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Dupré, D., Andelic, N., Moore, D. S., Morrison, G., & McKeown, G. J. (2020). Analysis of physiological changes related to emotions during a zipline activity. *Sports Engineering*, *23*(1), [15]. https://doi.org/10.1007/s12283-020-00328-9

Published in:
Sports Engineering

Document Version:
Peer reviewed version

Noname manuscript No.
(will be inserted by the editor)

Analysis of physiological changes related to emotions during a zipline activity

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Received: date / Accepted: date

Abstract Despite the popularity of physiological wearable sensors in sport activities to provide feedback on athletes' performance, understanding the factors influencing changes in athletes' physiological rhythms remains a challenge. Changes in physiological rhythms such as heart rate, breathing rate or galvanic skin response can be due to both physical exertion and psycho-emotional states. Separating the influence of physical exertion and psycho-emotional states in activities that involves both is complicated. As a result, the influence of psycho-emotional states is usually underestimated. In order to identify the specific influence of psycho-emotional states in physiological rhythm changes, 28 participants were asked to participate in a zipline activity, which involve little or no physical exertion while stimulating psycho-emotional states. By using nonlinear analyses, results show that specific changes in phys-

This research was supported and led by Sensum Ltd. in collaboration with Queen's University Belfast.

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iological rhythms can be associated with phases in ziplining, after which they can be related to emotional states felt during the activity. Regarding data analysis of wearable sensors, this paper presents a workflow to identify significant physiological patterns across multiple athletes performing the same outdoor activity.

Keywords Emotion · Physiology · Wearable monitoring · Multivatiate time-series · Nonlinear analysis ·

Mathematics Subject Classification (2000) 62M10 · 62H12 ·

1 Introduction

Wearable sensors are efficient tools for monitoring patients' physical [1, 2] and psychological health [3, 4] allowing the continuous and real-time tracking of physiological changes. The use of wearable sensors for exercise and sport performance monitoring have become common as the technology of the devices have improved [5]. Indeed, there are hundreds of commercial devices for tracking exercise or sports activities [6, 7]. Performance monitoring devices are often watches, belts or smart patches for individual [8, 9] or team sports [10–12]. By using these wearable sensors and the associated software, individuals are able to measure and analyse physiological rhythms in real time during exercise and sport.

With the use of wearable sensors, physiological rhythms can be evaluated both during controlled settings such as training [13, 14], as well as during outdoor competitions. Monitoring athletes in different settings is particularly important for accurate feedback, as outdoor competitions typically involve higher stakes and different results and outcomes than training [15]. However, understanding the factors influencing changes in athletes' physiological rhythms remains a challenge. While an athlete's physical exertion is one of the main drivers of the physiological rhythms, psycho-emotional states can also influence their evolution [16]. Outdoor activities triggering highly emotional experiences are related to intense physiological changes (e.g. skydiving [17] or kitesurfing [18]). A study on mountain biking revealed that physiological changes correlated not only with athletes' speed, which increased physical exertion, but also with the perceived difficulty of the track [19]. Therefore, by monitoring physiological rhythms during an outdoor activity that involves little to no physical exertion, the present study aims to identify the specific influence of psycho-emotional states on physiological rhythms.

Among the different outdoor sports that can be analysed, the nature of the zipline activity makes it particularly suitable when examining physiological changes [20]. For example, ziplining can trigger intense emotions due to the speed and height inherent of the activity, whilst also being a controlled activity [21]. All participants of a zipline activity perform the same quasi-linear pattern

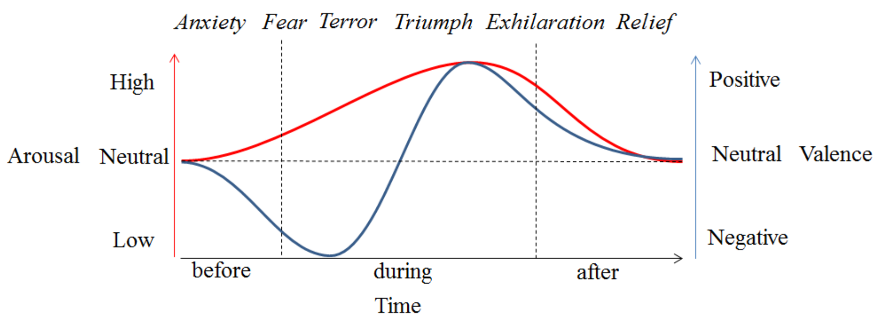

Fig. 1 Theoretical evolution of emotional states during the zipline activity according to valence and arousal dimensions [26].

of movement and are unable to deviate from it, providing a controlled environment for researchers studying physiological changes (see [22, 23]). Differences between zipline participants will affect how sensor inputs (mainly visual but also sound and vibrations) are appraised as well as the specific emotional reactions that are triggered [24]. People use a combination of experience and individual skills to manage the feelings elicited by the potential danger posed by elevated speed and height, as quickly as possible. Indeed, these physiological changes are patterns which are associated with different psychological states [16, 25] that follow a specific temporal evolution [19]: from anxiety to fear, terror, triumph, exhilaration and relief (Figure 1).

According to Russell [27], affective states and emotions in particular can be evaluated by their level of valence (i.e. if the emotion is positive or negative) and arousal (i.e. level of psycho-physiological activation from low to high). The dimensions of valence and arousal are key factors explaining the practice of sports and outdoor activities [26]. By monitoring these dimensions, it is possible to map the evolution of athletes' affective states throughout the practice (e.g. during motorbike driving [28], mountain biking [19], running [29], mountain hiking [30] or general training [31]). From a theoretical perspective, ziplining should induce high levels of stress just before and during the first few seconds of the activity [22, 32]. Therefore, initially a strong, negative emotional state should be triggered, which then evolves to a strong, positive emotion. This stress should also increase the physiological activation during the zipline.

By analyzing the dynamic changes of several physiological measures simultaneously it is possible to identify these individually triggered reactions. Consequently, the zipline activity provides an opportunity to measure the psycho-physiological correlates of individuals' emotional experiences during a high-intensity, controlled outdoor activity.

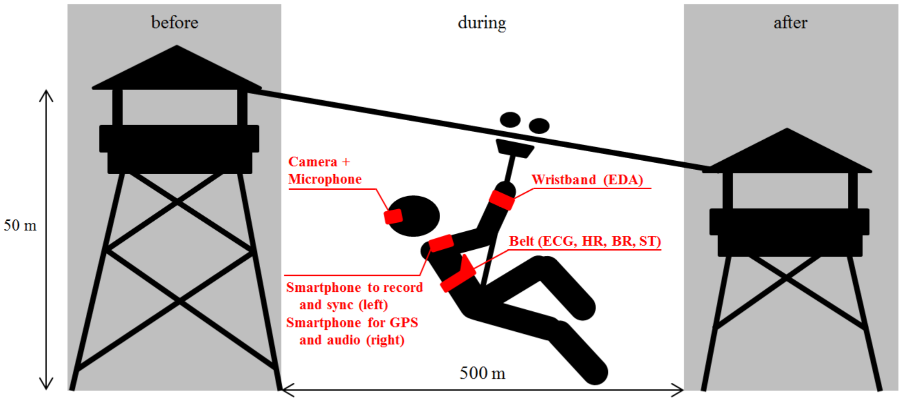

Fig. 2 Description of the multivariate physiological sensor recording set up (not to scale). EDA = Electrodermal Activity, ECG = Electrocardiogram, HR = Heart Rate, BR = Breathing Rate, ST = Skin Temperature.

2 Method

2.1 Participants

After providing their written informed consent, 30 participants volunteered for the study. This sample included 12 females and 18 males and their age distribution has a mean (M) 28.3 and a standard deviation (SD) of 6.33. The recruitment process included a medical check to ensure that no participants had a history of cardiac abnormalities and that they were not using cardioactive medication. Participants were informed that they could change their mind and withdraw their consent at any point during the experiment. Two participants decided not to take part in the experiment prior to the zipline task, leaving 28 participants in total. The research project and procedure received ethical approval by the School of Psychology Research Ethics Committee at Queen's University Belfast, United Kingdom (No 16-2016-17).

2.2 Measurements

For this experiment, the participants were equipped with five wearable sensors (Figure 2).

They wore a multiple sensor belt (Equivital EQ02, see [33, 34]) with two main components: a bio-compatible fabric embedding multiple sensors and an electronics module to gather and send data recorded by the sensors. The belt recorded participants' breathing rate (BR), external skin temperature (ST) and electrocardiogram (ECG) from which heart rate (HR) was calculated. The measurement accuracy of the Equivital EQ02 sensor belt is lower than for the gold standard device for HR monitoring from ECG peak detection.

All artifacts included, the mean difference (ΔM) between the Equivital EQ02 and the Holter ambulatory ECG Monitor is 7.08 bpm with a SD of 17%, and a Pearson correlation (r) of 0.724 [34]. However, no significant difference has been found between the Equivital EQ02 and the Polar S810i HR Monitor with a ΔM of 1.2 bpm, a standard error of the estimate (SEE) of 0.54, and a r of 0.98. Similarly, no significant difference has been found between the Equivital EQ02 and the ADInstruments Metabolic BR Monitor with a ΔM of 0.2 rpm, a SEE of 0.19, and a r of 0.97, as well as between the Equivital EQ02 and the ADInstruments ST Monitor with a ΔM of -0.1°C, a SEE of 0.02, and a r of 0.98 [33].

Participants also wore a wristband with two electrodes strapped on the first phalanges of the middle and the ring fingers (Shimmer2, see [35]). The wristband and electrodes recorded participants' sudation through their electrodermal activity (EDA). The Shimmer2 sensor is considered as the gold standard wearable device for EDA measurement [36] (see also [37] for a qualitative benchmark of EDA measurement devices).

To record participants' context and vocal expression, a front-facing camera (GoPro Hero 4) and a lavalier microphone (Sennheiser) were also worn. A smartphone was also strapped to each arm of the participants. On the right arm, a smartphone (iPhone 6, iOS v8.0) with the lavalier microphone recorded sound via the application (Apogee v1.2, see [38]) as well as Global Positioning System coordinates. On the left arm, a smartphone (One Plus X, Android v6.0.1) was used to run an application recording and synchronizing the physiological outputs from the wearable devices (SYNC v1.0, see [39]).

2.3 Procedure

The experiment took place in Todd's Leap Activity Center based in Ballygawley, Co. Tyrone, Northern Ireland. The Todd's Leap zipline hangs 50 meters above the ground and is 500 meters long. Prior to the activity, participants were provided with safety harnesses and given full safety advice by qualified instructors. The safety advice session was also a break allowing participants to rest after climbing the stairs of the takeoff tower so as to ensure that all participants were at a physiological resting state. A period of 40 seconds was recorded before leaving the jumping off platform and 40 seconds after reaching the landing platform to allow for comparisons before, during and after the zipline activity. Due to differences in duration of the zipline activity, all the participants' time-series data was rescaled on an index from 0 to 100.

2.4 Signal pre-processing

Participants were omitted from further analysis if one or more physiological measurements reached exclusion criteria (Table 1), i.e. displayed measures that are not physiologically possible [40, 41]. Following the application of these criteria, 10 participants were removed due to the presence of outliers and artifacts in their recordings. The following analyses were performed on the remaining 18 participants.

Table 1 Exclusion criteria given by unreasonably low or high physiological measures [40, 41].

Measurement	Minimun	Maximum
Heart Rate (bpm)	50	220
Breathing Rate (rpm)	10	60
Skin Temperature (°C)	30	40
Electrodermal Activity (μS)	2	20

To analyse the ECG signal, an R-peak detection algorithm was applied. Then, Heart Rate Variability (HRV) was extracted from the R-peak detection using a frequency-domain analysis technique with least asymmetric Daubechies wavelets. High Frequency HRV has been identified as a relevant feature to extract for emotion recognition [42] and the power temporal evolution in the High Frequency band has been shown to correlate with participants' emotional state [43, 44].

Finally, EDA data provides relevant features for analysis of participants' psychological state through the extraction of Skin Conductance Level (SCL) and Skin Conductance Response (SCR) [45–47]. SCL represents the tonic level of EDA which varies slowly over time, and can be interpreted as a representation of long-term responses to an event. In contrast, SCR represents the phasic response of EDA, and is an aggregation of EDA peaks that respond to events immediately.

2.5 Data analysis

Physiological time-series are challenging to analyse, mainly due to the residual distribution. A potential pattern in the residuals can indicate that linear models are not suitable for fitting physiological measurements. Therefore, a model with covariates and random effects should be implemented using Generalized Additive Mixed Models (GAMMs) to fit with nonlinear patterns [48, 49] implemented in the R-package mgcv [48, 50–53]. By estimating the degree of smoothness of a Bayesian spline smoothing using restricted maximum likelihood estimation [50, 54], GAMMs allow the identification of dynamic patterns underlying time-series while taking into account participants' idiosyncratic response as follows:

$$Y_{is} = \alpha_i + f(X_s) + a_{is} + \epsilon_{is} \tag{1}$$

where i is the participant index and s is the time in seconds. Y_{is} represents the response variable of one of the physiological measures (i.e. either HR, HF HRV, BR, ST, SCL or SCR) assuming a quasi-Gaussian distribution for the fitting [55]. The response variable Y_{is} includes a specific intercept for each participant (α_i). A smooth effect over time $f(X_s)$ is applied to model (Eq 1) to predict the nonlinear evolution of the physiological measure. This smooth effect $f(X_s)$ is built up in basic components, called the basis functions $b_j(X_s)$, such that:

$$f(X_s) = \sum_{j=1}^{k} \beta_j \times b_j(X_s) \tag{2}$$

where the regression parameters β_j are estimated by penalized likelihood maximization.

The model also includes the random effects term $a_{is} = Zb_i$ where Z is a random effects matrix and b_i is a vector of random effects described by $b_i \sim N(0, D)$. In this, D represents a covariance matrix. By adding random effects for each participant, the model assumes between-participant heterogeneity but homogeneity within a participant's data over time. The error term ϵ_{is} is assumed to be normally and independently distributed $\epsilon_{is} \sim N(0, \sigma^2)$. Because the data consists of time series, the assumption of model independence may be violated. Therefore, a residual auto-correlation structure AR-1 was added to the model error (see [56] for an application to spatio-temporal time-series):

$$\epsilon_{is} = \rho\epsilon_{i-1,s} + \eta_{is} \tag{3}$$

This implies the following correlation structure:

$$cor(\epsilon_{is}, \epsilon_{it}) = \begin{cases} 1 & \text{if } s = t \\ \rho^{|t-s|} & \text{else} \end{cases} \tag{4}$$

Degrees of freedom above one indicate the importance of the "smooth" term to estimate the variability of the data.

By using GAMMs it is possible to identify underlying trends in participants' physiological changes. However, even though GAMMs assess time-series changes, it does not provide a statistical analysis of where these changes happen. In contrast, a Significant Zero Crossing of the Derivatives (SiZer) approach is able to identify significant changes in the GAMM predicted values [57]. SiZer methods allow for meaningful statistical inference while doing exploratory data analysis using statistical smoothing methods [58]. The SiZer approach uses the first derivatives of GAMM predictions alongside confidence intervals as follow:

$$\hat{f}'_h(x) \pm q\hat{SD}(\hat{f}'_h(x)) \quad (5)$$

where q is an appropriate Gaussian quantile set to 99% point-wise confidence interval. The bandwidth parameter h is a positive number that determines the estimated density of smoothing $\hat{f}$ [59, 60]. If the bandwidth parameter h is too large, the fit has over-smoothed the data and thereby fails to detect the transition from an increasing to a flat (or possibly decreasing) function. If the bandwidth parameter h is too low, the fit is influenced by a very small number of data points and overestimates changes in peaks or valleys. The SiZer method (Eq 5) identifies when the curve of the slope shows a significant alteration by evaluating when zero falls outside these confidence limits. Consequently, by analyzing significant changes in physiological rhythms during a zipline activity in which there is no or little exertion, it is possible to attribute these fluctuations to changes in participants' emotions.

3 Results

After removing outliers and artifacts, differences during the zipline activity phases were observed for HR, BR, HF HRV, and SCL (Figure 3). However, no difference was found between phases mean for ST and SCR. The results provided by the GAMMs showed significant changes over time for participants' HR ($F(7.36) = 7.8$, $p < 0.001$), BR ($F(6.82) = 2.37$, $p = 0.013$), SCL ($F(8.63) = 49.4$, $p < 0.001$) and HRV ($F(2.66) = 6.96$, $p < 0.001$) whereas the physiological measures for ST ($F(1) = 0.31$, $p = 0.578$) and SCR ($F(1.87) = 1.15$, $p = 0.388$) remained stable.

As an evaluation of the model fit, the Akaike Information Criterion (AIC) was calculated for a simple Generalized Additive Model without random effects or autocorrelation, a GAMM without autocorrelation and a GAMM with random effects and autocorrelation (Table 2). The lowest AIC indicates the best model fit. The comparison of the AIC revealed that the GAMM with AR1 autocorrelation and participant as a random effect obtains the lowest AIC for each of the physiological measures.

Based on the trend prediction extracted from the GAMMs, a SiZer method was performed using a 99% point-wise confidence interval (Figure 4). Using GAMMs and SiZer methods, results indicated significant local changes in the physiological pattern, which can be associated with the sequence of predicted emotions (Table 3).

Before beginning the zipline activity, there was a significant increase in HR, BR and SCL, indicating an increase in participants' arousal due to the appraisal of potential 'danger'. During the first part of the zipline, there was a second significant increase in HR and SCL, and a significant decrease of BR. These changes can be explained by the thrill of jumping out and by the increase of zipline acceleration. In the second part of the activity, as the zipline speed decreases, participants' data showed a significant decrease in HR and

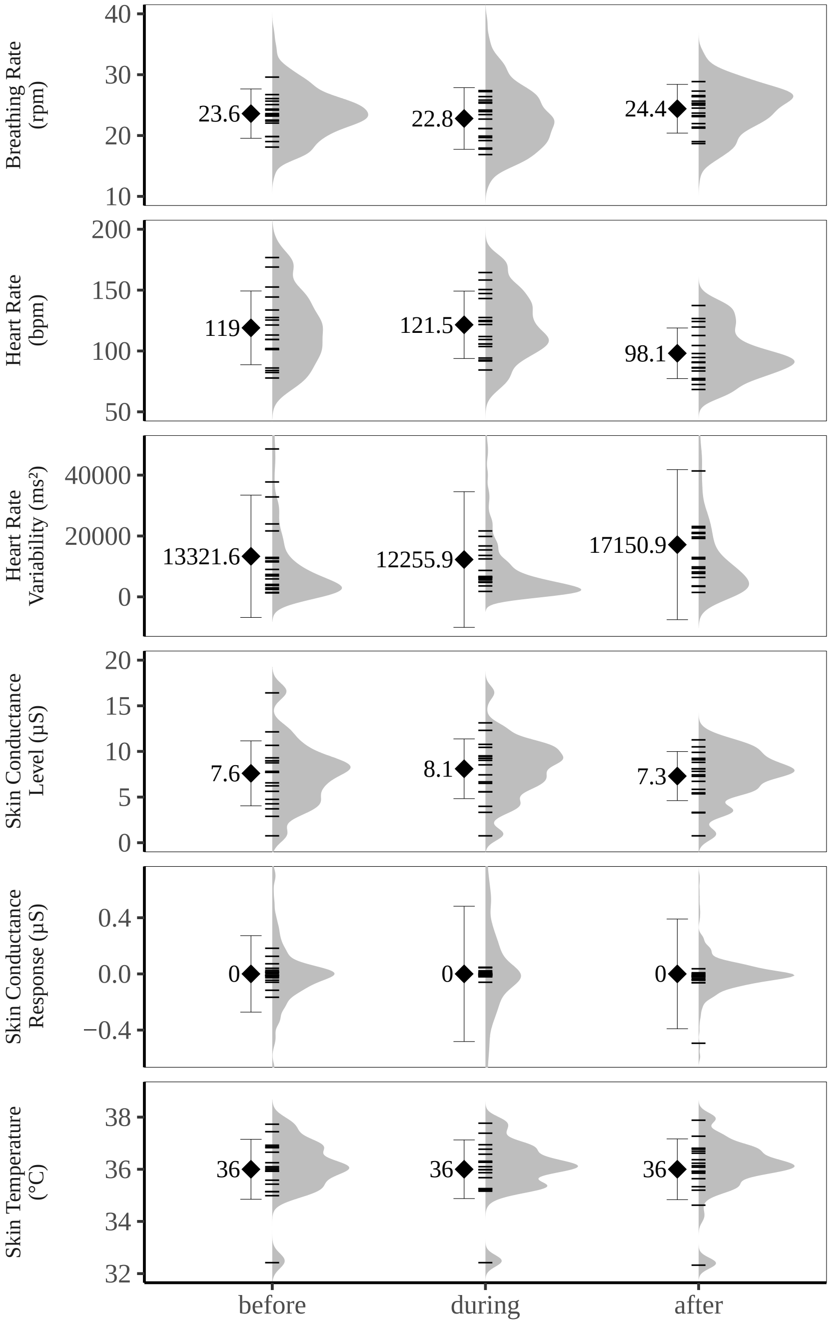

Fig. 3 Density distribution of physiological raw data for every participant (grey area) depending on the phase of the zipline activity. Square dots and error bars indicate overall mean and standard deviation. Dashes dots indicate participants' mean.

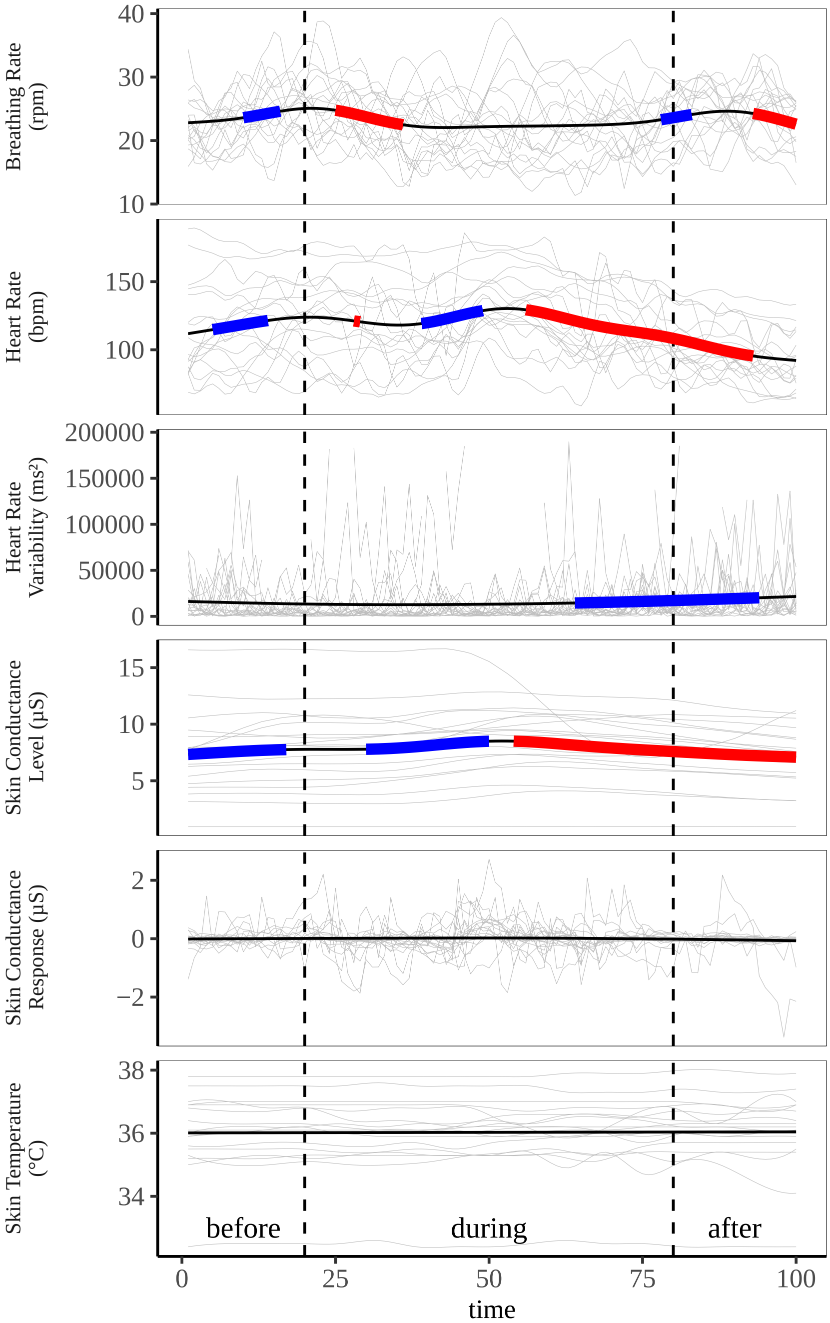

Fig. 4 SiZer analysis of the GAMM predicted values after signal pre-processing treatment and feature extraction. Significant periods are extracted from the first derivatives and reported on the actual GAMM predicted values where red periods indicate a significant decrease and blue periods indicate a significant increase. The period between the dashed vertical lines denotes the zipline activity. Gray time-series represent each participant's individual data.

Table 2 Comparison of the model fitness with AIC. GAM is the model without random effect or autocorrelation, GAMM no AR1 the model without autocorrelation and GAMM with random effect or autocorrelation.

model	GAM	GAMM no AR1	GAMM full
HR			
df	9.78	5.00	6.00
AIC	16910.35	14861.41	11186.83
BR			
df	10.12	5.00	6.00
AIC	10583.95	9827.13	6598.57
ST			
df	3.00	5.00	6.00
AIC	5574.77	-1207.23	-7919.51
HRV			
df	5.14	5.00	6.00
AIC	42383.69	41581.69	41308.01
SCL			
df	5.53	5.00	6.00
AIC	9313.66	5382.87	-4761.18
SCR			
df	10.66	5.00	6.00
AIC	1998.76	2039.72	1110.50

Table 3 Correspondence of physiological changes with the predicted emotions according to each phase of the zipline activity. The '+' sign indicates a significant increase of the physiological measure, the sign '-' a significant decrease and ns. indicates no significant change.

	before	take off	during		landing	after
Measure	Anxiety	Fear	Terror	Triumph	Exhilaration	Relief
Heart Rate	+	-	+	-	-	-
Breathing Rate	+	-	ns.	ns.	+	-
Skin Temperature	ns.	ns.	ns.	ns.	ns.	ns.
Heart Rate Variability	ns.	ns.	ns.	ns.	+	+
Skin Conductance Level	+	ns.	+	-	-	-
Skin Conductance Response	ns.	ns.	ns.	ns.	ns.	ns.

SCL. HRV did not increased until the participants reach the platform, which can be interpreted as a negative emotional state due to the potential difficulty of reaching the platform. Finally, a significant decrease in HR, BR and SCL was observed by the end of the activity. This increase could be a reflection of participants' relief after finishing the zipline activity.

4 Discussion

During a zipline activity, significant changes in participants' physiological rhythms were observed. Such changes in physiological rhythms can occur before or after an event [61]. An accurate response to an event is facilitated by a physiological pre-activation [62]: increases in heart rate and breathing rate lead to better blood irrigation of the muscles to provide the best behavioral response to the triggering event. Changes in skin temperature and sudation levels are typical side effects of the increase in heart rate and breathing rate. The skin regulates body temperature by increasing or decreasing sudation levels and thereby assist the body's thermoregulation system in order to maintain its homeostasis. In addition, an increase in hand sudation can also improve the individual's grip, which is particularly relevant in this activity. Thus, antecedent physiological changes are triggered not only by the comparison between sensor inputs and behavioral response expectation but also by the uncertainty of the results of the future behavioral response. Subsequent physiological changes happen because of changes in the physiological rhythms after the event. These are the behavioral responses to the event so that the body can adjust to a new accurate behavior depending on the consequences of the previous behavior [63].

Despite improvements in multimodal sensor recording and their decreased size, improvements to the shape and size of associated belts and wristbands can be made, particularly for the purposes of sport monitoring. Indeed, sensors can affect individuals' performance due to their inconvenience (e.g. the sensors can cause discomfort and a heightened awareness that data is being recorded can make the individuals uncomfortable). Furthermore, the EDA sensor on the finger may bother or limit the range of the movement for the user, highlighting the need for less obtrusive sensors [64]. This is particularly the case for sports involving the use of the hands to grip or manipulate the environment as well as for sports involving handlebars, steering wheels or sticks such as driving, cycling or skiing. While the use of EDA sensors in the former is limited, their use in the latter is promising. Therefore, future research should consider changing the sensor placement. For example, the thenar and hypothenar eminence or foot sites could be used instead of the proximal phalanx to measure EDA activity. This may reduce distortion in the data due to the sensors rubbing against the zipline equipment.

While the naturalistic environment is an advantage of the current study, recording physiological measurement of outdoor activities is difficult. The context itself is a challenge due to the vibration which can interfere with the measurements taken. Contrary to lab experiments, field experiments bring a high percentage of artifacts and corrupted data. For example, some incoherent data from the Global Positioning System coordinates, HR, ECG and EDA measures had to be removed in this study. Other technical limitations such as battery life of the sensors and potential network disconnection provide additional problems that need to be solved. The accurate synchronization of data streams is also a challenge. These limitations need to be taken into account for the monitoring of athletes in practice contexts and measures can be implemented to reduce the effect of artifacts and corrupted data in the analysis. Simple measures to implement would be to increase the number of participants and to increase the number of repeated measures in the experimental design.

Furthermore, there are some limitations to the experiment design. As participants were not asked to disclose their familiarity with ziplining and other extreme sports, it is possible that some had prior experience of highly sensational activities such as bungee jumping, skydiving or even ziplining. The extent to which experienced participants are emotionally influenced by such activities is likely to be less than novice participants. However, if this is the case, the effect size found in the current paper is likely to be underestimated in comparison with the true effect size. To take this participant effect into account, future investigations could use a repeated measure design to measure the potential decrease within participants' emotional response (e.g. comparing multiple laps on multiple days in motor sports or repeated trail/slopes for downhill biking/skiing/snowboarding). An alternative procedure would be to perform a repeated measurement experiment design by comparing zipline slope angles and lengths in a randomized order to evaluate the intensity of participants' physiological response.

Finally, even if contextual and technical variables are controlled between the participants, inter-individual variables continue to be a potential limitation. For example, although all participants wore the closest fitting belt size, differences in body shape and size still led to minor artifacts in the data streams. Similarly, it is difficult to control for participants' overall health, diet, resistance to cold weather and even their mood on the day, all of which can influence the recording of physiological measurement. Even if the participant experiences warmth or cold during emotional experiences, the external temperature variability for each participant is low. As the duration of the zipline activity was less than 10 minutes, it is likely that the time period was too short for fluctuations in the skin temperature data. Skin conductance response is derived from the electrodermal activity which in turn occur due to an affective response to a specific stimuli. The distribution of the skin conductance data reveal that these responses were limited during experiment. Rather, the electrodermal activity in the current study reflect a general level of stress rather than specific stimuli responses.

By measuring physiological changes during an outdoor activity which involves little to no exertion, this study reveals there is a significant influence of psycho-emotional states on the manifestation of physiological rhythms. While wearable sensors are becoming more common in the evaluation of athletes' performance, the importance of taking psycho-emotional states into account for monitoring athletes is essential when interpreting results from the sensors. Even if it is difficult to separate the physical exertion from the psycho-emotional influence, the latter play an important role in athletic performance for many of sports [65, 66].

5 Conclusion

Wearable technologies can provide substantial physiological data, allowing individuals to monitor their performance during physical activity. Knowing when heart rate, breathing rate or electrodermal activity changes is essential for the production and reproduction of high-performance activities. It is even more important to understand why these physiological signals change. Among the factors underpinning physiological changes, athletes' emotions have a clear influence on performance even if it is difficult to measure this influence. In this study, ziplining offers a convenient setting to evaluate the variability of physiological rhythms during activities which are otherwise highly similar across several trials. As physiological changes triggered before or after an event are related to the context rather than physical exertion, their variability is a relevant indicator of whether athletes' decision making process is correct. By monitoring physiological changes, it is possible to analyse the optimal patterns and thereby infer individuals' psychological response that occurs during outdoor activities. Taking the influence of athletes' psychological states into account can provide important information for athletes to evaluate their progress, helping them to differentiate between emotion and exertion.

6 Acknowledgement

The authors thank the anonymous reviewers for their insightful comments and suggestions. The authors also would like to thank the developers of the following R packages used to process, analyse, display and report data: R [67] and the R-packages *broom* [68], *captioner* [69], *dplyr* [70], *facetscales* [71], *forcats* [72], *ggplot2* [73], *ggpubr* [74], *gridExtra* [75], *gtools* [76], *here* [77], *kableExtra* [78], *magrittr* [79], *mgcv* [51–53], *nlme* [80], *papaja* [81], *plyr* [70, 82], *png* [83], *purrr* [84], *readr* [85], *stringr* [86], *tibble* [87], *tidyr* [88], and *tidyverse* [89].

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