Discovering the influence of interruptions in cycling training: A data science study

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Abstract. The usage of wearables in different sports has resulted in the potential of recording vast amounts of data that allow us to dive even deeper into sports training. This paper provides a novel approach to classifying stoppage events in cycling, and shows an analysis of interruptions in training that are caused when a cyclist encounters a road intersection where he/she must stop while cycling on the track. From 2,629 recorded cycling training sessions 3,731 viable intersection events were identified on which analysis was performed of heart-rate and speed data. It was discovered that individual intersections took an average of 4.08 seconds, affecting the speed and heart-rate of the cyclist before and after the event. We've also discovered that, after the intersection disruptions, the speed of the cyclist decreased and his heart-rate increased in comparison to his pre intersection event values.

Keywords: artificial sport trainer · data science · smart sports training · cycling · wearables

1 Introduction

Cycling is considered as one of the most pleasant ways of doing recreation. It is definitely popular all over the world. People are cycling for transportation, commuting and maintaining a healthy lifestyle on the one hand, while some others are also cycling competitively, participating in various cycling race competitions. The professional sports scene has become more and more competitive in recent years, and various new training regimes and tactics have been discovered incorporating digital technology [17]. This is also, in part, due to the introduction of the Internet of Things (IoT) devices to the Sports Training domain [7]. The data generated by such devices are, nowadays, used for building Machine Learning models, which can be used to optimize training and actual competition performance in sports [13]. A recent survey [13] identified that many sports have already undergone the new smart training revolution. Cycling is definitely one of them, where researchers developed various applications for tackling the process of sport training using more data-driven approaches.

Current research indicates that the focus on the researched domain has focused on planning fitness exercises [5], generating training plans [14], planning match day strategies [10] and generating eating plans [2].

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In this paper, we go a step forward, and approach the process of sport training from another perspective. We focus on the role of interruptions within a sports activity. The characteristic of carrying out cycling training or activity is that it can take a very long time (up to 7 hours or even more), and during this time interruptions are inevitable.

Therefore, it is important to investigate how cyclists approach the interruptions and what are the side effects of those interruptions. Usually, interruptions are not planned in advance, but they appear spontaneously.

We investigated the actual interruptions during a training exercise. In fact, studies investigating training interruption in other sports were only related to the interruption of training routines over prolonged periods of missed training days [1, 8, 9, 15, 16] and not interruption during the training itself.

The events which interrupt the standard training procedure certainly influence the training performance and results of the training conducted. Since the interruptions in training have not been studied thoroughly yet, their frequency is not yet known. The interruptions are certainly an important factor in cycling since, due to the outdoor nature of training and the fact that the training happens on public roads and paths, the performance of the cyclist also depends on his highly volatile and changing environment in contrast with other sports where the environment can be controlled fully (e.g. swimming in indoor pools, training sports in gyms), or at least partially (e.g. soccer training in a closed stadium).

In a nutshell, the purpose of this paper is to propose a methodology for discovering the influence of interruptions in cycling training's on the athletes' performances. The main contributions of this paper are summarized as follows:

- proposal of taxonomy of cycling training interruptions,
- a novel algorithm proposal for detection of stoppage interruption events, and
- data analysis of effects the interruption events have on the training session.

2 Interruptions in cycling training

For the purpose of this paper, interruptions in cycling training relate to interruptions during the actual training which were not anticipated in advance, and not the interruptions [8] which are sometimes defined as missed training days. Since no previous works on interruption detection in cycling training have been identified, a taxonomy of interruptions was constructed, based on the general cause for the interruption. As such, we divided the most probable interruptions which can impact the cyclists' training into four main categories: **Environmental factors**, which are factors over which the cyclist has no influence, or his influence was limited to the planning part of the exercise; **Biological factors**, which are factors related to the physical condition and current state of the athlete; **Equipment factors** that can be semi-controlled by proper equipment maintenance and using quality equipment, and **Other factors** which are all the other factors which may or may not be controlled and predicted. The aforementioned factors and their sub-factors are shown in Figure 1.

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Environmental factors are related to: Intersections*[1] which are one of the most common causes for cycling interruptions. This means that traffic lights, priority roads and roundabouts may force the cyclist to reduce his speed or come to a complete stop; Poor track conditions resulting from unexpected potholes, obstacles and traffic on the road; Weather factors, unfavorable weather conditions may interrupt the training. Weather conditions may impact visibility (e.g. fog), decrease the stability of the cyclist on the track (e.g. snow, rain, wind, road ice), or increase the workload of the cyclist (e.g. high humidity, high temperatures, low temperatures) and also unfavorable vision conditions (e.g. sunset, sunrise) which may block the view of the cyclist.

Biological factors which are factors that can be split into **Need fulfilment** which is the result of an unfulfilled need, such as tiredness, thirst, hunger and when nature calls; and **Health factors** that can interrupt the training, and may be a result of an injury sustained during the training, feeling unwell and falling, when the cyclist loses control of his bicycle.

Equipment factors which relate mostly to **Defects and failures**, that may be caused by a flat tire or failure of the bicycle's mechanical parts (e.g. gearbox failure, detachment of the chain).

Other factors which can be grouped into **Social factors** resulting mostly from calling and receiving phone calls, meeting a known person while training and stopping to greet them, but may also be caused when a cyclist is stopped by the authorities for a traffic control. There are countless *Other events*, that may interrupt the training, such as issues with motivation, forgetting something at home (e.g. wallet with documents).

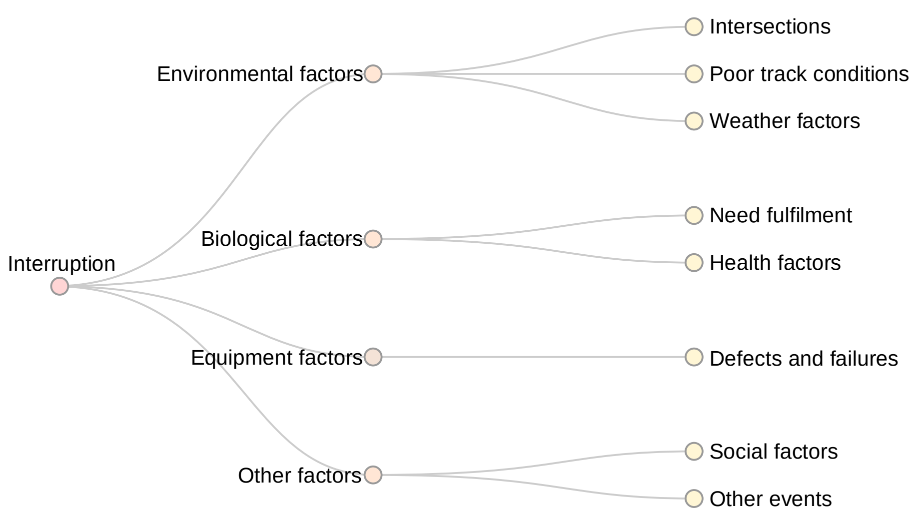

Fig. 1. Taxonomy of interruption events

[1] Interruption factors marked with asterisk (*) were the ones monitored in our research

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3 Materials and methods

3.1 OpenStreetMap

OpenStreetMap [12] is a project that creates and distributes free geographic data for the world. The map data are saved and distributed in a collection of XML documents which consist of four main elements [11], namely **nodes**, **ways**, **relations** and **tags**. **Nodes** represent specific points (locations) on planet Earth. Each node has an id, latitude and longitude. **Ways** represent ordered lists between at least 2 and up to 2,000 nodes defining a poly-line. Ways are used to represent rivers, roads and areas (e.g. forest, municipality, building, etc.) If something is described by a boundary of more than 2,000 nodes then multiple ways are combined with relations. **Relations** are used to describe a relationship between two or more data elements. Tags describe the purpose of the relation. These relations may be a route relation (on which the roads are defined in a way), turn restriction, direction restriction, etc. **Tags** are data elements which can be included in all of the other elements, and are used to give meaning to the attached elements.

3.2 Method for interruption detection

All the methods described refer to detection and classification of interruption events in cycling sports training data. The detected interruption events are classified as events where speed dropped below 2 km/h, or the cyclist came to a complete stop. The data used were in the form of TCX [3] and GPX [4] training records.

The initial data pre-processing was divided in two parts. In the Section 3.3 the algorithm for detecting interruptions from exercise data is described, and in the Section 3.4 the algorithm is described for detecting the nearest intersections from the interruption locations. A visualization of the event data is seen in Figure 2, indexes 1-60 represent the speed and heart-rate at 1 to 60 seconds pre and post the event. For the event, the i represents the duration of the event, since the events lasted different amounts of time. The pre and post event data points

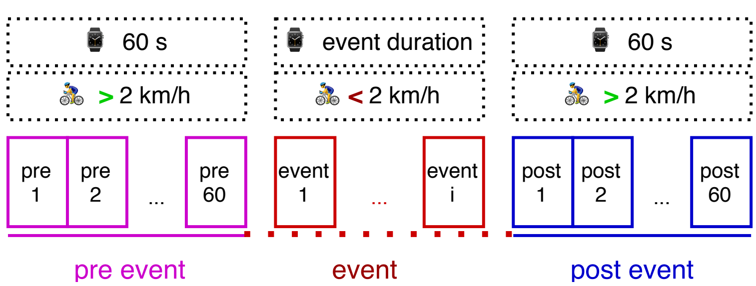

Fig. 2. Combined event data.

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all span 60 seconds before and after the event. In each of those points the speed is above 2 km/h, while the length of the event itself varies, since stoppage by each intersection event varied, and some demanded more time off than others. It should be noted that when comparing values between pre and post event data, a pre_1 point can be compared to a $post_{60}$ point, since they both span the same amount of time from the actual interruption event.

3.3 Algorithm for interruption detection

The goal of this algorithm was to detect interruption events where speed dropped below 2 km/h. The input of the algorithm is a list of lines between different GPX/TCX points, and the output of the algorithm is the list of detected stoppage events. Each event consists of the pre-event (what happened before the

Algorithm 1: Algorithm for detecting exercise stoppage events

Input: List of lines between GPX/TCX points (two succeeding track points are connected to calculate their average speed and heart-rate) $L = (l_{x_1x_2}, l_{x_2x_3}, ..., l_{x_n-1x_{n-1}}), min\_speed, time\_interval$

Output: List of detected stoppage events $E = (e_1, e_2, ...e_n)$, $e_n = (en_{pre}, en_{mid}, en_{post})$

for i=1 ***to*** i=n-1 **do**
- $event = false$
- $i = 1$
- **while** $L[i]_{speed} \leq SPEED\_MIN$ *and* $i \leq n$ **do**
  - // Add to main event (actual stoppage)
  - $event = true$
  - $en_{mid} = insertToEn_{mid}(l[i])$
  - $i = i + 1$
- $i_{postEvent} = i$
- $timeStamp = time(L[i])$
- **while** $i_{postEvent} \leq n - 1$ *and* $timeStamp \leq time(l[i]) + timeInterval$ **do**
  - // Add to post event event (what happens after the stoppage)
  - $en_{post} = insertToEn_{post}(l[i_{postEvent}])$
  - $timeStamp = time(L[i_{postEvent}])$
  - $i_{postEvent} = i_{postEvent} + 1$
- $timeStampStart = time(i_{preEven})$
- **while** $i_{preEvent} \geq 1$ ***and*** $timeStamp \geq timeStampStart - timeInterval$ **do**
  - // Add to pre event event (what happens before the stoppage)
  - $en_{mid} = InsertToStartEn_{pre}(l[i_{preEvent}])$
  - $timeStamp = time(L[i_{preEvent}])$
  - $i_{preEvent} = i_{preEvent} - 1$
- **if** $event == true$ **then**
  - $e = (en_{pre}, en_{mid}, en_{post})$
  - $addToEventList(e)$

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event), event (the time period during which speed was below 2 km/h), and post event (what happened after the event). The boundaries of pre and post event are defined by the *time_interval* variable, which defines the maximum difference between the time of the event and the surrounding data. The algorithm goes through each point in the training data, and detects and groups those where the cyclists dropped below the determined minimum speed (*min_speed* variable), after such an event was detected. After the event is detected in the first sub-loop (lines 1-6), in the following two sub loops (9-17) pre and post events are identified, it is necessary to compare the time stamps, since not all recording equipment records data at the same frequency.

3.4 Algorithm for detecting nearby road intersections

The input of the algorithm are the identified events of the previous algorithm. For each event, thelocations of said event points are inspected. In addition to that, OpenStreetMap data from Geofabrik [6], described in 3.1, was needed to give meaning to the coordinates, *maximum_distance* defined the maximum distance between the intersection and an event location to still be identified as such.

Algorithm 2: Algorithm for detecting nearby road intersections

Input: List of events with locations $E = (e_1, e_2, e_3 ... e_n)$, OpenStreetMap data, max_distance
Output: List of events with nearby intersections $E = e_{1*}, e_{2*}, e_{3*} ... e_{n*}$

for *i=1* ***to*** *i=n-1* **do**
  $nearbyIntersection = false$ // each location has altitude and longitude
  $location = getLocation(e_i)$
  $topBorderLongitude = location.longitude + 0.005$
  $bottomBorderLongitude = location.longitude - 0.005$
  $topBorderAltitude = location.altitude + 0.005$
  $bottomBorderAltitude = location.altitude - 0.005$
  // get intersections in box is a query to the openstreet map to discover all intersections in the box with maximum and minimums of longitudes and altitudes
  $intersectionsList =$
   $getIntersectionsInBox(topLong, bottomLong, topAlt, bottomAlt)$
  $closestDistance = \infty$
  $closestIntersection = null$
  for *intersection* ***in*** *intersectionsList* **do**
    $distance = calculateGeodesic(location, intersection.location)$
    if $distance \leq closestDistance$ ***and*** $distance < max\_distance$ **then**
      $closestDistance = distance$
      $closestIntersection = intersection$
  $e_{i*} = e_i$ $e_{i*}.intersection = closestIntersection$

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The output of this algorithm is a list of all events of type intersection, with their corresponding intersections.

The output was also visualized on the training route visualization, and its display is shown in Figure 3, where the event is marked with the green box, and the identified closest intersection, which was identified by the algorithm, is shown by a blue circle. The direction of the route is shown by semi-transparent blue arrows. Each other color coded (in reference to speed) circle represents a recorded point of the exercise. It can be seen that the speed when approaching the intersection drops rapidly, and reaches the lowest point at the intersection, where the cyclist must take extra precautions, and increases rapidly again after leaving the intersection.

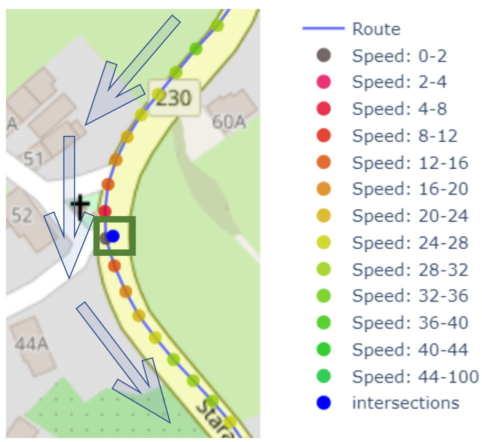

Fig. 3. Visualization of an stoppage event with a known intersection cause

The algorithm receives the list of all identified events, and then checks for each of the events if there are any intersections in the near vicinity ($latitude \pm 0.005$, $longitude \pm 0.005$). It then goes through all the identified intersections and calculates the distance between the event and the intersection.

After each distance is calculated it is compared if it is smaller than the previous closest distance and the maximum distance. If both checks are returned true, this becomes the new closest intersection. After all the intersections are checked, and if any with the matching conditions were found, the closest intersection is added to the event.

3.5 Algorithm for filtering viable exercise stoppage events

Further filtering of viable events among intersection events was conducted to determine the actual effects the event had on the pre-event and post-event per-

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formances. Only the events which had no additional stoppage events in the surrounding 60 seconds before and after the actual interruption were considered, which means that we eliminated any events that were less than 60 seconds apart themselves. The input of this filtering algorithm was a list of all previously detected intersection events, and the output were the viable events. In a loop each event had it's pre-event and post-event points checked. Had no drops of speed (*stoppage events*) occurred, the event was considered viable and added to the list for further analysis.

4 Experiments and results

The purpose of the experiments was to discover the effects the interruptions had on the heart rate and pace (speed) of the cyclist before and after the event happened. We wanted to explore if the cyclist speed and heart-rate changed after the event compared to the value beforehand.

A total of 2629 training records were examined from 7 different athletes, where each athlete had a minimum of 148 training sessions recorded. Only data from athletes training exclusively in the Cycling and Road Cycling training category were used, and Mountain biking, Triathlon and Multi-sport athlete training sessions were excluded. A total of 3,914 intersection events were identified. This does not mean that the cyclist rode only past 3,914 intersections, but that not all intersections resulted in a drop of speed below 2 km/h. The events were then filtered further, so that only events where, in the preceding and succeeding minutes no other stoppage events occurred; this led to a total of 3,731 events which were then analysed further. Analysis of intersection events showed that an average intersection event lasted an average of 4.08 seconds. The analysis of viable events is presented in this Section. The values[2] were analyzed in reference to changes in heart-rate and speed as a result of an intersection event. Special attention was focused on how to represent data properly. Because of heart-rate and cycling speed differences between athletes and individual intersections events, the data of each individual event were first standardized by calculating the arithmetic mean speed and heart-rate of each individual intersection event. After that, all the values were divided by their respective means, so that speed and heart-rate in reference to average speed were presented, as shown in Equation 1.

$$a_{standardized} = \frac{a_{actual}}{Mean} \tag{1}$$

where:

$a_{standardized}$ = standardized speed ratio with respect to mean speed recorded
a_{actual} = actual speed at a point
a_{Mean} = calculated mean speed of the pre and post event points.

These standardized values were than compared at 20, 40 and 60 second pre/post intervals, so that we could investigate how the intersection event influenced the cyclist. The difference between these values represented a change in

[2] When referring to values the same calculation was done for heart-rate and speed

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value in respect to the calculated means (e.g. so a difference between two points in respect to the average value). The Equation 2 describes the calculated delta values, which were then used in individual 4.1 Heart-rate analysis and 4.2 Speed analysis subsections. The t used in post-speed value was deducted from 60, since we wanted to get the values at the same interval from the pre-post events.

$$\Delta a = a_{post\_event}(t) - a_{pre\_event}(60 - t) \tag{2}$$

where:

t	= 0-60 seconds, point of time at the recorded event
$a_{post\_event}(60 - t)$	= calculated mean value at the t time of the post event
$a_{pre\_event}(t)$	= calculated mean value at the t time of the pre event

For the resulting values, the statistics are presented in Table 1. The values are presented to an accuracy of 3 significant digits. The calculated values can be higher than 1, because they represent differences between average values and not percentage ratios, so as not to skew the values in any direction.

4.1 Speed analysis

The aim of the speed analysis subsection was to discover what the relationship between interruptions and speed was, and if the speed changed in any meaningful way after the event compared to the previous baseline. What was discovered was that, in 54.8 % of all cases (*20 s* - 54.7, *40 s* - 54.2, *60 s* - 54.8), the speed at the end of the post-event was **lower** than the speed at the start of the pre-event. This may mean that either (1) The athlete needs more than one minute to accelerate to the previous speed, or that (2) The extra work caused to accelerate from the stoppage event tired out the cyclist temporarily, resulting in his lag in speed. We found some evidence pointing out that the real cause is the explanation offered in the 2nd scenario, as explained in Subsection 4.2. It is also interesting to observe the speed of the cyclist and at which point it started decreasing, as shown in Figure 4. The pre and post event values presented on the chart are shown for median, the first quartile (q1) and the third quartile (q3), and the values are normalized with reference to average speeds. It can be seen that the majority of the steepest speed drop happened in the last 20 seconds before the event.

4.2 Heart-rate analysis

The aim of the heart-rate analysis subsection was to discover what the relationship between interruptions and heart-rate was, and if the stoppage event influenced the heart-rate compared to the previous baseline. We discovered that, in 51.4 % of all events, the heart rate at the end of the post-event was **higher** than the heart rate at the start of the pre-event, for the 60 second comparison interval. It was, however, higher in only 46.9 % of cases for the 20 and 48.2 % of cases for the 40 second interval. This further points towards the proposed explanation offered in Subsection 4.1. From the perspective of actions performed, the heart

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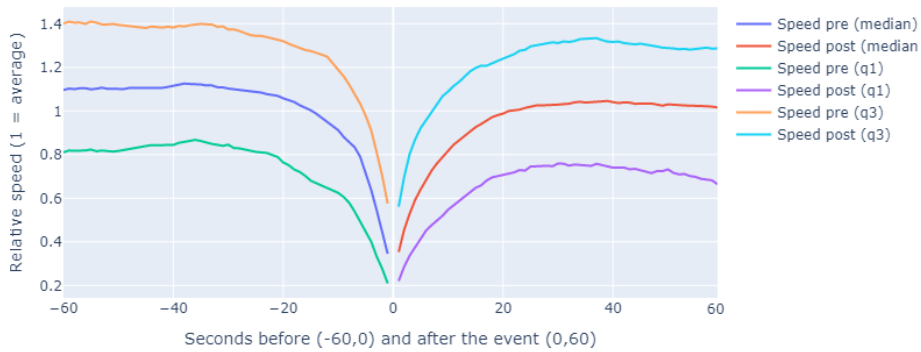

Fig. 4. Line plot speed

rate was lower immediately after the event, because the interruption (stoppage) also served as a very short rest for the cyclist, lowering his heart rate as seen on Figure 5.

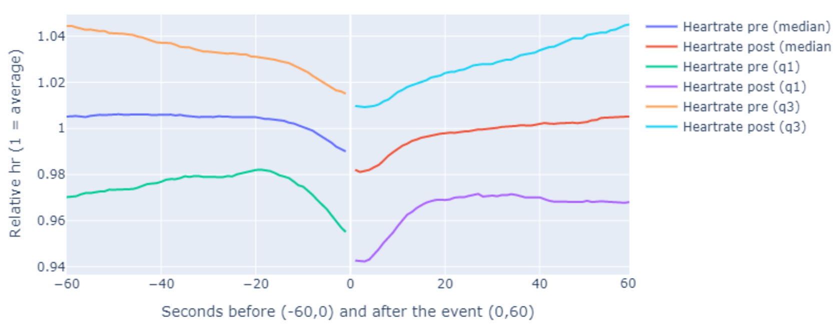

Fig. 5. Line plot of normalized heart-rate averages

The heart rate increased, however, as the cyclist had to spend energy to accelerate, and at the end of the event was higher than before, while the speed at the end was, on average, still lower than at the start. This can also be seen if heart rate values from all events are categorized by seconds before and after the event, and their first quartile (q1), median and third quartile (q3) values are plotted as shown in Figure 5, and the HR appears to be slightly higher at the median and third quartile values at the end of the event.

It can also be seen again that the interruption slightly lowers (notice the gap between the end of the pre-event line and the start of the post-event line) the heart-rate, as it provides a short break for the cyclist.

The slight increase of heart rate we are discussing, however, is only true for an average case of interruption and not when individual heart-rates are plotted

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on an line chart, as seen in Figure 6. We deliberately chose some events where

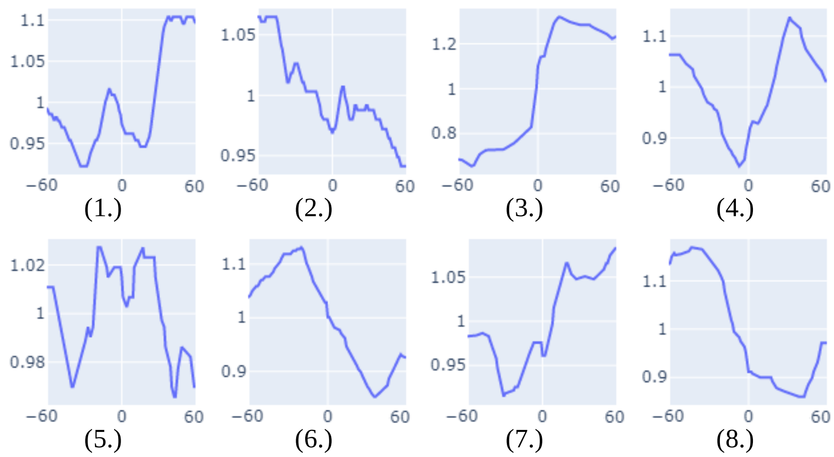

Fig. 6. Examples of changes in heart-rate (pre/post) event

		Mean	σ	min	Q_1	Q_2	Q_3	max	$x_{post} < x_{pre}$
Δhr	20 s	$-.00720$	.0963	$-.487$	$-.0566$	$-.00600$	.0393	.568	53.1 %
	40 s	$-.00348$	.123	$-.508$	$-.0623$	$-.00397$	.0517	.563	51.8 %
	60 s	.00246	.138	$-.650$	$-.0653$	0	.0628	.597	48.4 %
$\Delta speed$	20 s	$-.0789$	.729	-2.51	$-.522$	$-.0706$	.387	2.39	54.7 %
	40 s	$-.0776$	.738	-2.22	$-.532$	$-.0646$	.370	2.55	54.2 %
	60 s	$-.0952$	.801	-3.13	$-.568$	$-.0640$	.346	3.72	54.8 %

Table 1. Statistical data of HR and speed difference between pre-post event based on standardised values

the heart-rate was lower after the conclusion of the post event than at the start of the pre event. But what can be seen is that, after some events, the heart rate might actually decrease (cases 2, 4, 5, 6, 8). This is completely normal, and might happen for a number of cases that depend on the environment (e.g. the cyclist was riding on a slight downhill slope; the cycle track entered a road in a forest and the surrounding temperature dropped). Over a large number of cases these favorable or unfavorable environments even out, and the slightly increased value can still be observed.

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5 Conclusion

Nowadays, many athletes use various sport trackers for tracking the sport activities. During the activity, many parameters are monitored, which can later be analyzed in order to improve the performance of an athlete.

In this paper, the data monitored by sport trackers were used for the investigation of the interruptions that appear during the sport training resulting from intersections on the cyclist training track. A new method was proposed for identification of stoppage events and discovering intersection events during cycling training. Our research showed that an average intersection provided 4.08 seconds of stoppage time, which meant that, on average, these were only short stops, where the cyclist stopped gradually before the intersection, possibly due to safety concerns, and shortly resumed with his cycling training.

We've also discovered that in 54.8 % of all intersection events (*20 s* - 54.7, *40 s* - 54.2, *60 s* - 54.8) the speed at the same interval, i.e. 20 seconds before and after the event, was **lower**, which shows that intersection interruptions result in lower speed of the cyclist after the event has concluded. We also discovered that immediately after the event the heart-rate was higher in only 46.9 % of cases for the 20 and 48.2 % of cases for the 40 second pre versus post interval. This ratio, however, changed at the end of the one minute interval, where, in 51.4 % of all intersection events, the post event heart rate was **higher** than the heart rate at the start of the pre event. This implies that, while the short rest induced by the intersection interruption at first reduced the heart rate of the cyclist, the extra effort and work to try and attain the previous cycling speed resulted in a higher ending heart rate than before the interruption.

In the future, our approach will also be applied for the analysis of interruptions that appear in other sports, i.e. running. By the same token, we are also planning to conduct the study for analyzing the interruptions that are the result of poor track conditions, and also analysis of the effect weather conditions pose on the individual training sessions.

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