, \overline{HR}_{rec}, repeats \rangle, \tag{3}$$

where Int_type is the type of the interval training session, t_{spe} the duration and $\overline{HR}_{spe}$ the average HR of the speed interval, t_{rec} the duration and $\overline{HR}_{rec}$ the average HR of the recovery interval, and *repeats* denotes the frequency of the interval training session.

The algorithm for implementing the interval training in cycling is developed using three algorithms:

- training plan observer;
- digital twin feedback system;
- digital twin prediction.

The first component is devoted to communication with the central AST module and building the framework of the model. The digital twin feedback system is responsible for: (1) obtaining data from sensors during the implementation process, (2) analyzing the data, and (3) predicting the decision of the digital twin and displaying this to an athlete.

3.2.1. Training Plan Observer

The pseudo-code of the training plan observer is presented in Algorithm 1, from which it can be seen that the training plan observer first provides an archive of the interval training sessions described in EasyTrain from the AST system (in function RECEIVE line 1). Then, a list of collection of sport training sessions in JSON data-interchange format is generated by the EasyTrain in function EASYTRAIN (line 2). The collection is presented on a user display, from which the proper sport training session identified with ID is selected in the function SELECT (line 3). This session is then loaded into the digital twin as a model in the function LOAD (line 4), which guides the cyclist during the implementation of a training session. The implementation starts by pressing the <start> button on the display in the function RECEIVE (line 5). Finally, the implementation is performed in the **for** loop (lines 6–9), where the digital twin feedback system for the speed in the function DIGITALTWIN (line 7) and recovery intervals in the function DIGITALTWIN (line 8) is called.

Algorithm 1 Training plan observer.

Require: AST
1: RECEIVE(AST,$Archive$) ▷ Receive an archive from AST
2: $Collection$ =EASYTRAIN($Archive$) ▷ Make a TS collection
3: ID =SELECT($Collection$) ▷ Select ID from a collection
4: TS =LOAD($Collection$,ID) ▷ Load the proper TS
5: WAIT_FOR_START_BUTTON ▷ Start by pressing button
6: **for** $interval \leftarrow 1$ to $repeats$ **do** ▷ For each interval...
7: $TRIMP_{spe} \leftarrow$DIGITALTWIN($\langle TS.\overline{HR}_{spe}, TS.t_{spe}\rangle$)
8: $TRIMP_{rec} \leftarrow$DIGITALTWIN($\langle TS.\overline{HR}_{rec}, TS.t_{rec}\rangle$)
9: **end for**

3.2.2. Digital Twin Feedback System

Algorithm 2 illustrates a feedback system implementation of a digital twin for guiding the cyclist during the implementation of the interval training session. This starts with the parameters average proposed heart rate $\overline{HR}_{prop}$ and proposed duration t_{prop}, where $prop \in \{spe, rec\}$. This means that the same code is used for both intervals, i.e., speed and recovery. After initialization (lines 1–5), the feedback system continues until the duration of the speed/recovery interval is not exceeded (line 6). The algorithm supports all the mentioned components of the digital twin as follows: (1) data are obtained in the function READCONTROLDATA (line 7), (2) data modeling is performed (lines 8–10), and (3) prediction is calculated in the function PREDICTION (line 11). The predicted value of the heart rate is displayed on the cyclist's screen in the function VISUALCONTROLDATA (line 12).

Algorithm 2 Digital twin feedback system.

Require: $\overline{HR}_{prop}$, t_{prop}
Ensure: $TRIMP$
$n \leftarrow 1$ ▷ Times of sampling
$\langle t_{n-1}, t_n \rangle \leftarrow 0$ ▷ Elapsed time of cycling
$\overline{HR}_{n-1} \leftarrow 0$ ▷ Average HR calculation
$\langle plus, minus \rangle \leftarrow 0$ ▷ Initialization of TRIMP areas
$TRIMP \leftarrow 0$ ▷ Initialization of summary TRIMP
while $t_n \leq t_{prop}$ **do**
  $\langle \overline{HR}_n, t_n \rangle \leftarrow$ READCONTROLDATA; ▷ Obtain sample data
  $\overline{HR} \leftarrow \overline{HR} + \frac{1}{n}(HR_n - \overline{HR})$; ▷ Calculate average HR
  $\Delta t_n \leftarrow t_n - t_{n-1}$
  $\Delta TRIMP \leftarrow \frac{1}{2}\left(\overline{HR}_n - \overline{HR}_{n-1}\right) \cdot \Delta t_n - \overline{HR}_{prop} \cdot \Delta t_n$
  $\overline{HR}_{pred} \leftarrow$ PREDICTION($\Delta TRIMP, \overline{HR}, \overline{HR}_{prop}, t_{prop} - t_n, \&minus, \&plus$)
  VISUALCONTROLDATA($\overline{HR}_{pred}$) ▷ Predict to an athlete
  $n \leftarrow n + 1$; $t_{n-1} \leftarrow t_n$; $\overline{HR}_{n-1} \leftarrow \overline{HR}_n$ ▷ Update
  $TRIMP \leftarrow TRIMP + \Delta TRIMP$ ▷ Update TRIMP
end while

3.2.3. Digital Twin Prediction

Although a lot of AI prediction tools exist nowadays (e.g., linear regression, Bayesian inference), the preliminary tests showed that the application of these tools is not possible on limited hardware. Therefore, we searched for our own mathematical prediction model that is simple and fast enough to prevail over these hardware limitations. Indeed, the interval training session consists of speed and recovery intervals. Typically, a cyclist in the speed interval tries to overcome the proposed $\overline{HR}_{spe}$ as fast as possible. When the cyclist's HR_n in the n-th interval is under the $\overline{HR}_{spe}$, the corresponding TRIMP values are negative but become positive, when the HR_n increases over the $\overline{HR}_{spe}$ in the same interval. The opposite is true for the recovery interval. Consequently, two TRIMP areas can be distinguished by an integration of the HR_n by time slices Δt_n for $n \in [1, T]$, i.e., $plus$ and $minus$, where the former denotes the positive and the latter the negative values of the integrated TRIMP. For the integration, the trapezoidal rule is applied as follows:

$$area = \sum_{n=1}^{T} \left(\frac{\overline{HR}_{n+1} - \overline{HR}_n}{2} \cdot \Delta t_n - \overline{HR}_{pred} \cdot \Delta t_n \right), \tag{4}$$

where $area$ denotes either $plus$ or $minus$, and $\overline{HR}_{pred}$ is predicted average HR. Let us mention that the second term in Equation (4) denotes the TRIMP value needed for overcoming the observed time slice to the proposed average heart rate, and must be subtracted from the total TRIMP value.

The motivation behind predicting the intensity value $\overline{HR}_{pred}$ is to make up for the deficit of TRIMP before reaching the $\overline{HR}_{spe}$ proposed in a training plan by increasing this value in the later phases of the speed interval. It holds also in the opposite way, i.e., to expend an overproduced TRIMP before reaching the $\overline{HR}_{rec}$ by decreasing this value in the latter phases of the recovery interval.

Let us emphasize that the proposed prediction is directed toward determining the predicted value of the heart rate by fixing the duration of the time intervals. The goal of the prediction is to balance the TRIMP values of $plus$ and $minus$ by considering the expected, remaining number of the training intervals n_{expect}, expressed mathematically as:

$$plus + n_{expect} \cdot \overline{HR}_{pred}(t_{prop} - t_n) = minus, \tag{5}$$

from which the predicted $\overline{HR}_{pred}$ is derived as:

$$\overline{HR}_{pred} = \frac{minus - plus}{n_{expect}(t_{prop} - t_n)}, \tag{6}$$

and the n_{expect} is calculated according to deductive calculus as:

$$n_{expect} = \frac{t_{prop} \cdot n}{t_n}. \tag{7}$$

Let us notice that $t_{prop} \in \{t_{spe}, t_{rec}\}$.

A pseudo-code of the prediction component of the proposed solution is illustrated in Algorithm 3, from which it can be seen that the TRIMP areas *plus* and *minus* are first updated by the $\Delta TRIMP$ value obtained during the last time slice. Then, either the proposed value of average heart rate is taken when the proposed $\overline{HR}_{prop}$ value is not reached yet, or the predicted value is calculated according to Equation (6).

Algorithm 3 Digital twin prediction calculation.

```
Require: ΔTRIMP, HR̄, HR̄_prop, ΔT, minus, plus
Ensure: HR̄_pred
if ΔTRIMP < 0 then
    minus = minus + ΔTRIMP
else
    plus = plus + ΔTRIMP
end if
if HR̄ < HR̄_prop then
    HR̄_pred = HR̄_prop;                                ▷ under/over proposed HR
else
    HR̄_pred = HR̄_prop + (minus−plus)/(n_expect·ΔT)      ▷ Equation (6)
end if
```

4. Experiments and Results

The purpose of the experiments was to show that the proposed digital twin could be applied in practice for advising an athlete on how to achieve the training plan goals online during the implementation of the interval training session. In line with this, more tests were conducted, and the results are illustrated in the next section.

The digital twin algorithms were implemented in the Python programming language, while EasyTrain was implemented in Ruby due to its incorporated language extension capabilities [29]. Thus, data from the sensors were captured in one-second interval rates that ensure an athlete's training demonstrates real-time performance. The digital twin was run on a mobile device that is based on the Raspberry Pi computer equipped with GPS and WiFi modules and ANT+ USB (Table 2).

Table 2. Specifications of the hardware equipment.

Index	Component
1	Raspberry Pi 4v Model B with Raspberry Operating System
2	4″ LCD touch screen
3	USB ANT+ stick
4	Adafruit's Ultimate GPS HAT module
5	Kingston SDHC 32GB Canvas
6	Garmin HRM PRO Chest strap with ANT+ Transmitter

The GPS module allows access to positioning services, the WiFi module connection of the computer to the Internet, while the ANT+ USB serves as a hub for communication with IoT devices (HR monitors, power meters, etc.).

All kinds of athletes perform the same interval training sessions as illustrated in Algorithm 4, from which it can be seen that the intensity of the prescribed training session is moderate, because the average heart rate in the speed interval $\overline{HR}_{spe} = 150$ bpm belongs to the moderate HR zone (Table 1).

Algorithm 4 Description of the interval training in EasyTrain.

```
training = Ast.build(My collection) do
  interval(Sample interval) do
    sport: cycling
    info: Moderate
    speed_duration: 1
    recovery_duration: 2
    speed_heart_rate: 150
    recovery_heart_rate: 90
    repetitions: 10
    type: fixed
  end
end
```

The efficiency of the interval sport training implementation was estimated using a proprietary developed measure considering the speed and recovery interval separately. The success rate for the speed interval (SR_{spe}) is calculated according to a following equation:

$$SR_{spe} = \frac{1}{repeats} \sum_{n=1}^{repeats} \left(\frac{TRIMP_{spe,n}}{\overline{TRIMP}_{spe,n}} \right), \tag{8}$$

where the variable $\overline{TRIMP}_{spe,n}$ is calculated from the training plan in Algorithm 4, and variable $TRIMP_{spe,n}$ can be measured using the mobile device. Obviously, the variable n refers to an observed interval.

The efficiency of implementing the recovery interval SR_{rec} is evaluated in a similar way, in other words:

$$SR_{rec} = \frac{1}{repeats} \sum_{n=1}^{repeats} \left(\frac{TRIMP_{rec,n}}{\overline{TRIMP}_{rec,n}} \right), \tag{9}$$

where we operate with variables referring to recovery instead of a speed interval.

In summary, the average efficiency of the interval training implementation $\overline{SR}$ is highlighted by the following equation:

$$\overline{SR} = 1,0 - \frac{1}{2}\Big((1,0 - SR_{spe}) - (1,0 - SR_{rec})\Big), \tag{10}$$

which denotes the success rate as the average difference between the success rates achieved in both intervals. It holds that the higher the value of the average success rate, the better the efficiency of the implementation.

4.1. Results

The purpose of presenting the results of the experimental work is to show that the proposed digital twin for cycling is user-friendly, robust, reliable, and accurate, and, therefore, has a huge potential to be applied in a real-world environment. In line with this, the results obtained in more tests are summarized as follows:

- the analysis of a graphical user interface (GUI),
- Case Study 1: The results of a professional cyclist;
- Case Study 2: The results of an amateur athlete.

The results of the performed experiments are illustrated in the remainder of the section, while the interpretation of the findings is discussed in Section 4.2.

4.1.1. Analysis of GUI

A GUI in computer science allows seamless interaction between an application and a user. The GUI for a digital twin allows two functionalities: (1) selecting and loading the appropriate interval cycling training session, and (2) controlling the implementation of the loaded session.

The GUI of the proposed digital twin is designed according to the following guidelines [30]:

- minimalist and aesthetic design;
- operating system compatibility;
- data integrity;
- easy navigation and usability;
- security.

The minimalist design means that unimportant and not relevant information is kept to a minimum. That is, the display must be reduced for displaying only those elements that are necessary for the implementation of the interval cycling training session. The central point of the digital twin GUI presents an implementation of the interval cycling training session (Figure 3), where only five icons are presented, denoting five training load indicators. The icon in the center of the screen denotes the difference between the proposed and average heart rate. In the perception process of the cyclist, the image of the icon gets relayed back to his/her brain. Obviously, a motivated athlete wants to minimize the negative value of the difference as fast as possible. These icons are designed in an aesthetic way that attracts the athlete to look at the screen. In the sense of virtual reality, the real situation is additionally emphasized by using sound besides the visual display elements. For instance, when either the end of the current interval or the start of the next one has occurred, the event is announced by a sound signal to the athlete. Although a more detailed heartrate GUI could be displayed in Figure 3, the minimalist design guideline prevents us to made it more complex.

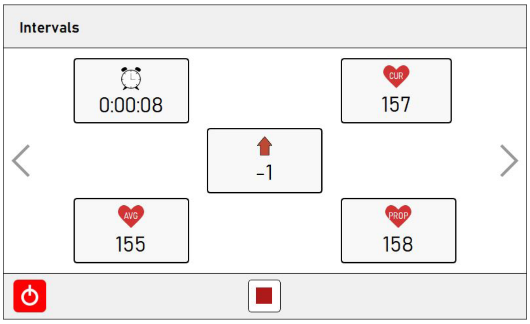

Figure 3. Implementation of the interval training session with the depiction of the digital twin prediction on a Raspberry Pi computer.

Operating system compatibility demands that the GUI design should ensure portability on similar platforms. The digital twin GUI is implemented in the Python programming language with the use of the PyQt5 framework. Although it is intended to be used on a Raspberry Pi device, PyQt5 ensures broad portability to various computer platforms.

Data arising in a digital twin do not remain on the origin platform for a long time, because they are copied after finishing each implementation onto the AST central system. Obviously, this is equipped with data integrity mechanisms as well.

Navigation of this GUI is simple due to the limited number of screens. Moreover, this is not even desired for the implementation screen, which is devoted to monitoring performance and prediction data only, where even navigation is excessive.

The security of the mobile device is ensured using an encrypted communication channel and allowing access to the application to the registered users only.

4.1.2. Case Study 1: Results of the Professional Cyclist

In Case Study 1, a professional cyclist was invited to implement a proposed interval training session as presented in Algorithm 4. The interval training session was estimated by a sport trainer as moderate, because it consisted of 10 repeats of the speed/recovery intervals, where the speed interval lasts 1 min at an intensity of 150 bpm (i.e., the tempo HR zone), while the recovery one lasts 2 min at an intensity of 90 bpm (i.e., the active recovery HR zone).

Research Question 1 (RQ-1) in the Case Study 1 was set as: "How to determine that the cyclist implementing the interval training session is a professional by using the DT in cycling?". The average efficiency of the implementation was measured and recorded by the DT. The experimental period was of duration 10×3 min $= 30$ min, where 10 denotes the number of experimental phases and 3 is duration of one speed/recovery interval. Normally, the implementation of the sport training session was conducted 2 h after eating. Here, a time series analysis was performed for the participant and the results of the analysis were visualized. The following criterion was asserted for accepting the proposition: "If the efficiency of the implemented interval training session is higher than 90%, then the cyclist is a professional cyclist".

The implementation of the interval training session was performed in sunny and calm weather at 24°, while a straight round track with little traffic was selected for the implementation. Consequently, the cyclist can be focused only on his riding on the track. The results of the implementation of the interval training session are illustrated graphically in Figure 4, which is divided into 10 speed/recovery intervals, displayed according to the overcoming time (x-axis) by the heart rate (y-axis). Actually, there are two different heart rate curves drawn: the proposed $\overline{HR}_{spe}$ or $\overline{HR}_{rec}$, and the measured $\overline{HR}$. Thus, the proposed heart rate curve is drawn in red, while the measured one in blue.

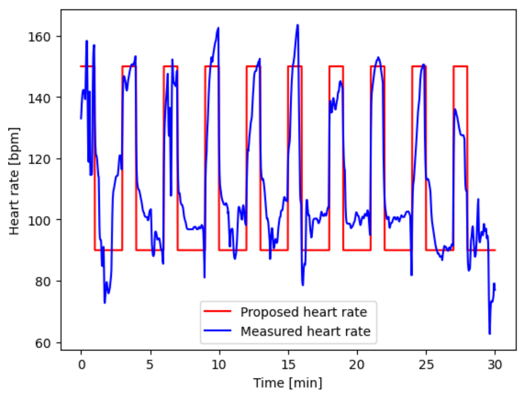

Figure 4. Professional sport training.

As can be seen in the diagram, the cyclist's measured $\overline{HR}$ tries to follow the proposed $\overline{HR}_{spe}$ or $\overline{HR}_{rec}$ as closely as possible. Interestingly, only in speed intervals 1, 4, and 6, the measured $\overline{HR}$ overcomes the proposed $\overline{HR}_{spe}$ substantially, while, in the other cases, the $\overline{HR}$ is near to or below the proposed $\overline{HR}_{spe}$. When the recovery intervals are observed, it can be concluded that the prominent valleys overcoming the proposed $\overline{HR}_{rec}$ arose in the recovery intervals 1, 3, 6, and 10. In the other recovery intervals, the measured $\overline{HR}$ is near to the proposed $\overline{HR}_{rec}$. Let us emphasize that the prominent peaks and valleys are a necessary condition for achieving the average for either $\overline{HR}_{spe}$ or $\overline{HR}_{rec}$.

Although the diagram in Figure 4 illustrates explicitly how the measured $\overline{HR}$ adapts to the proposed $\overline{HR}_{spe}$ and $\overline{HR}_{rec}$ based on the predicted $\overline{HR}_{pred}$ online, we are interested in how efficient was the implementation of the interval training sessions in the sense of the training load indicator TRIMP. In line with this, the $TRIMP_{spe}$ and $TRIMP_{rec}$ are calculated for each speed and recovery interval, respectively.

The calculated results for the speed intervals are presented in Table 3, which is divided into more columns denoting the proposed average TRIMP for the speed interval $\overline{TRIMP}_{spe}$, the measured TRIMP in the same interval $TRIMP_{spe}$, the difference between the proposed average and measured speed intervals $\Delta TRIMP_{spe}$, and the corresponding efficiency SR_{spe}.

Table 3. Professional cyclist results by interval speed intervals.

Int.	$\overline{TRIMP}_{spe}$	$TRIMP_{spe}$	$\Delta TRIMP_{spe}$	SR_{spe}
1	150	136.53	−13.47	0.9102
2	150	146.91	−3.09	0.9794
3	150	137.01	−12.99	0.9134
4	150	146.31	−3.69	0.9754
5	150	138.23	−11.77	0.9215
6	150	139.40	−10.60	0.9294
7	150	139.34	−10.66	0.9289
8	150	144.53	−5.47	0.9635
9	150	131.97	−18.03	0.8798
10	150	126.39	−23.61	0.8426
$\sum$	1500	1386.62	−113.38	0.9244

Let us emphasize that the negative values of the differences show that the professional cyclist did not succeed in satisfying the demands of the interval training session totally. The same fact is also justified when the efficiency of the interval training is observed (i.e., $SR_{spe} = 92.44\%$).

The situation becomes even worse when the recovery intervals are taken into account (Table 4).

Table 4. Professional cyclist results by interval recovery phase.

Int.	$\overline{TRIMP}_{rec}$	$TRIMP_{rec}$	$\Delta TRIMP_{rec}$	SR_{rec}
1	180	201.49	21.49	1.1194
2	180	198.72	18.72	1.1040
3	180	198.72	18.72	1.1040
4	180	201.78	21.78	1.121
5	180	203.48	23.48	1.1305
6	180	196.55	16.55	1.0919
7	180	203.18	23.18	1.1288
8	180	200.25	20.25	1.1125
9	180	190.69	10.69	1.0594
10	180	177.66	−2.34	0.9870
$\sum$	1800	1972.52	172.52	1.0958

In this case, the value of measured TRIMP in recovery interval $TRIMP_{rec}$ outdoes the proposed average $\overline{TRIMP}_{rec}$ as can be seen by observing the positive values of the recovery differences $\Delta TRIMP_{rec}$. In total, the efficiency decreases to $SR_{rec} = 90.41\%$.

4.1.3. Case Study 2: Results of the Amateur Cyclist

In Case Study 2, an amateur cyclist underwent the same interval training session as the professional due to a more realistic comparison between each other. This means that the male cyclist needs to overcome the interval training session consisting of a 1 min speed interval at 150 bpm followed by a 2 min recovery interval at 90 bpm.

Research Question 2 (RQ-2) in Case Study 2 was set as: "How to determine that the cyclist implementing the interval training session is not a professional by using the DT in cycling?". The developing propositions, the case study design, and the performed data analysis were the same as in Case Study 1, while the criterion for accepting the proposition was asserted as follows: "If the efficiency of the implemented interval training session is lesser than 90%, then the cyclist is not a professional".

The graphical results of the amateur cyclist are illustrated in Figure 5, where the meaning of the displayed variables is the same as by the professional cyclist.

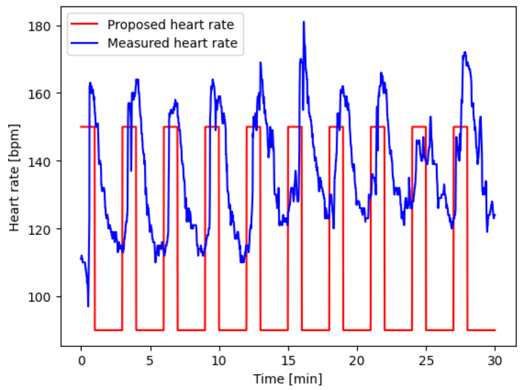

Figure 5. Amateur sport training.

As can be seen from Figure 5, the amateur cyclist did not achieve the demands of the sport trainer in the recovery interval. Although measured heart rate $\overline{HR}$ strongly surpasses the proposed value of the speed interval $\overline{HR}_{spe}$, the proposed value of the recovery interval $\overline{HR}_{rec}$ is never achieved by the cyclist.

The detailed analytical results of the implemented speed intervals by the amateur cyclist are presented in Table 5, from which it can be seen that the cyclist achieved even better results according to the TRIMP load indicator in the speed intervals than the professional one. The efficiency of the professional training is even $SR_{spe} = 93.98\%$ in total.

Table 5. Amateur cyclist results by interval speed phase.

Int.	$\overline{TRIMP}_{spe}$	$TRIMP_{spe}$	$\Delta TRIMP_{spe}$	SR_{spe}
1	150	128.25	−21.75	0.8550
2	150	141.26	−8.74	0.9417
3	150	140.38	−9.62	0.9358
4	150	144.24	−5.76	0.9616
5	150	138.04	−11.96	0.9203
6	150	136.44	−13.56	0.9096
7	150	141.77	−8.23	0.9451
8	150	148.92	−1.08	0.9928
9	150	139.38	−10.62	0.9292
10	150	151.05	1.05	1.0070
$\sum$	1500	1409.73	−90.27	0.9398

Unfortunately, the same cyclist failed to satisfy the demands of the sport trainer when the recovery intervals are observed (Table 6).

The efficiency of the implementation is now only $SR_{rec} = 50.25\%$ in total.

Table 6. Amateur cyclist results by interval recovery phase.

Int.	$\overline{TRIMP}_{rec}$	$TRIMP_{rec}$	$\Delta TRIMP_{rec}$	SR_{rec}
1	180	253.66	73.66	1.4092
2	180	258.95	78.95	1.4386
3	180	251.29	71.29	1.3961
4	180	257.14	77.14	1.4286
5	180	276.77	96.77	1.5376
6	180	288.24	108.24	1.6013
7	180	273.24	93.24	1.5180
8	180	269.79	89.79	1.4988
9	180	266.02	86.02	1.4779
10	180	282.46	102.46	1.5692
$\sum$	1800	2677.56	877.56	1.4875

4.2. Discussion

The proposed digital twin in sport is distinguished by four characteristics: user-friendliness, robustness, reliability, and accuracy. The first characteristic refers to the usage of the application. As shown in the analysis of the GUI, the interface is simple and easy to use. The graphical design is minimalist, and consists of only those elements that are necessary for efficient decision making. Both the cyclists involved in the study helped the designers by improving the GUI with their comments and advice. Robustness means that the digital twin works well in mobile circumstances, where the computer is subject to vibration. The results of the predictions by the digital twin are reliable and accurate.

The results of the mentioned Case Studies 1 and 2 confirmed that the behavior of the professional and amateur cyclists in cycling training are enormously different, and, therefore, easily identified by using the DT for cycling. While the professional cyclist did not have any problem in achieving the border values of the upper-speed interval and the lower-recovery interval heart rates, the amateur cyclist never achieved the lower interval heart rate. This means that the trained cyclist is capable of adapting the heart rate quicker than the non-trained one. Moreover, the transitions from the lower to upper heart rate values and vice versa are more prominent for the professional cyclist.

The aggregate results of both cyclists are illustrated in Table 7, from which it can be seen that the efficiency of the proposed interval training session was $\overline{SR} = 91.45\%$ for the professional cyclist (confirming RQ-1), and only $\overline{SR} = 72.61\%$ for the amateur one (confirming RQ-2). Indeed, the digital twin informs the athlete what to do, but not how to do it. As an answer to the question, the information of sport trainers still remains valuable.

Table 7. Final results of both results.

Training	$\Delta TRIMP_{spe}$	$\Delta TRIMP_{rec}$	$\Delta TRIMP$	$\overline{SR}$
Professional	−113.38	−172.52	−285.90	0.9143
Amateur	−90.27	−877.56	−967.83	0.7262

5. Conclusions

A digital twin is a digital replica of a physical object, and, as such, it has emerged in different domains of human life, such as engineering, automobile manufacturing, aircraft production, and building construction, to mention only the more important ones. This paper uncovers the usage of the digital twin in the sport domain, more precisely, its application in interval sport training in cycling. The digital twin concept was tested using two case studies in which: (1) a professional, and (2) an amateur cyclist were involved. The case studies justified that the concept could also be applied in practice.

Limitations and Future Works

However, the proposed digital twin is limited only to interval training in cycling. Additionally, the mobile device presents some kinds of limitations because it must be worn either by athletes or their equipment. Consequently, the device needs to be small in size and high in performance. Last, energy consumption plays a huge role in selecting the proper hardware.

As a matter of fact, there are many potential directions to continue the work in the future. For instance, the digital twin could be used for other sport disciplines, such as running, triathlon, and duathlon. In line with this, a smaller mobile device should be developed for running. Furthermore, the heart rate load indicator should be exchanged with a power meter, due to its higher sensitivity to the changes in the cyclist's intensity.

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