IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received August 29, 2019, accepted October 7, 2019, date of publication October 17, 2019, date of current version October 30, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2948024

Investigation of Complexity and Regulatory Role of Physiological Activities During a Pacing Exercise

MAIA ANGELOVA[1], SERGIY SHELYAG[1], SUTHARSHAN RAJASEGARAR[1], DINESHEN CHUCKRAVANEN[2], SUJAN RAJBHANDARI[3], (Senior Member, IEEE), PAUL B. GASTIN[4,6], AND ALAN ST CLAIR GIBSON[5]

[1]School of Information Technology, Deakin University, Geelong, VIC 3217, Australia
[2]Department of Computing, Aberystwyth University, Mauritius Branch Campus, Aberystwyth SY23 3FL, U.K.
[3]Centre for Mobility & Transport, School of Computing, Engineering and Mathematics, Coventry University, Coventry CV1 5FB, U.K.
[4]La Trobe Sports and Exercise Medicine Research Centre, School of Allied Health, La Trobe University, Melbourne, VIC 3086, Australia
[5]Faculty of Health and Sciences, University of Essex, Colchester CO4 3SQ, U.K.
[6]Deakin University, Burwood, VIC 3125, Australia

Corresponding author: Maia Angelova (maia.a@deakin.edu.au)

ABSTRACT Existing physiological control fatigue models propose that there may be a regulator in the central nervous system which modulates our daily physical activity. Within limits, this regulator ensures physical activity is completed without physiological system failure through interactive communications between the peripheral systems and the central systems. The ability of the central nervous system to regulate exercise is vital to optimise sport performance when severe intensity exercise might be required for prolonged or frequent periods. Based on mathematical models, this investigation explores the complex relationship between some of the mechanisms controlling physical activity and behaviour. In order to analyse the system control mechanisms, heart rate, volume of oxygen consumption and power output were measured for a well-trained male cyclist. Using power spectrum analysis, fractal analysis and continuous wavelet transforms, we show that the system control mechanisms regulating physiological systems, have distinct complexity. Moreover, the potential central controller uses specific frequency bands simultaneously to control and communicate with the various physiological systems. We show that pacing trials are regulated by different physiological systems.

INDEX TERMS Pacing, fractal analysis, wavelet analysis, complexity, exercise dynamics.

I. INTRODUCTION

Hypothetical models were developed in the last 15 years in exercise physiology to explain the influence of fatigue on athletes' physical performance during exercise [1], [2]. These physiological control models postulate that the human body works as a complex integrative control system through continuous communication between the peripheral systems and the central systems [2]. Physiological systems that regulate homeostasis act upon afferent feedback and efferent command concerning: (i) continuous changes in physiological variables at rest and during exercise, (ii) the deviation of a particular variable from its metabolic setpoint value and (iii) its returning speed to the baseline point [3], [4].

The associate editor coordinating the review of this manuscript and approving it for publication was Mohammad Abdul Hannan.

The importance of studying the metabolic setpoint lies in understanding the complex interaction between the peripheral and central physiological systems. When a metabolic variable changes, information from the peripheral system is carried by an affector to a central controller located in the hypothalamus [5]. The controller integrates and transduces the information into an effector signal to correct any deviations in metabolic variables from the setpoint. Metabolic activity is continuously regulated at rest and during exercise by different homeostatic control mechanisms in the brain and peripheral physiological systems to prevent catastrophic system failure. Essential for the function of these regulatory processes are baseline ''setpoint'' levels of metabolic function. How these setpoint levels of all metabolic variables in the different peripheral physiological systems are created and maintained, and why they are similar in different

individuals, has not been understood well. What is actually known about the system regulators of metabolic setpoint levels is described as follows: (i) innate setpoint values are stored in a certain region of the central nervous system, such as the hypothalamus; (ii) setpoint values are created and maintained as a response to continuous external perturbations; (iii) setpoint values are created and maintained by complex system dynamical activity in the different peripheral systems, where setpoint levels are regulated by the ongoing feedback control activity between different peripheral variables; (iv) human anatomical and biomechanical constraints contribute to the creation and maintenance of metabolic setpoints values; or (v) a combination of all these four different mechanisms occurs [4].

The aim of this study is to obtain insights in the regulation of homeostasis via mathematical investigation of the signals measured from a cyclist in laboratory-based time trials with the three pacing strategies.

To date, few studies [6]–[13] have been carried out to investigate the nature of the underlying control mechanisms of the physiological systems. Furthermore, exercise physiology studies have focused on the use of statistical tests to determine relationships or significant changes in physiological variables, such as heart rate (HR), volume of oxygen consumption per minute (VO_2, $L \cdot min^{-1}$), Rating of Perceived Exertion (RPE), blood lactate concentration (BLC). This approach does not provide much insight into the nature of the mechanisms responsible for these findings [14]. Also, because physiological and brain activities change irregularly in time [15]–[18], mathematical methods are needed to model and analyse the mechanisms that control homeostasis and sustain physical performance among the various physiological systems [2], [3].

The commonly used types of pacing in time trialed exercise are self-paced, constant-paced and variable-paced [19]. The data collected consist of HR, VO_2 and power output. One way to analyse pacing is through time trial exercise and these can be assessed in terms of energy efficiency. In this study, therefore, the energy produced from aerobic and anaerobic metabolic processes is investigated for various types of pacing, and assessed with respect to work rate and energy expenditure for a 20-km cycling time trial. The metabolic setpoint mechanism is an inbuilt survival mechanism, and any time something changes, the body fights hard to maintain what has been accepted as normal for an individual. The body controls the metabolic setpoint by adjusting the metabolism. The metabolism refers to the chemical processes that carry on continuously to assist ongoing function of the body.

Despite the vast progress and achievements in integrative physiology in the last decades, there is still a significant gap in understanding how diverse physiological systems and organs coordinate their functions over a broad range of space and time scales and horizontally integrate to generate distinct physiologic states at the organism level. The emerging field network physiology aims to address these fundamental questions [9], [11], [20], [20]–[24]. Recent developments in this field [9], [20]–[22] address similar questions of how integrated function and transition across states emerge from the network of physiological interactions [21]. The focus of the field is to get insights of how homeostasis and its counterpart of homeostenosis emerge as different physiological states from the interaction between many different physiological variables, with an objective to improve diagnosis, prognosis and preventive medicine, and to better understand physiological function [8], [9], [11], [20], [20]–[24].

Novel concepts and approaches derived from recent advances in network theory, coupled dynamical systems, statistical and computational physics show promise to provide new insights into the complexity of physiological structure and function in health and disease, bridging the genetic and subcellular level with intercellular interactions and communications among integrated organ systems and subsystems.

This study focuses on the mathematical analysis of the signals measured during pacing exercise. This gives insights of the system control mechanisms (present in the physiological systems), which are responsible for the regulation of homeostasis (i.e., balance or harmony within the physical body system) required to enhance sports performance. Various mathematical methods, commonly utilised in the biological and medical field [8], [9], [25] are used in order to see how the physiological systems dynamically interact and function. In essence, this research endeavours to shed light on the following main hypotheses:

Hypothesis 1: The null hypothesis (H_{o1}) states that there is no significant difference in the complexity of a particular physiological activity and, in particular for HR, (in terms of fractal dimension value) during various types of pacing that are self-paced, even-paced and variable-paced. However, for the alternate hypothesis (H_{a1}), there are significant differences in the complexity of the various pacing strategies.

Hypothesis 2: For the null hypothesis (H_{o2}), there is no significant difference in frequency band powers (High Frequency, Low Frequency, Very Low Frequency) for a particular physiological activity (that is heart rate and volume of oxygen consumption), while for the alternate hypothesis (H_{a2}) there is a significant difference in frequency band powers for a particular physiological activity (i.e, heart rate and volume of oxygen consumption).

The paper is organised as follows: Section II describes the data for this study, Section III is devoted to the mathematical methods, the results are given in Section IV, while discussion and conclusions are given in Section V and Section VI respectively.

II. DATA

In order to analyse the system control mechanisms, HR (bpm), VO_2 ($L \cdot min^{-1}$), and power output were obtained from a healthy and well-trained male cyclist. For this pilot study, we consider data for one cyclist. The cyclist was required to complete a 20-km cycling bout in the minimum time possible on separate occasions using three different pacing strategies in laboratory conditions. The study was

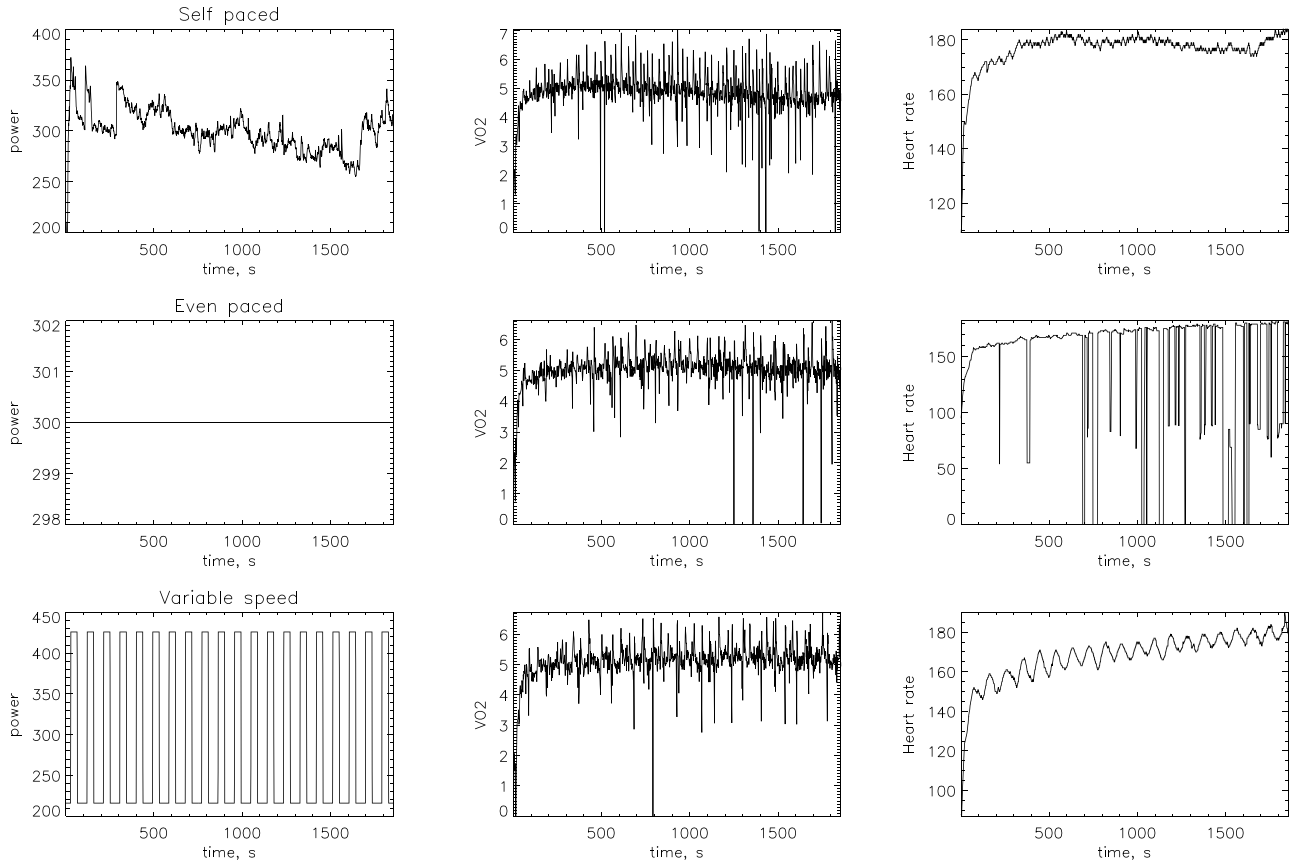

FIGURE 1. Time series of the power (first column), VO_2 (second column) and heart rate (third column) for the cyclist for the three types of pacing strategies: self-paced (top row); even-paced (middle row); and variable-paced (bottom row).

approved by the Ethical Committee of Northumbria University. We analysed the collected time series data using fractal and wavelet techniques.

The measured physiological time series for the three pacing trials are shown in Figure 1. The rows represent self-paced, even-paced and variable-paced regimes, while the columns show the power output, HR and VO_2 of the cyclist. The figure shows the unprocessed data, which have gaps and missing values.

We have applied standard procedures to input missing data. Specifically, we interpolated single missing values with the nearest neighbours.

In athletic competition, pacing is important so that the available metabolic resources are utilised effectively to finish a physical activity in the minimum possible time, and to maintain enough metabolic resources to complete that task successfully [26].

The pacing strategies were: self-paced (cycle as hard as could at any moment in time), where participants were able to freely choose their exercise loading; even-paced, where the exercise load was fixed; and variable-paced trials based on 70% and 140% of the subject's respective self-paced average power output [16], [26]. The self-paced trial is considered to be less physically challenging than enforced constant-paced exercise of the same intensity [34].

The cyclist completed these three different pacing time trials on separate occasions in the physiology laboratory with at least one week rest in between the trials for their recovery purposes and to prevent a training effect [28].

Physiological data including HR (bpm) were recorded using a data acquisition system (Powerlab, ADI Instruments, Australia), and VO_2 ($L \cdot min^{-1}$) was measured using an online gas analyser (Cortex Metalyser, Cortex Biophysik, Germany). Power outputs were recorded at a frequency rate of 11 Hz using Velotron 3D software, which was interfaced with the Cycle Ergometer (VelotronPRO, RacerMate Inc., USA), that was used for all cycling time trials. The data were collected only for the duration of the trial.

All the collected and computed data were tested for parametricity using Kolmogorov-Smirnov (K-S) test to find out whether they follow a normal distribution so as to ensure the appropriate parametric or non-parametric tests were identified for comparison purposes [30], [31].

The preceding studies used mathematical modelling techniques to elucidate the nature of the physiological control systems regulating physical activity [14], [32], [33], while

participants undertook different types of paced exercise during 20-km laboratory based cycling trials.

III. METHODS

A. SPECTRAL POWER

The spectral energy densities of the physiological data for the self-paced, even-paced and variably-paced power of the cyclist were calculated to find out how spectral power changes with frequency f. By doing so, we were able to demonstrate the presence or the absence of the system control mechanism in the physiological data. Power spectral density (PSD) describes how the power of a signal or time series is distributed over the different frequencies.

In analysing the frequency content of a signal $x(t)$, it is advantageous to work with a truncated Fourier transform, $\hat{x}_T(\omega)$, where the signal is integrated only over a finite interval $[0, T]$:

$$\hat{x}_T(\omega) = \frac{1}{\sqrt{T}} \int_0^T x(t) e^{i\omega t} dt. \tag{1}$$

Here ω is the angular frequency of the signal. Then, PSD can be defined as:

$$S_{xx}(\omega) = \lim_{(T\to\infty)} E[|\hat{x}_T(\omega)|^2], \tag{2}$$

where the $E(.)$ denotes the expected value. Explicitly, we have,

$$\begin{aligned} E[|\hat{x}_T(\omega)|^2] &= E\left[\frac{1}{T}\int_0^T x^*(t)e^{i\omega t}dt \int_0^T x^*(t')e^{-i\omega t'}dt'\right] \\ &= \frac{1}{T}\int_0^T \int_0^T E[x^*(t)x^*(t')]e^{i\omega(t-t')}dtdt' \end{aligned} \tag{3}$$

Note that the frequency f is given by $f = \frac{\omega}{2\pi}$. In the frequency domain, PSD can follow a power law, $P \sim f^{-\beta}$, where β is a scaling parameter [35]. A scaling parameter $0.5 \leq \beta \leq 1.5$ indicates $1/f$ type of scaling, which signifies the presence of long-range correlations. Scaling $\beta = 0$ characterises uncorrelated time series (white noise), while $\beta \sim 2$ is linked with the presence of short range correlations (Brownian noise).

B. FRACTAL ANALYSIS

In physiology, fractal power laws play an important role. The time series of healthy heart rate, fractal lungs, blood pressure and walking all show power law $1/f$, which indicates long-range correlation and corresponds to pink noise (see for example [39]). In order to investigate the complexity of the metabolic setpoint function [7], fractal analysis was applied to the power outputs of the various pacing time trials as well as the measured physiological data for all types of pacing that were used for the 20-km cycling time trials. The fractal dimension was determined using Higuchi's algorithm [36], [37], and the algorithm implementation was tested using a number of different functions of known fractal dimensions [38]. The expectation was: the greater the complexity of a biological signal, the higher the fractal dimension value. We speculate that the fractal dimensions of the physiological data (or the system control mechanisms) were similar regardless of the different types of pacing strategies being used (see Hypothesis 1). The measures that describe the non-linearity and fractal nature of objects are the power laws, represented with PSD, the complexity parameter β and fractal dimension (FD), D.

A time series with $f^{-\beta}$ scaling can be considered as a theoretical fractal Brownian motion, f_{Bm}. According to the fractal motion classification, it corresponds to $1 < \beta < 3$; with $\beta = 2$ is Wiener process corresponding to Brownian motion. A fractional Gaussian noise, f_{Gn}, corresponds to $-1 < \beta < 1$), where $\beta = 0$ is stationary Gaussian noise (white noise).

For theoretical f_{Bm}, the relation between the FD and other nonlinear characteristics of the series is [58],

$$D = E + 1 - H \tag{4}$$

and

$$\beta = 2H + 1. \tag{5}$$

Eliminating H gives,

$$D = E + (3 - \beta)/2 \tag{6}$$

Real physiological time series often deviate from the theoretical f_{Bm}, and the relation (6) is used only for guidance.

In one dimension, $E = 1$, thus [37], [58] the relationship between the fractal dimension D and the power index β is

$$D = (5 - \beta)/2. \tag{7}$$

Higuchi [37] showed that:

$$1 \leq \beta \leq 3, \quad \beta = 2H + 1 = 5 - 2D. \tag{8}$$

Thus, formally, for white noise, $\beta \sim 0$, $D \sim 2$, for pink noise, $\beta \sim 1, D \sim 2$, while for red noise (Brownian motion), $D \sim 1.5$.

There are different algorithms to compute the FD. Higuchi's algorithm [37] calculates the FD, D, of a time series. In order to obtain the fractal dimension D, Higuchi considered a finite set of observations, taken at regular intervals: $x : x(1), x(2), x(3), \ldots, x(N)$. From this series a new $x(k, m)$ is constructed, which is defined as follows:

$$\begin{aligned} x(k,m) = \{&x(m), x(m+k), x(m+2k), \ldots, \\ &x(m + \left[\frac{N-k}{k}\right]k)\}, \end{aligned} \tag{9}$$

for $m = 1, 2, .., k$, where [.] is an integer function, representing the lower value of the integer (floor) of the number in [.].

Higuchi's algorithm defines the length of the curve, $L(k)$, associated with each time series $x(k, m)$ [36], [37] as follows:

$$\begin{aligned} L_m(k) = \frac{1}{k}\left(\sum_{i=1}^{\left[\frac{N-k}{k}\right]} x(m+ik) - x(m+(i-1)k)\right) \\ \times \left(\frac{N-1}{[(N-m)/k]k}\right), \end{aligned} \tag{10}$$

where the term $\frac{N-1}{[\frac{N-m}{k}]k}$ represents a normalization factor.

Then the fragments, $L_m(k)$, are summed to give the length of the fractal curve,

$$L(k) = \sum_{m=1}^{\left[\frac{N-k}{k}\right]} L_m(k). \tag{11}$$

Here, an important part of the calculation is to determine the value of k_{max}. As previous studies recommend (see for example [58]), this is done by scanning the computations ($k = 1, \ldots, k_{max}$). The choice of k_{max} is based on tests with the artificial series of the same size as the physiological data and containing the functions with known fractal dimensions. In our case, $k_{max} = 20$, for all trials for all physiological systems.

Higuchi's algorithm takes the average value $\langle L(k) \rangle$ of the length associated to the time series given by Equation (10). If the average value follows a power law, $\langle L(k) \rangle \propto k^{-D}$, then the curve is a fractal with dimension D. In practice, D can be determined as the negative of the slope of the least square best fit from the plot of $\ln L(k)$ versus $\ln k$.

We will use FD as one of the measurements of complexity of the physiological system. Note, that in the physiological context, increased complexity (larger FD in this case) means there are more independent sources or external sources controlling that physiological system.

C. CONTINUOUS WAVELET TRANSFORM

We use continuous wavelet analysis to find out how a central regulator paces the human body during exercise. Time-based and frequency-based analysis are not suitable for studying the irregular and non-stationary patterns of the complex biological signals [40]. Continuous wavelet transform (CWT) was used to denoise the physiological data [41], [42] and then perform a time scale analysis of the real-time signals. CWT [43] was chosen over the Discrete Wavelet Transform (DWT) as it operates at every scale and temporal position to establish any changes at different frequency bands of the physiological signals that assess indirectly the functions [25] of the central system (*i.e.*, the brain and brain stem). In addition, CWT has the ability to produce a two-dimensional view of the physiological signal. It enables us to observe and analyse the physiological signals which control the pacing behaviour [40] of the cyclist during the race.

CWT is used to divide a continuous-time function into wavelets. Unlike Fourier transform, CWT possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization. The CWT of a function $x(t)$ at a scale $a \in \Re^{+*}$ and translational value $b \in \Re$ is expressed by the following integral:

$$X_\omega(a, b) = \frac{1}{|a|^{\frac{1}{2}}} \int_{-\infty}^{\infty} x(t) \bar{\psi}\left(\frac{t-b}{a}\right) dt, \tag{12}$$

where ψ is a continuous function in both the time domain and the frequency domain, known as mother wavelet.

TABLE 1. HF, LF and VLF band frequencies.

	HF	LF	VLF
Frequency [Hz]	0.15-0.4	0.04-0.15	0.003-0.04

The overline above ψ represents operation of complex conjugation. The main purpose of the mother wavelet is to provide a source function to generate the daughter wavelets which are the translated and scaled versions of the mother wavelet. The wavelet scale, a, uniquely corresponds to a temporally-local signal pseudo-frequency, f, in the Fourier sense.

CWT, using Morlet wavelet, was applied to the rate of VO_2 ($L \cdot min^{-1}$), heart rate, and power outputs to obtain the corresponding continuous wavelet spectra. The full frequency range was then subdivided into regions or bands that were high frequency (HF), low frequency (LF) and very low frequency (VLF) bands [44]–[47]. Then, the respective mean wavelet normalised powers were computed to investigate any changes at these frequency bands of the physiological signals to observe indirectly how the central system interacts with these physiological systems. The frequency bands are given in Table 1. The cone of influence has been taken into account to exclude the effect of boundaries on measured power.

IV. RESULTS

Visual inspection of the data in Fig. 1 suggests that: (i) in the self-paced regime, the power gradually decreases until about 1600 s time, and then increases during the final part of the race. This results in a small increase in VO_2 signal and a significant increase in the heart rate in the same time interval; (ii) in the even-paced cycling regime, VO_2 remains nearly constant, while HR gradually increases over the temporal extent of the race; (iii) for variable speed regime, HR signal has a strongly pronounced component with the period equal to the period of change in the power signal, while the large-scale trend of increasing HR also exists.

A. PRESENCE OF THE SYSTEM CONTROL MECHANISMS UNDERLYING PHYSIOLOGICAL DATA

The PSD or the spectrum of a signal captures the frequency content of signals and helps in identifying periodicity (*i.e.*, occurrences at regular intervals), however the temporal information is lost [27]. The PSDs of the self-paced, even-paced and variable-paced power outputs of the cyclist are given in Fig. 2. The horizontal dashed line in the figure represents the 95% confidence level. Least squares linear fit was used to compute the indices β for the power laws $f^{-\beta}$ (plotted in green). The fitting was done above the 95% confidence level only. The values of the indices β, known as the complexity parameters, are also shown in Table 2. The results demonstrate clearly that all pacing trials show $1/f$ behaviour with different values for β. While for the self-paced regime β is close to 1.5 for the power output and 1.7 for the HR, this coefficient is close to 1 for VO_2, indicating long-range correlations. For self pace, the value of β for VO_2 is 1,

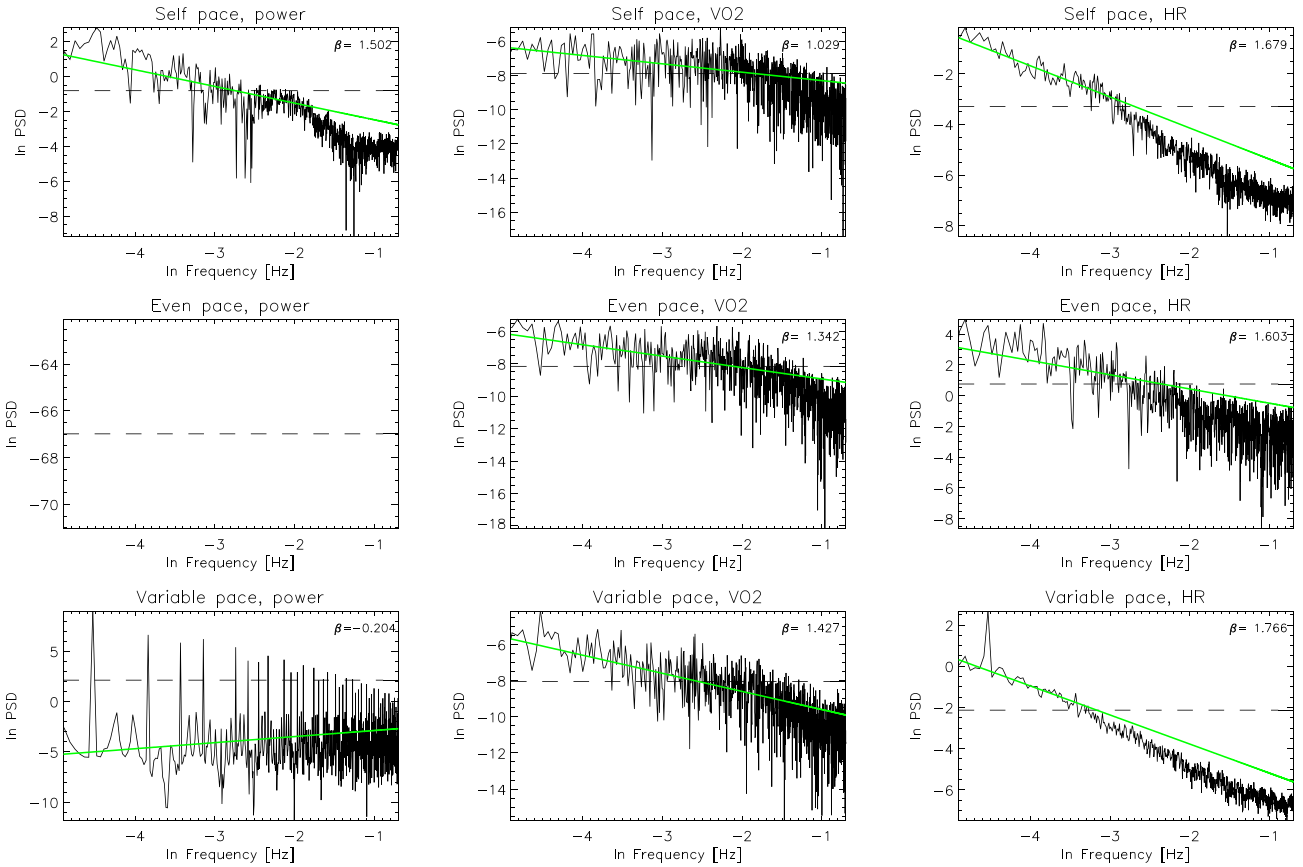

FIGURE 2. PSD distributions for the measured data for the three types of pacing strategies: self-paced (top row); even-paced (middle row); variable-paced (bottom row). The PSDs are shown for the measured power (left column), VO2 (middle column) and heart rate (right column). The horizontal dashed line indicates 95% confidence level. The green straight line in the plots (where exists) corresponds to the least-squares linear fit for the power law with the index β within the confidence interval.

TABLE 2. Power law indices β for the three pacing strategies for power output, HR and VO_2.

	Power Output	VO_2	HR
self pace	1.502	1.029	1.679
even pace	-	1.342	1.603
variable pace	-	1.427	1.756

increasing to 1.3 for even pace and 1.4 for variable pace. This shows a presence of long range correlation in all three regimes, $1 \leq \beta < 2$.

The even pace gives constant power and variable pace produces square wave for the power regime (changes from 70% to 140%). These signals do not produce values for β as the corresponding PSDs are δ-functions.

B. ANALYSIS OF THE NATURE OF METABOLIC SETPOINT FUNCTION USING FRACTAL ANALYSIS

To verify if the physiological system control mechanisms were similar, fractal analysis using Higuchi's algorithm [37] was performed on the physiological data.

For VO_2 (second column), FD for self-paced regime is between 1.4 and 1.8 (depending on the choice of k_{max} in Higuchi algorithm). There is, however, a noticeable decrease in FD for even-paced and variable-paced regimes for VO_2 by about 0.05. Thus, for all three regimes for these three regulating systems, the FD is within the range [1, 1.8], which is in the range of fractional Brownian motion and above the range of fractional Gaussian motion. Furthermore, there was a significant difference between FDs of heart rate and volume of oxygen consumption, meaning that each physiological system had different complexity. This proves the alternate hypothesis H_1, H_{a1}.

C. CONTINUOUS WAVELET TRANSFORM ON PHYSIOLOGICAL DATA

The wavelet spectra of the power output for the cyclist together with the associated physiological data that include VO_2 and HR signals during the 20-km cycling time trials are displayed in Fig. 4. In the figure, the x-axis represents time (in seconds) and y-axis represents the physical frequency in Hz. The horizontal lines separate different frequency bands as given in Table 1. The higher amplitudes or change in transition are shown as bright areas of the CWT. Using the two-dimensional view of the signal, the general (large-scale structure) and local (small-scale structure) behaviour

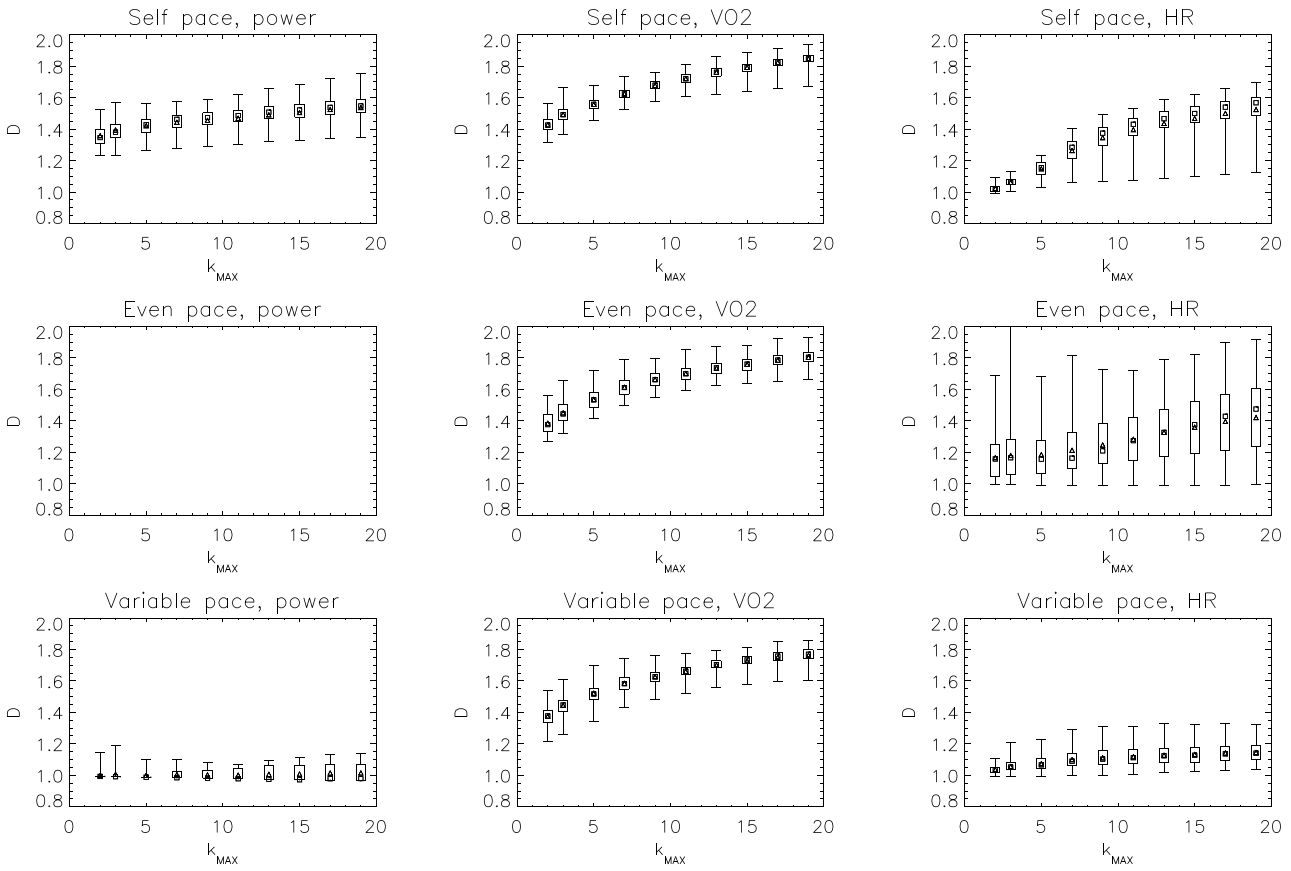

FIGURE 3. Dependence of the FD D on the range of $k = 1, \ldots, k_{max}$, calculated for the measurements of power (left column), VO2 (middle column), and HR (right column) and for self-paced (top row), even-paced (middle row) and variably-paced (bottom row) regimes. Each box plot in the plot is the FD D obtained from the least square linear fit of the ln-ln dependence of the curve length L vs k. The box plots are calculated based on the 2-second shifts of the starting point within the FD calculation window, which is 200 seconds.

and characteristics of the signal in time are clearly shown, which are not obvious from the one-dimensional view of the raw physiological signals. The wavelet spectra, represented as wavelet logarithmic power maps in Fig. 4 also show the cone of influence, above which the edge effects cannot be neglected. In the self-paced regime (first row), the high frequency component in the power (first panel) and the heart rate (third panel) is weaker compared to the VO_2 signal (first row, second panel). The wavelet spectrum of the even pace power is constant (middle row first panel), thus the transform is constant, and not presented. The VO_2 (middle row, second panel) shows an increasing high frequency component over the duration of the trial, which may be linked to increase of fatigue of the cyclist, while the heart rate is more or less constant (middle row, third panel). For the variable speed trial, all signals show considerable presence of 10 mHz frequency component due to variable-paced trials based on 70% and 140%, notably less pronounced for VO_2 signal. The VO_2 signal (third row, second panel) shows some small increase in the power of high-frequency component on time. On the other hand the HR (third row, right panel) does not show such an increase. This is an evidence that the body reacts in a different way to different kind of externally introduced drivers. In general, there were more abrupt changes at high frequencies than at low frequencies of the spectra for all physiological signals.

Moreover, during the trial there were frequent small changes in HR activities as shown by the green regions. In this manner, the lighter shades of green (Fig. 4) were classified as high transition (change in amplitude) whilst the darker shades were classified as low transition.

In Fig. 5 integrated power in different bands, as given in Table 1, is shown. It was observed that in the VLF band (green curves) there were peaks at the start of the cycling time trial, which did not always correspond to the peaks in the LF (red curves) and HF (black curves) bands. Recurring changes in LF and HF bands at specific intervals about 200 seconds can be observed as the peaks on positions in time as compared to the broader small ripple peaks depicted between the time 200 seconds to 1400 seconds.

Table 3 represents the mean normalised wavelet power for HR for each pacing and for each frequency band (HF, LF and VLF). Both VLF and LF band wavelet powers were significant with the values above 1 (see Table 3 and 0.011 respectively for all pacing time trials. For any particular pacing time-trial, there was a significant difference (10 times

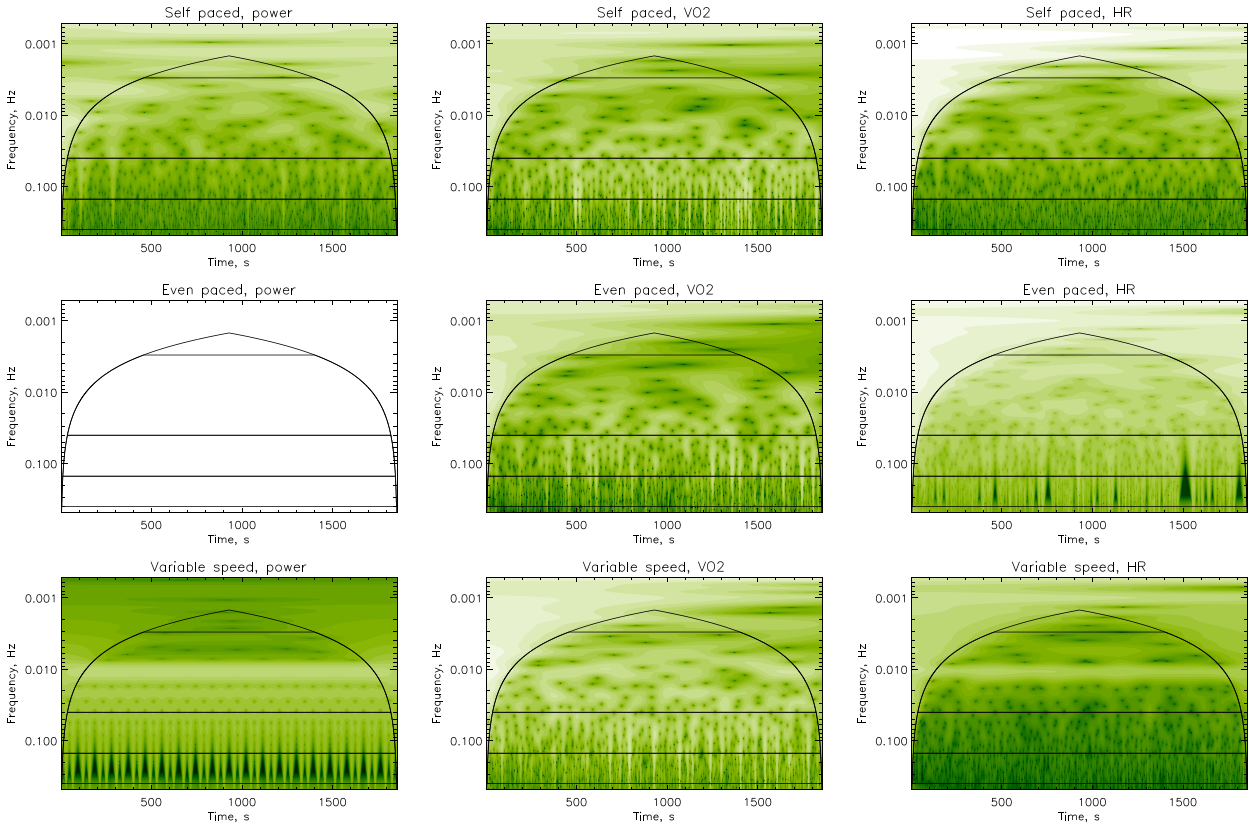

FIGURE 4. Wavelet logarithmic power maps for the studied signals. Three rows correspond to the different trial regimes. The columns represent different quantities measured in the study. The curve in each of the plots identifies the cone of influence, above which the displayed power values are affected by the boundary effects. These regions are excluded from the mean power calculations. The horizontal lines represent the frequencies separating the bands, as given in Table 1.

TABLE 3. The ratio of the mean power for each frequency band to the mean power in all frequencies, obtained from the wavelet analysis of the heart rate HR for each pacing regime.

Band	self pace	even pace	variable pace
HF	0.0061	0.0118	0.0014
LF	0.0861	0.1445	0.0132
VLF	1.2157	1.6197	2.0302

TABLE 4. The ratio of the mean power for each frequency band to the mean power in all frequencies, obtained from the wavelet analysis of the volume of oxygen consumption per minute VO_2 for each pacing regime.

Band power	self pace	even pace	variable pace
HF	0.4275	0.3264	0.1869
LF	1.3817	1.2596	0.8363
VLF	1.0920	1.2192	1.4734

difference in magnitude) between HF and LF, but there was also a significant difference between HF and VLF bands (∼100 times difference in magnitude).

Table 4 represents VO_2 for each pacing and for each frequency band. For the VO_2-related physiological activities, it was found that there was a significant difference between the VLF and LF wavelet powers compared to HF powers that were determined for each type of pacing as shown in Table 4. However, there was a smaller difference between LF and VLF wavelet powers. Thus, these results show that we can accept the alternate hypothesis, H_{a2}, for Hypothesis 2 as there was in fact a significant difference between VLF and LF as compared to HF.

V. DISCUSSION

The aim of this study was to obtain better insights and understanding of the complexity of interactions between different physiological states and mechanisms that regulate homeostasis. This was done by mathematical investigation and spectral analysis of the physiological signals measured in laboratory-based time trials of a cyclist with three different pacing strategies. PSDs shown in Fig. 2 of the self-paced power outputs demonstrated the existence of the complexity indicated by $1/f$-scaling factor. This confirms long-range correlations and the presence of underlying control mechanisms. It agrees with previous studies [6] which posited that this was not a consequence of noise because noise would have a broad and constant spectrum for any particular frequency f. It was also observed that the highest spectral power occurred at a very low frequency in a $1/f$-scaling trend for the cyclist.

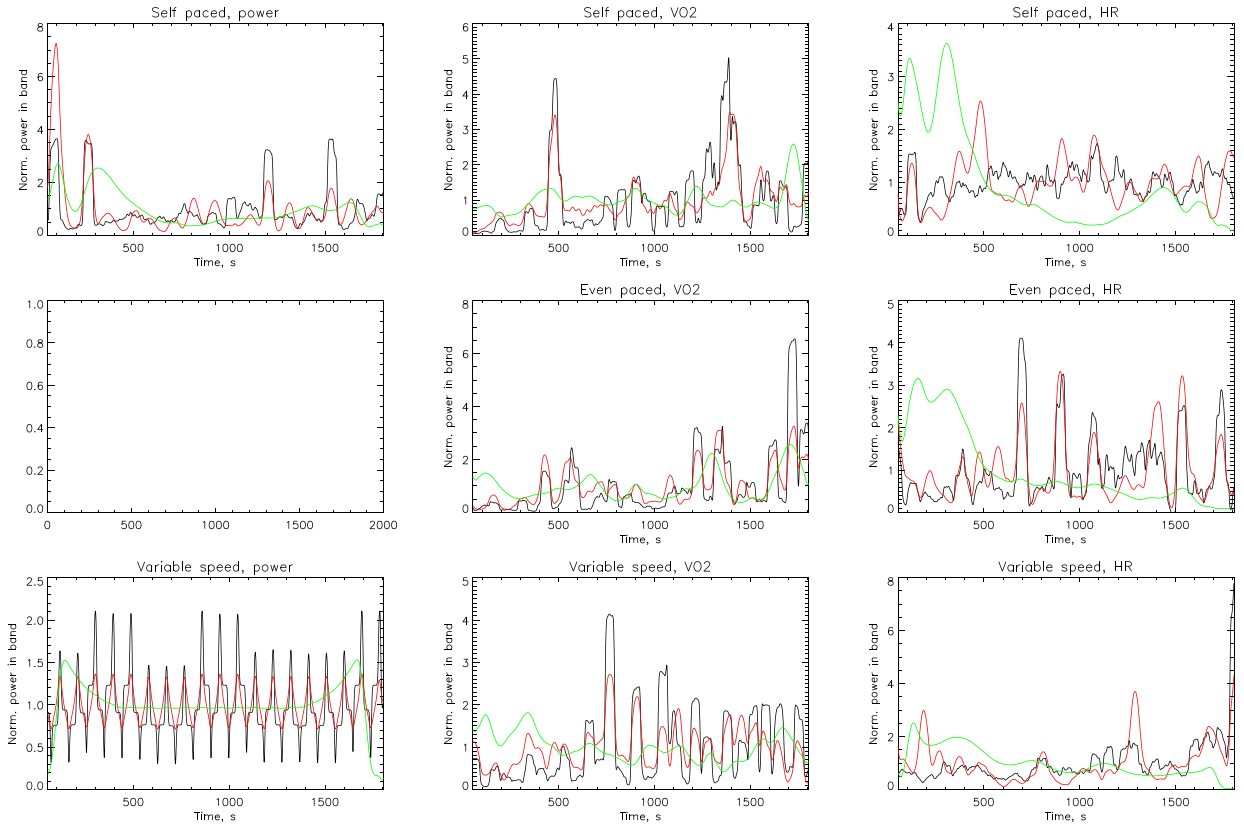

FIGURE 5. Integrated wavelet power in bands for the studied signals, boxcar-averaged with width of 50 seconds. Three rows correspond to the different trial regimes. The columns represent different quantities measured in the study. The black, red and green curves correspond to the HF, LF and VLF frequency band powers.

These were investigated further using wavelet analysis to understand the behaviour of the signals at various frequency bands.

To verify the similarity of these physiological system control mechanisms, fractal analysis using Higuchi's algorithm [37] was performed on the physiological data. The fractal dimensions for self-paced, even-paced and variable-paced trials showed variations.

It was observed (Fig. 2) that the complexity of a self-paced power output (a non-imposed pacing) signal is lower then that of even and variable-paced power output.

The complexity of the system control mechanisms for a particular physiological system depends on the number of independent sources modulating that system [49], [50]. As such, for the complexity of a signal to increase, there should be an increase in the number of independent control mechanisms controlling that physical system.

The increase in the complexity of the interactive communication process between the central system and the physiological systems may be the cause for the sensation of fatigue [51]–[53]. Okogbaa *et al.* [53] observed (with Fast Fourier and correlation analyses) an increase in complexity (as observed in the PSD and related $1/f$ behaviour) in repetitive knowledge worker related tasks leads to increased cognitive fatigue effects, reduction in productivity and alternation in cardiovascular and neurophysiological functioning. In addition, the FD for the rate of VO_2 as well as for HR activities for all pacing time trials were $\sim$1.6 and $\sim$1.4, respectively. The difference between the FD values of HR and the rate of VO_2 implies that the system control mechanisms that control these different physiological systems are different in complexity. In addition, the higher the β value, the more complex is the system control mechanism. From our data, it appears that the system control mechanisms for the cardiovascular system are more complex than that of the respiratory system.

To verify to what extent the system control mechanisms are similar, fractal analysis was performed. In Fig. 3, it was observed that the complexity of a self-paced signal, represented by FD, lies in between the FD values obtained for self-paced VO_2 and HR signals.

Based on the difference in complexity of the pacing strategies for VO_2 in terms of fractal dimension, we need to accept the alternate hypothesis, H_{a1}, for Hypothesis 1. The complexity of the system control mechanisms for a particular physiological system depends on the number of independent sources controlling that system [49], [50].

Our results demonstrate that the three pacing regimes show variation in complexity, with $1/f$ behaviour observed for all pacing regimes. As such, for the complexity of a signal to

increase, there should be an increase in the number of independent control centres modulating a physiological system. This leads to an increase in the information processing load (as each control centre provides a separate information input) between the central system (e.g. the brain or the brain stem) and the peripheral systems that may be the cause for the sensation of fatigue as investigated in the case of cognitive fatigue in [51]–[53]. This was experienced by the cyclist. Furthermore, the difference in complexity of the biological system activities may be attributed to the notion that when the system is more complex, the more robust it might be, or it does not allow the system to collapse completely even if a single control mechanism fails [2], [54].

The difference in complexity of the system control mechanisms demonstrated that the human body works as a complex system (as hypothesized by the Central Integrative Regulator model [2] and the Network Physiology models [20]–[22]). This complexity may be due to the complex interaction of the biological processes that occurred between the central systems and the peripheral systems. The behavioural characteristics of the physiological systems in terms of resilience to change subjected to a physical activity (a particular type of pacing) and predictability form an important part of the possible features of the control mechanisms that influence the onset of fatigue that are supported by the predictions of the task dependency model. Some physiological systems are more stringently protected by this control system as per the high trapping time of the biological activities of the cardiovascular system as compared to that of respiratory system [2]. The predictability of the behaviour of the physiological activities of the biological organ systems, as supported by the task dependency model, may also contribute to the onset of exercise-induced fatigue and affect sport performance accordingly.

To assess how a central regulator paces the physiological systems during exercise, a CWT was applied to these data to split the complex biological signals into frequency bands [44]. For the self-paced time-trial, it was observed that there were significant changes in the power output and physiological data (Figs. 4 and 5) at low frequencies especially at the start (acceleration phase), and at the end of the race (endspurt). These changes at low frequencies coincided with the increase in speed or acceleration at the beginning and at the end of the race that were common observations during a time-trial exercise [1], [6], [14], [17]. It was also observed that there were also changes at high frequencies for self-paced power output. The factors that govern the power output are the force applied at the pedals by the cyclist and the velocity at which the cyclist is moving. These factors are dependent on the type and number of muscle fibres that are recruited or activated to produce the required force and velocity. According to previous studies [55], small motoneurones fire slowly and continually (for a long period of time) and they innervate motor units that are resistant to fatigue in contrast to large motoneurones which fire rapidly and in bursts that innervate motor units that are fatigable (for a short period of time). This is perhaps why there were abrupt changes at the start and at the end of the race as large motoneurones were activated as compared to slow and continual firing rates of small motoneurones that appeared during the race.

The VLF band wavelet power was found significantly higher than powers in the other frequency bands, and therefore, it was the frequency band where there was highest interactive communication between this particular physiological system and the central system as the respiratory control centres were found in the brain stem and generated the rhythmic pattern of breathing [56]. This is supported by the values of the wavelet coefficients as shown in Fig. 4.

Here, we can accept the alternate hypothesis for Hypothesis 2, H_{a2}, as there was in fact a significant difference between VLF as compared to the other two frequency bands.

This suggests that there may be a control communication between the central regulator and this peripheral system that affected the performance of the cyclist. Moreover, the significant difference in the HF band power as compared to the other frequency bands for the HR activities, means that this might be the frequency band that the potential central controller [46], [57] was utilising to regulate physical activity and hence performance of the cyclist. Based on the wavelet analysis of the HR activities in terms of frequency bands, the alternate hypothesis for Hypothesis 2 is again accepted as there was a significant difference between HF as compared to other two frequencies.

VI. CONCLUSION

In this study, the existence of the $1/f$-scaling factor in the measured signals suggests the presence of the system control mechanisms within the different physical body systems. Moreover, fractal analysis showed that the complexity of the power output for each type of pacing is different, and the complexity of each physiological system is different. Therefore, it can be used as a mathematical tool in determining the complexity of pacing and it can be used to optimise the physiological performance of the athlete. This was in line with the philosophy of treating the human body as an integrated complex system, which motivates the quantification of emergent complexity in the physiological output signals.

Furthermore, the system control mechanisms underlying physiological data were investigated to see how a potential central controller paces the human body during exercise. It was found that there was a difference in the HF band power, most significant for HR activities. The significant difference of these specific wavelet band powers, as compared to the other frequency bands, for each physiological system implies that there may be a regulator that paces the human body during physical activity through the use of appropriate frequency bands to control and communicate with that particular peripheral system. In addition, the simultaneous use of these specific frequency bands also insinuate that the level of control should be higher than the peripheral systems and this control may happen in the central systems of the human organism.

ACKNOWLEDGMENT

D. Chuckravanen and A. St Clair Gibson were with the Department of Sport Sciences, Northumbria University, Newcastle upon Tyne NE1 8ST, U.K. M. Angelova and S. Rajbhandari were with the Department of Mathematics, Physics and Electrical Eng., Northumbria University, Newcastle upon Tyne NE1 8ST, U.K. The authors would like to thank all the sports science research colleagues who made this research study possible in terms of availability of physiological equipment or help in physiological data collection. DC thanks Northumbria University for the PhD Fellowship. MA acknowledges the partial support of the European FP7 project 247541 MATSIQEL, Marie Curie Actions-IRSES. DC, MA and ZSCG thank K. G. Thompson for valuable discussions of pacing strategies for cyclists. This research was undertaken with the assistance of resources and services from the National Computational Infrastructure (NCI), which is supported by the Australian Government. This work was supported by the MASSIVE HPC facility (www.massive.org.au). The authors thank Chandan Karmakar for the clarifications of CWT time-frequency analysis and Ye Zhu for the technical help in preparing the manuscript. This research study was approved by the Ethical Committee of the School of Sports Science and Psychology at Northumbria University to pursue studies on human subjects and researchers adhered to risk assessments before conducting this research study.

REFERENCES

[1] A. S. C. Gibson and T. D. Noakes, "Evidence for complex system integration and dynamic neural regulation of skeletal muscle recruitment during exercise in humans," *Brit. J. Sports Med.*, vol. 38, no. 6, pp. 797–806, 2004.

[2] E. V. Lambert, A. S. C. Gibson, and T. D. Noakes, "Complex systems model of fatigue: Integrative homoeostatic control of peripheral physiological systems during exercise in humans," *Brit. J. Sports Med.*, vol. 39, no. 1, pp. 52–62, 2005.

[3] A. S. C. Gibson, J. H. Goedecke, Y. X. Harley, L. J. Myers, M. I. Lambert, T. D. Noakes, and E. V. Lambert, "Metabolic setpoint control mechanisms in different physiological systems at rest and during exercise," *J. Theor. Biol.*, vol. 235, pp. 60–72, Sep. 2005.

[4] A. S. C. Gibson, J. Swart, and R. Tucker, "The interaction of psychological and physiological homeostatic drives and role of general control principles in the regulation of physiological systems, exercise and the fatigue process—The Integrative Governor theory," *Eur. J. Sport Sci.*, vol. 18, pp. 25–36, May 2017.

[5] S. C. Woods and D. A. D'Alessio, "Central control of body weight and appetite," *J. Clin. Endocrinol. Metabolism*, vol. 93, no. 1, pp. S37–S50, 2008.

[6] R. Tucker, A. Bester, E. V. Lambert, T. D. Noakes, C. L. Vaughan, and A. S. C. Gibson, "Non-random fluctuations in power output during self-paced exercise," *Brit. J. Sports Med.*, vol. 40, no. 11, pp. 912–917, 2006.

[7] G. Atkinson, O. Peacock, A. S. C. Gibson, and R. Tucker, "Distribution of power output during cycling," *Sports Med.*, vol. 37, no. 8, pp. 647–667, 2007.

[8] P. M. Holloway, M. Angelova, S. Lombardo, A. S. C. Gibson, D. Lee, and J. Ellis, "Complexity analysis of sleep and alterations with insomnia based on non-invasive techniques," *J. Roy. Soc. Interface*, vol. 11, no. 93, p. 20131112, 2014.

[9] R. Fossion, A. L. Rivera, J. C. Toledo-Roy, J. Ellis, and M. Angelova, "Multiscale adaptive analysis of circadian rhythms and intradaily variability: Application to actigraphy time series in acute insomnia subjects," *PloS One*, vol. 12, no. 7, Jul. 2017, Art. no. e0181762.

[10] R. Fossion, A. L. Rivera, J. C. Toledo-Roy, and M. Angelova, "Quantification of irregular rhythms in chrono-biology: A time-series perspective," in *Circadian Rhythm: Cellular and Molecular Mechanisms*, M. A. El-Esawi, Ed. London, U.K.: InTech, 2018, pp. 33–58.

[11] A. Bashan, R. P. Bartsch, J. W. Kantelhardt, S. Havlin, and P. C. Ivanov, "Network physiology reveals relations between network topology and physiological function," *Nature Commun.*, vol. 3, Feb. 2012, Art. no. 702.

[12] G. Wingfield, F. Marino, and M. Skein, "The influence of knowledge of performance endpoint on pacing strategies, perception of effort, and neural activity during 30-km cycling time trials," *Physiol. Rep.*, vol. 6, no. 21, 2018, Art. no. e13892.

[13] A. Venhorst, D. P. Micklewright, and T. D. Noakes, "The psychophysiological regulation of pacing behaviour and performance fatigability during long-distance running with locomotor muscle fatigue and exercise-induced muscle damage in highly trained runners," *Sports Med Open.*, vol. 4, no. 1, 2018, Art. no. 29.

[14] J. T. Ottesen, M. S. Olufsen, and J. K. Larsen, *Applied Mathematical Models in Human Physiology*. Philadelphia, PA, USA: SIAM, 2004.

[15] L. Glass and M. C. Mackey, *From Clocks to Chaos—The Rhythms of Life*. Princeton, NJ, USA: Princeton Univ. Press, 1988.

[16] J. B. Bassingthwaighte, L. S. Liebovitch, and B. West, *Fractal Physiology*. New York, NY, USA: Oxford Univ. Press, 1994, pp. 1–28.

[17] A. M. Sabatini, "Wavelet-based estimation of 1/f-type signal parameters: Confidence intervals using the bootstrap," *IEEE Trans. Signal Process.*, vol. 47, no. 12, pp. 3406–3409, Dec. 1999.

[18] A. T. Winfree, *The Geometry of Biological Time*, 2nd ed. New York, NY, USA: Springer, 2001, pp. 198–228.

[19] P. Lander, R. J. Butterly, and A. M. Edwards, "Self-paced exercise is less physically challenging than enforced constant pace exercise of the same intensity: Influence of complex central metabolic control," *Brit. J. Sports Med.*, vol. 43, no. 10, pp. 785–795, 2009.

[20] P. C. Ivanov, K. K. L. Liu, and R. P. Bartsch, "Focus on the emerging new fields of network physiology and network medicine," *New J. Phys.*, vol. 18, no. 10, 2016, Art. no. 100201.

[21] R. P. Bartsch, K. K. L. Liu, A. Bashan, and P. C. Ivanov, "Network physiology: How organ systems dynamically interact," *PLoS One*, vol. 10, no. 11, 2015, Art. no. e0142143.

[22] P. C. Ivanov, K. K. L. Liu, A. Lin, and R. P. Bartsch, "Network physiology: From neural plasticity to organ network interactions," in *Emergent Complexity From Nonlinearity, in Physics, Engineering and the Life Sciences*. Cham, Switzerland: Springer, 2017, pp. 145–165.

[23] P. C. Ivanov and R. P. Bartsch, "Network physiology: Mapping interactions between networks of physiologic networks," in *Networks of Networks: The Last Frontier of Complexity* (Understanding Complex Systems), G. D'Agostino and A. Scala, Eds. Cham, Switzerland: Springer, 2014, pp. 203–222.

[24] K. K. L. Liu, R. P. Bartsch, A. Lin, R. N. Mantegna, and P. C. Ivanov, "Plasticity of brain wave network interactions and evolution across physiologic states," *Frontiers Neural Circuits*, vol. 9, p. 62, Oct. 2015.

[25] O. Rioul and M. Vetterli, "Wavelets and signal processing," *IEEE Signal Process. Mag.*, vol. 8, no. 4, pp. 14–38, Oct. 1991.

[26] H.-V. Ulmer, "Concept of an extracellular regulation of muscular metabolic rate during heavy exercise in humans by psychophysiological feedback," *Experimentia*, vol. 52, pp. 416–420, May 1996.

[27] J. J. de Koning, C. Foster, A. Bakkum, S. Kloppenburg, C. Thiel, T. Joseph, J. Cohen, and J. P. Porcari, "Regulation of pacing strategy during athletic competition," *PLoS One*, vol. 6, no. 1, 2011, Art. no. e15863.

[28] G. S. Palmer, L. B. Borghouts, T. D. Noakes, and J. A. Hawley, "Metabolic and performance responses to constant load vs. variable-intensity exercise in trained cyclists," *J. Appl. Physiol.*, vol. 87, no. 3, pp. 1186–1196, 1999. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/10484594

[29] *Perceived Exertion (Borg Rating of Perceived Exertion Scale)*. Accessed: Jul. 20, 2019. [Online]. Available: https://www.cdc.gov/physicalactivity/basics/measuring/exertion.htm

[30] M. G. Flynn, F. X. Pizza, J. B. Boone, Jr., F. F. Andres, T. A. Michaud, and J. R. Rodriguez-Zayas, "Indices of training stress during competitive running and swimming seasons," *Int. J. Sports Med.*, vol. 15, no. 1, pp. 21–26, 1994.

[31] G. Fasano and A. Franceschini, "A multidimensional version of the Kolmogorov–Smirnov test," *Monthly Notices Roy. Astronomical Soc.*, vol. 225, pp. 155–170, Mar. 1987.

[32] J. T. Ottesen, "Modelling of the baroreflex-feedback mechanism with time-delay," *J. Math. Biol.*, vol. 36, no. 1, pp. 41–63, 1997.
[33] P. E. McSharry, M. J. McGuinness, and A. C. Fowler, "Confronting a cardiovascular system model with heart rate and blood pressure data," in *Proc. Comput. Cardiol.*, vol. 32, Sep. 2005, pp. 587–590.
[34] A. Findlay, *The Phase Rule and Its Applications*, 3rd ed. Harlow, U.K.: Longmans, 1911, p. 8.
[35] J. M. Blackledge, *Digital Image Processing: Mathematical and Computational Methods*. Chichester, U.K.: Horwood Publishing, 2005.
[36] R. G. Brown and P. Y. C. Hwang, *Introduction to Random Signals and Applied Kalman Filtering With MATLAB Exercises*. Hoboken, NJ, USA: Wiley, 1997.
[37] T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," *Phys. D, Nonlinear Phenom.*, vol. 31, no. 2, pp. 277–283, 1988.
[38] P. Paramanathan and R. Uthayakumar, "An algorithm for computing the fractal dimension of waveforms," *Appl. Math. Comput.*, vol. 195, pp. 598–603, Feb. 2008.
[39] J. B. Bassingthwaighte, L. S. Liebovitch, and B. J. West, *Fractal Physiology*. Berlin, Germany: Springer-Verlag, 1994.
[40] B. B. Mandelbrot, *The Fractal Geometry of Nature*. San Francisco, CA, USA: Freeman, 1982.
[41] S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-11, no. 7, pp. 674–693, Jul. 1989.
[42] Q. Pan, L. Zhang, G. Dai, and H. Zhang, "Two denoising methods by wavelet transform," *IEEE Trans. Signal Process.*, vol. 47, no. 12, pp. 3401–3406, Dec. 1999.
[43] S. A. Chouakri, F. Bereksi-Reguig, S. Ahmaldi, and O. Fokapu, "Wavelet denoising of the electrocardiogram signal based on the corrupted noise estimation," in *Proc. Comput. Cardiol.*, vol. 32, Sep. 2005, pp. 1021–1024.
[44] M. David, M. Hirsch, J. Karin, E. Toledo, and S. Akselrod, "An estimate of fetal autonomic state by time-frequency analysis of fetal heart rate variability," *J. Appl. Physiol.*, vol. 102, no. 3, pp. 1057–1064, 2007.
[45] C. Yamaguchi, "Fourier and wavelet analyses of normal and epileptic electroencephalogram (EEG)," in *Proc. 1st IEEE EMBS Int. Conf. Neural Eng.*, Mar. 2003, pp. 406–409.
[46] P. S. Addison, "Wavelet transforms and the ECG: A review," *Physiol. Meas.*, vol. 26, no. 5, pp. 155–199, 2005.
[47] S. Lu, H. Yang, W. Ye, D. Xiao, and X. Wu, "Dynamic analysis of heart rate variability based on orthogonal wavelet transform," in *Proc. IEEE-EMBS*, Jan. 2006, pp. 5548–5550.
[48] V. Pichot, J.-M. Gaspoz, S. Molliex, A. Antoniadis, T. Busso, F. Roche, F. Costes, L. Quintin, J.-R. Lacour, and J.-C. Barthélémy, "Wavelet transform to quantify heart rate variability and to assess its instantaneous changes," *J. Appl. Physiol.*, vol. 86, no. 3, pp. 1081–1091, 1999.
[49] B. Dubuc, J. F. Quiniou, C. Roques-Carmes, C. Tricot, and S. W. Zucker, "Evaluating the fractal dimension of profiles," *Phys. Rev. A, Gen. Phys.*, vol. 39, p. 1500, Feb. 1989.
[50] D. Hoyer, B. Frank, C. Götze, P. K. Stein, J. J. Zebrowski, R. Baranowski, and G. Schmidt, "Interactions between short-term and long-term cardiovascular control mechanisms," *Chaos, Interdiscipl. J. Nonlinear Sci.*, vol. 17, no. 1, pp. 015110-1–015110-8, 2007.
[51] P. Pajunen, "Blind source separation using algorithmic information theory," *Neurocomputing*, vol. 22, pp. 35–48, Nov. 1998.
[52] N. Okamura, "Effect of mental fatigue induced by repeated continuous calculation tasks on event-related brain potential (P300)," *J. Occupational Health*, vol. 49, no. 5, pp. 203–208, 2007.
[53] O. G. Okogbaa, R. L. Shell, and D. Filipusic, "On the investigation of the Neurophysiological correlates of knowledge worker mental fatigue using the EEG signal," *Appl. Ergonom.*, vol. 25, no. 6, pp. 355–365, 1994.
[54] A. C. S. Gibson, E. V. Lambert, L. H. G. Rauch, R. Tucker, D. A. Baden, C. Foster, and T. D. Noakes, "The role of information processing between the brain and peripheral physiological systems in pacing and perception of effort," *Sports Med.*, vol. 36, no. 8, pp. 705–722, 2006.
[55] S. M. Pincus, "Greater signal regularity may indicate increased system isolation," *Math Biosci.*, vol. 122, pp. 161–181, Aug. 1994.
[56] A. J. McComas, *Skeletal Muscle: Form and Function*, vol. 14. Champaign, IL, USA: Human Kinetics, 1996, p. 401.
[57] L. Sherwood, *Fundamentals of Physiology: A Human Perspective*, 3rd ed. Sherwood, 2005, pp. 394–396.
[58] A. Eke, P. Herman, L. Kocsis, and L. R. Kozak, "Fractal characterization of complexity in temporal physiological signals," *Physiol. Meas.*, vol. 23, no. 1, p. R1, 2002.

MAIA ANGELOVA received the Ph.D. degree from the University of Sofia. She was a Lecturer in physics with the Somerville College, University of Oxford, and a Professor of mathematical physics with Northumbria University, U.K., until 2016. She is currently a Professor of data analytics and machine learning with the School of Information Technology, Deakin University, Victoria, Australia. She is the Director of the Data to Intelligence Research Centre and leads the Data Analytics Research Lab, Deakin University. Her research interests include mathematical modeling, data analytics, time series, machine learning, and dynamical systems with applications to health.

SERGIY SHELYAG received the Ph.D. degree from the University of Göttingen, Germany, in 2004. He was a Research Fellow with the Department of Applied Mathematics, University of Sheffield, U.K., and with the Department of Mathematics and Physics, Queen's University, Belfast, U.K., was a Future Fellow with the Department of Mathematical Sciences, Monash University, Australia, and was a Senior Lecturer with the University of Northumbria, Newcastle, U.K. He is currently a Senior Lecturer with the School of Information Technology, Deakin University, Victoria, Australia. His current research interests include mathematical and computational modeling of complex physical processes, data analytics, machine learning, and dynamical systems.

SUTHARSHAN RAJASEGARAR received the Ph.D. degree from the University of Melbourne, Melbourne, VIC, Australia, in 2009. He was a Research Fellow with the Department of Electrical and Electronic Engineering, University of Melbourne, and as a Researcher in machine learning with the National ICT Australia (NICTA). He is currently a Senior Lecturer with the School of Information Technology, Deakin University, VIC. His current research interests include anomaly/outlier detection, distributed machine learning, pattern recognition, signal processing, health analytics, wireless communications, and the Internet of Things.

DINESHEN CHUCKRAVANEN received the Ph.D. degree from the University of Northumbria, Newcastle, U.K., in 2012. He was a Faculty Research Fellow with the Department of Life Sciences, University of Northumbria. He was a Lecturer in computer science with Aberystwyth University, Mauritius Branch Campus. His research interests include signal processing, signal analysis, machine learning, neural network for pattern analysis and prediction, biotechnology, and bioinformatics.

SUJAN RAJBHANDARI received the Ph.D. degree from Northumbria University, in 2010. He was a Senior Research Assistant and a Research Fellow with Northumbria University, from 2009 to 2012. He joined communications research group with the University of Oxford, in 2012, and worked in the prestigious EPSRC's funded ultraparallel visible light communications (UP-VLC) project which was collaboration of five UK's leading Universities (Oxford, Cambridge, St Andrews, Edinburgh, and Strathclyde). In 2015, he joined Coventry University as a Lecturer in electrical and electronic engineering and promoted to Senior Lecturer, in 2017. He is currently a Senior Lecturer with Coventry University, where he is working in the field of optical wireless communication. He is an Associate Member of the Institute of Physics.

PAUL B. GASTIN is currently a Professor and the Head of sport and exercise science with La Trobe University. His teaching and research focus on innovation in sport science and coaching to enhance the performance of people and organizations across the sport participation spectrum. He has worked in Olympic/Paralympic and professional sport in Australia and overseas holding senior positions with the Victorian Institute of Sport, the UK Sports Institute, and UK Sport. He is an ESSA Fellow and an accredited level 2 Sport Scientist and High Performance Manager.

ALAN ST CLAIR GIBSON received the MBChB, Ph.D., and MD degrees. He is currently the Deputy Dean (Research) of the Faculty of Science and Health, University of Essex. He has published more than 150 articles, which have been cited more than 10 000 times, since being published. His research interests include integrative control of human performance and physiological systems, psychobiological determinants of behavior, and pacing of events.