Wavelet Analysis of Physiological Control Mechanisms during Physical Activity

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Abstract: ***In exercise physiology, a novel model based on the regulation of neural effort and fatigue has been recently proposed. This model theorizes that physical activity is controlled by a central regulator in the brain, and the human body works as a complex integral system, unlike the Cardiovascular/Anaerobic/Catastrophe model of Sir A.V. Hill of exercise physiology. In this study, physiological data were collected from club-level cyclists for different types of pacing that were self pace, even pace, and variable pace for a 20-km cycling time trial. These physiological data were analyzed to assess the underlying system control mechanisms that show how the central regulator paces the human body during exercise. Continuous Wavelet Transform (CWT) was used to analyze the non-stationary physiological signals that were heart rate (HR/bpm) and rate of volume of oxygen consumption rate (VO2/ Lmin^{-1}). Normalised mean wavelet powers were used to compare the powers at different frequency bands of the continuous wavelet spectrum. These frequency bands were classified as High Frequency (HF), Low Frequency (LF) and Ultra Low Frequency (ULF) bands. There was a significant difference in the ULF band for the rate of volume of oxygen consumption ($p<0.01$) that decreased with increasing performance times of the cyclists for all types of pacing. As for the heart rate activities, both ULF and LF band powers were practically constant for all cyclists, and there was a significant difference in the HF band power compared to the other frequency bands. Here we show that the central system regulator paces the human body during physical activity by using specific frequency bands to control and communicate with a particular peripheral system in the aims to reach the end of that physical task without homeostasis failure.***

Keywords: continuous wavelet transform, central regulator, physical activity, physiological system, frequency bands

1. Introduction

In exercise physiology, there is an increasing need to assess the various complex physiological signals to verify the theories of physiological exercise models (Lambert et al., 2004; St Clair Gibson and Noakes, 2004; St Clair Gibson et al., 2006). These models posited that physical exercise is modulated by a central regulator in the central nervous system, and the human body works as a complex integrative system. Previous research showed the presence of system control mechanisms (Tucker et al., 2006a) but not much was known about how these system control mechanisms sustain homeostasis in any physiological system especially during physical activity. Therefore, this study utilised a novel mathematical method to exercise physiology to investigate how the physiological systems are regulated. In order to find how the physiological systems are controlled, a mathematical method was needed to assess the biological activities both in time and frequency. However, time-based and frequency-based mathematical analyses are not suitable for the exploration of the irregular and non-stationary patterns of the complex biological signals (Mallat, 1989). Therefore, the continuous wavelet transform (CWT) was utilised to conduct time-scale analysis of the real-time signals which occur at every scale and time-position unlike the Discrete Wavelet Transform (Rioul and Vetterli, 1991). The advantage of CWT is that it enables any changes at different frequency bands of the physiological signals to be observed in order to provide an indirect assessment of the corresponding physiological system functions (Whittingstall & Logothetis, 2009; Rosso et al, 2002; Matsuyama et al, 2007).

2. Methods

Ten healthy and well-trained male cyclists took part in this research study, and it was approved by the Ethics Committee of the School of Life Sciences at Northumbria University. Their mean (± standard deviation) height and body mass index (BMI) were 1.77 (±0.06) m, and 24.2 (±1.8) kg·m^{-2} respectively. The age of the participants ranged from 25.5 to 40.1 years.

2.1 Study Protocol and Data Collection

This research study was ethically approved by the School of Life Sciences Ethics Committee, University of Northumbria at Newcastle. The healthy and well-trained participants were required to complete a 20-km cycling exercise bout in the minimum possible time employing different pacing trials. These were: self pace (cycle as hard as they felt they could at any moment in time), even pace using the mean output from their self pace cycling time trial, and a variable pace based on 70% and 140% of the subject's respective self pace average power output (de Koning et al., 2011; Palmer et al., 1999). The participants completed these three different pacing time trials on separate occasions, in the physiology lab of the School of Life Sciences in Northumbria University, with at least one week rest in-between the trials for them recovery purposes and prevent a training effect (Flynn et al., 1994).

Physiological data including heart rate (BPM) were recorded using a data acquisition system (Powerlab, ADI Instruments, Australia), and volume of oxygen consumption ($\dot{V}O_2$/L·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 rating of Perceived Exertion (RPE) was used as a subjective measure for the sensation of fatigue the cyclists felt during the 20-km cycling time trial, and these RPE scores were obtained at every 2-km interval while blood samples were collected for every 4 km interval to determine blood lactate concentration (mmolL^{-1}). These data were used to investigate how the system control mechanisms modulated physical activity.

2.2 Data analysis

The Matlab software platform version R2008a and Wavelet Toolbox^{TM} 4 were used for this research study. The continuous wavelet transform (CWT), using Morlet wavelet, was applied to physiological signals including rate of volume of oxygen consumption, heart rate and power outputs (which integrate all the physiological activities of the various physiological systems) to obtain continuous wavelet spectrum coefficients. These coefficients were then subdivided into regions or bands that were Ultra Low Frequency (ULF), Low Frequency (LF) and High Frequency (HF) bands. The observed frequency regions were then classified in frequency bands (Addison, 2005; Yamaguchi, 2003) based on the wavelet transform scales (n) where integer variable n ranges from 1 to 256: the scales ranging from 1 to 8 were classified as high frequency; scales 9 to 64 were classified as low frequency; and scales 65 to 256 were classified as ultra-low frequency (Lu et al., 2006; Pichot et al., 1999). The inverse relationship between the pseudofrequency (Hz) and the scale factor using Morlet wavelet is depicted in Figure 1. In this way the respective mean wavelet normalised powers (Indiradevi et al., 2007; Latka et al., 2003) were determined for each frequency band (Equ. 1) to investigate the frequency changes (if any) and monitor the respective duration of these events at various scales or frequencies of the physiological signals to determine how a central regulator regulates these physiological systems. The mean normalised wavelet spectrum power was found from equation 1 where the variable i represents the time events at every second of the physiological signal up to m which represents the total duration of the physiological activity whereas the variable j represents the scale number, and finally, *Coefs (i, j)* represents the continuous wavelet transform coefficients at time i and scale number j with limits n and m representing the scale number and time respectively.

$$P = \left\{ \frac{1}{\max\left(Coefs(i,j)\right)} \sum_{j=1}^{n} \sum_{i=1}^{m} Coefs\,(i,j) \right\} \quad \ldots\text{Equ. 1}$$

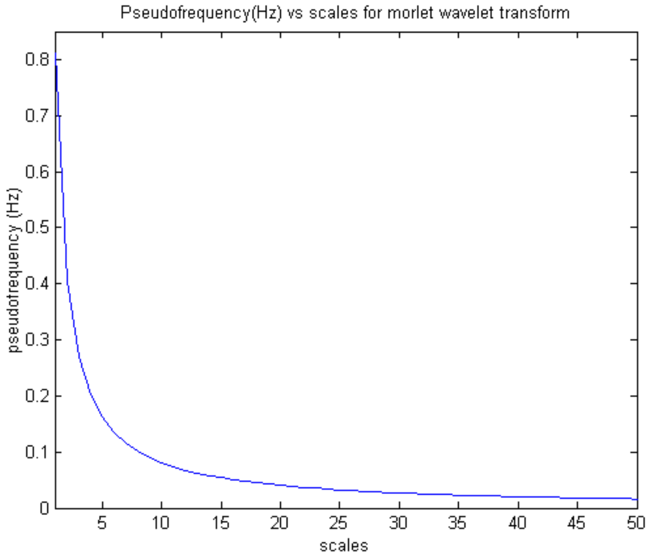

Figure 1: Relationship between pseudofrequency (Hz) and scales

2.3 Statistical analysis

The wavelet powers that were determined for self pace, even pace and variable pace trials were tested for parametricity using Kolmogorov-Smirnov test (Fasano and Franceschini, 1987). In addition a 3x3 (frequency band x pacing trial) factorial ANOVA with repeated measures was used to compare the means of the various frequency bands and any significant difference occurred when statistical p was less than 0.05 (Berger and Casella, 2001). Then, Tukey's HSD post-hoc test was used following the ANOVA to find any significant difference in the analysed variables (Field, 2009). If significance occurred, relationships between variables were then examined by calculating the product moment correlation coefficient r. Results were then presented as means ± standard deviation (*S.D*).

3. Results

The Kolmogorov-Smirnov tests showed that all the wavelet power data were normally distributed and the Z scores were in fact within the ±2 acceptable region for normality. Results from continuous wavelet transform analysis and correlation analysis are described in subsequent sections.

3.1 Continuous Wavelet Transform on Physiological Data

Figure 2 displays the wavelet spectrum analysis profiles of the self pace power output for a particular cyclist together with the associated physiological data that include the rate of volume of oxygen consumption and heart rate activities during the 20-km cycling time trial. In these wavelet spectrums, the shift from a dark region (low) to light coloured region (high) represents a transition in the signal, or the occurrence of an event. For example, for the heart rate data (Figure 2), a dark region suggests that the heart rate activity is homogeneous (*i.e.* there is no large fluctuation) whereas when a light coloured region is observed there is an abrupt change in heart rate activity. The higher amplitudes or change in transition are shown as lighter or brighter areas of the continuous wavelet spectrum. Using the two dimensional view of the signal, the general (large-scale structure) and local (small-scale structure) behaviour and characteristics of the signal in time are clearly shown, which are not obvious from the one dimensional view of the raw physiological signals as depicted on top of each wavelet coefficient profile for each physiological variable.

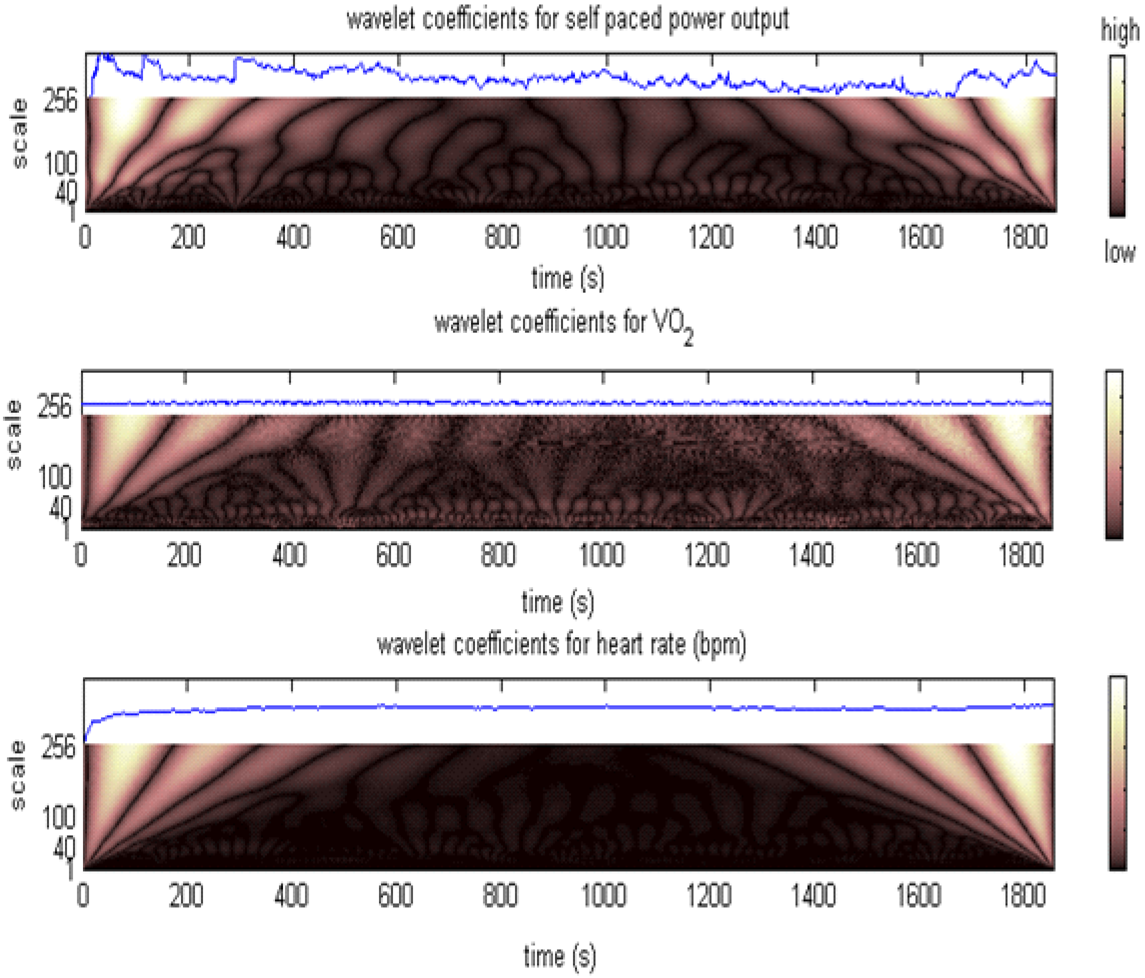

Figure 2: Continuous Wavelet Transform (Scale vs. time) on self pace power output, rate of volume of oxygen consumption and heart rate for one particular cyclist who ranked 2nd.

In Figure 2, the *x*-axis represents time (in seconds) and *y*-axis represents the scale *n* which varies from 1 to 256. There were more abrupt changes at low frequencies than at high frequencies of the spectrum for all physiological signals (power output, the rate of volume of oxygen consumption and heart rate), and there were more changes but less abrupt at high frequencies. By abrupt, it is meant that there is a big transition such as moving from a white region to a dark region of the wavelet spectrum. So using the example of the heart rate data, it was observed that heart rate activity increased abruptly at the beginning of the race and at the near end of the race (about three minutes before the end of the race which represents the endspurt) depicted by the light coloured regions. Moreover, during the race there were frequent small changes in heart rate activities as shown by the dark regions. In this manner the bright colour (Figure 2) was classified as high transition (change in amplitude) whilst the dark colour was classified as low transition.

In addition to that, Figure 3 shows the variation in amplitude and frequency of the self pace power output profiles obtained after the wavelet transform was applied at three different scales 16, 128 and 200 to show the happenings or events in these regions. The *y*-axis of Figure 3 represents changes in the amplitudes of the power output signal for three chosen scales as drawn with a white line on the continuous wavelet transform figure and presented subsequently on three time-series figures. It was clearly observed that there were high peaks at the start and end of the cycling time trial. By moving to the higher data capture rate or frequency, recurring changes at specific intervals about 200 seconds can be observed by the small peaks on scale 16 and positions in time as compared to the broader small ripple peaks depicted in the scales 128 and 200 between the time 200 seconds to 1400 seconds. Therefore, by moving to higher capture rate, it was possible to know precisely the happening of an event in time, as well as its corresponding pseudofrequency.

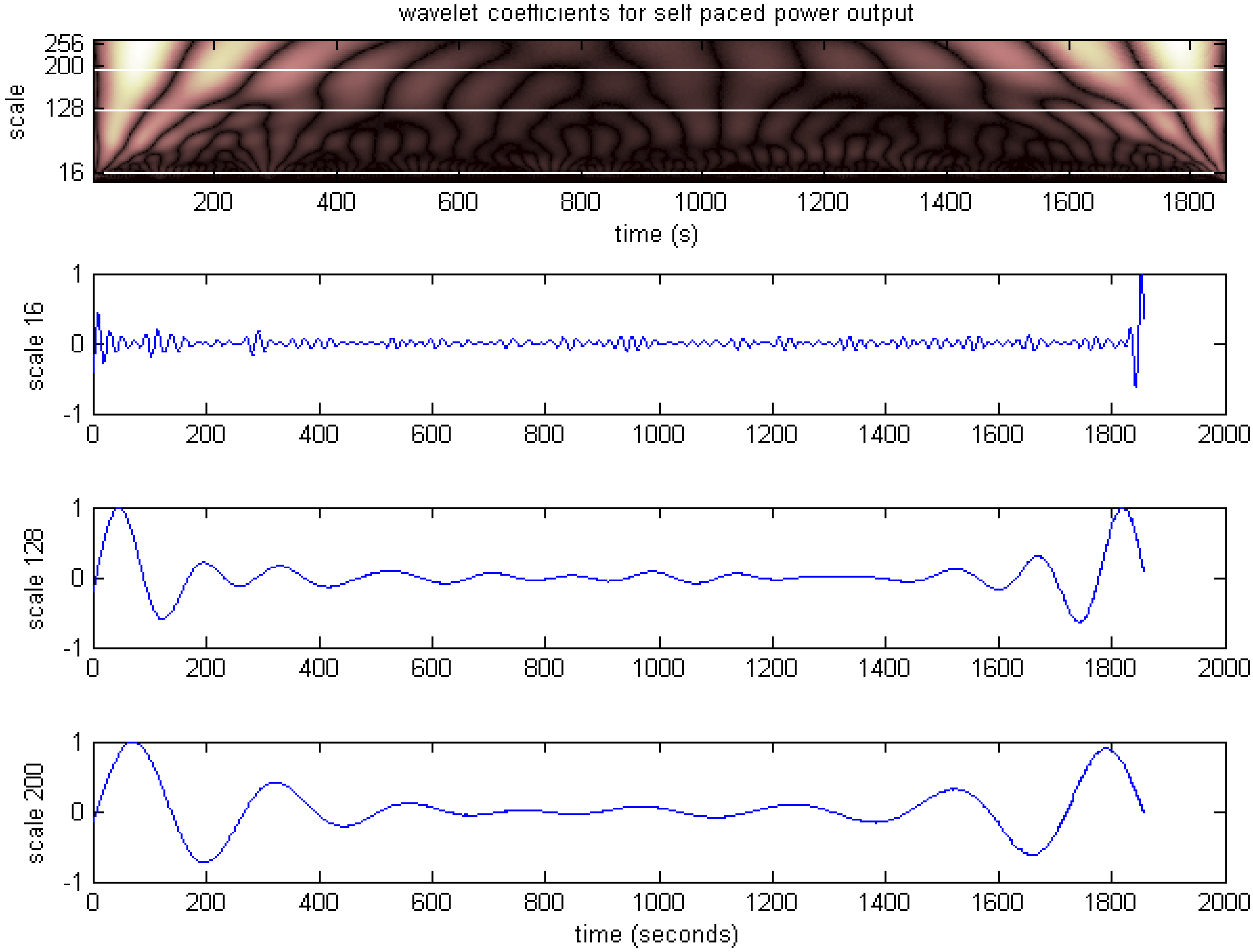

Figure 3: One dimensional view at specific scales (16, 128 and 200 from top to bottom respectively) of the wavelet coefficients obtained after CWT has been applied to self pace power output.

3.2 Wavelet band powers for rate of volume of oxygen consumption for all cyclists

For the rate of volume of oxygen consumption physiological activities, it was found that there was a significant difference ($p < 0.01$) between the ULF wavelet power as compared to both HF and LF wavelet powers that were determined for each type of pacing (See Table 1). However, there was no significant difference ($p > 0.05$) between HF and LF wavelet powers (See Appendix A, Figure A.1). In addition a small decrease in ULF band power with increasing performance times of the cyclists was also observed whereby more prominent decreases in ULF band power were evident for self pace (r = -0.77), and even pace (r = -0.66) trials than in variable pace trial(r = -0.16).

Table 1: This table represents the mean normalised power of the wavelet coefficients together with the standard deviation for the rate of volume of oxygen consumption ($\dot{V}O_2$) for each type of pacing and for each frequency band (HF, LF and ULF). The symbol * means there was a significant difference between that frequency band power and the other frequency bands with statistical $p < 0.05$.

Variables	Self pace	Even pace	Variable pace
HF band power	0.033 ± 0.009	0.030 ± 0.012	0.025 ± 0.011
LF band power	0.024 ± 0.007	0.024 ± 0.008	0.024 ± 0.008
ULF band power	0.068 ± 0.004*	0.066 ± 0.003*	0.073 ± 0.005*

3.3 Wavelet band powers for heart rate for all cyclists

Both ULF and LF band wavelet powers were not significant with mean values 0.06 (±0.4%) and 0.012 (±0.1%) respectively for all cyclists and for all pacing time trials (See Table 2). For any particular pacing time-trial, there was no significant difference ($p > 0.05$) between HF and ULF ($p > 0.05$) but there was a significant difference between HF and LF bands ($p < 0.01$). Furthermore, there was a small positive correlation between the HF band power of heart rate physiological activities and performance times ($r = 0.3$; $p = 0.03$) (See Appendix A, Figure A.2).

Table 2: This table represents the mean normalised power of the wavelet coefficients together with the associated standard deviation for heart rate (HR) for each pacing and for each frequency band (HF, LF and ULF). The symbol * means there was a significant difference between that frequency band power and the other frequency bands with statistical $p < 0.05$.

Variables	Self pace	Even pace	Variable pace
HF band power	0.1658 ± 0.1805*	0.1452 ± 0.1585*	0.1339 ± 0.1331*
LF band power	0.0128 ± 0.001	0.022 ± 0.027	0.0132 ± 0.001
ULF band power	0.066 ± 0.005	0.079 ± 0.004	0.066 ± 0.004

4. Discussions

In order to analyse the physiological data to assess how a central control paces the human body or the peripheral systems during exercise, a continuous wavelet transform analysis was applied to these data to split these complex biological signals into specific scales and hence frequency bands (Mallat, 1989). For the self pace trial, there were sudden changes at low frequencies in the power output and physiological data especially at the start and at the end of the race (endspurt). These abrupt changes at low frequencies coincided with the acceleration at the beginning and at the end of the race (endspurt) and were consistent with common observations during a time-trial exercise (Ansley et al., 2004; St Clair Gibson and Noakes, 2004; Tucker et al., 2006a; Tucker et al., 2006b). Furthermore, smoother frequent changes occurred at high frequencies for self pace power output. The factors that govern the power output are the force applied at the pedal by the cyclist as well as the velocity (or cadence) at which the cyclist is moving (Gordon and Papadopoulos, 2004). These factors depend on the number and type of muscle fibres that are activated or recruited to generate the required force and velocity. According to McComas (1996), small motoneurones fire slowly and continually (observed as small changes in amplitude) and they innervate motor units that are resistant to fatigue as compared to large motoneurones which fire rapidly (the changes are for short duration) and in bursts (as shown by large amplitudes) that innervate motor units that are fatigable. This was perhaps why there were sudden changes in low frequency band as large motoneurones were triggered especially at the start and at the end of the race in contrast to slow and continual firing rates of small motoneurones that occurred in the low frequency bands during the race.

4.1 Wavelet band powers for the rate of volume of oxygen consumption for all cyclists

For the rate of volume of oxygen consumption, the ULF band wavelet power was highest as compared to the other frequency bands for the whole duration of the race. Therefore, this might be the frequency band where there was interactive communication between the central regulator to this particular physiological system. According to Sherwood (2005), it is the brain stem that consists of the respiratory control centers and generates the periodic pattern of breathing (Sherwood, 2005). In addition, there was a slight decrease in ULF band wavelet power with increasing cyclists' performance times, and this suggests that this control centre used this frequency band to regulate this particular physiological system (via feedforward and feedback information) which subsequently affected the sport performance of the cyclists.

4.2 Wavelet band powers for heart rate for all cyclists

As for the observed heart rate activities, both LF and ULF band powers were almost constant for all cyclists. In addition, the significant difference in the HF band power as compared to the other frequency bands, however, means that there was some external drive or controller (Lu et al., 2006; Pichot et al., 1999; Xu et al., 1998) which was using this frequency band, or specific range of frequencies, to control this particular physiological activities of that particular athlete despite the poor correlation between HF band power and increasing performance times.

5. Conclusion

In this study, the system control mechanisms underlying physiological data were investigated to see how a central regulator within the central nervous system paces the human body during exercise. It was found that the ULF band power for the rate of volume of oxygen consumption was highest for all cyclists and this ULF power decreases with increasing cyclists' performance times. Moreover, there was a significant difference in the HF wavelet band power as compared to other frequency bands (*i.e.* HF was highest for heart rate activities for all cyclists). As such, there may be a regulator that paces the human body which uses specific frequency bands to control and communicate with the different physiological peripheral systems simultaneously. For there to be the simultaneous allocation of frequencies to modulate the physiological activities of the organ systems, there should be a higher level of control to these physiological systems. The strength in the wavelet power in the ULF band for respiratory system and HF band for heart rate activities suggest that these frequencies in fact depicted the behaviour of the sympathetic or parasympathetic drive which means that these system control mechanisms role were to reduce or increase such physiological system activities to complete a race or competition without catastrophic physiological system failure.

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Appendix A

A.1 The frequency band power for volume of oxygen consumption ($\dot{V}O_2$)

The mean normalized wavelet power for each frequency band for the rate of volume of oxygen consumption physiological activity for all cyclists for each pacing time trial is depicted in Figure A.1. Moreover, the changes in HF band, LF band and ULF band for this particular physiological activity are compared as shown below.

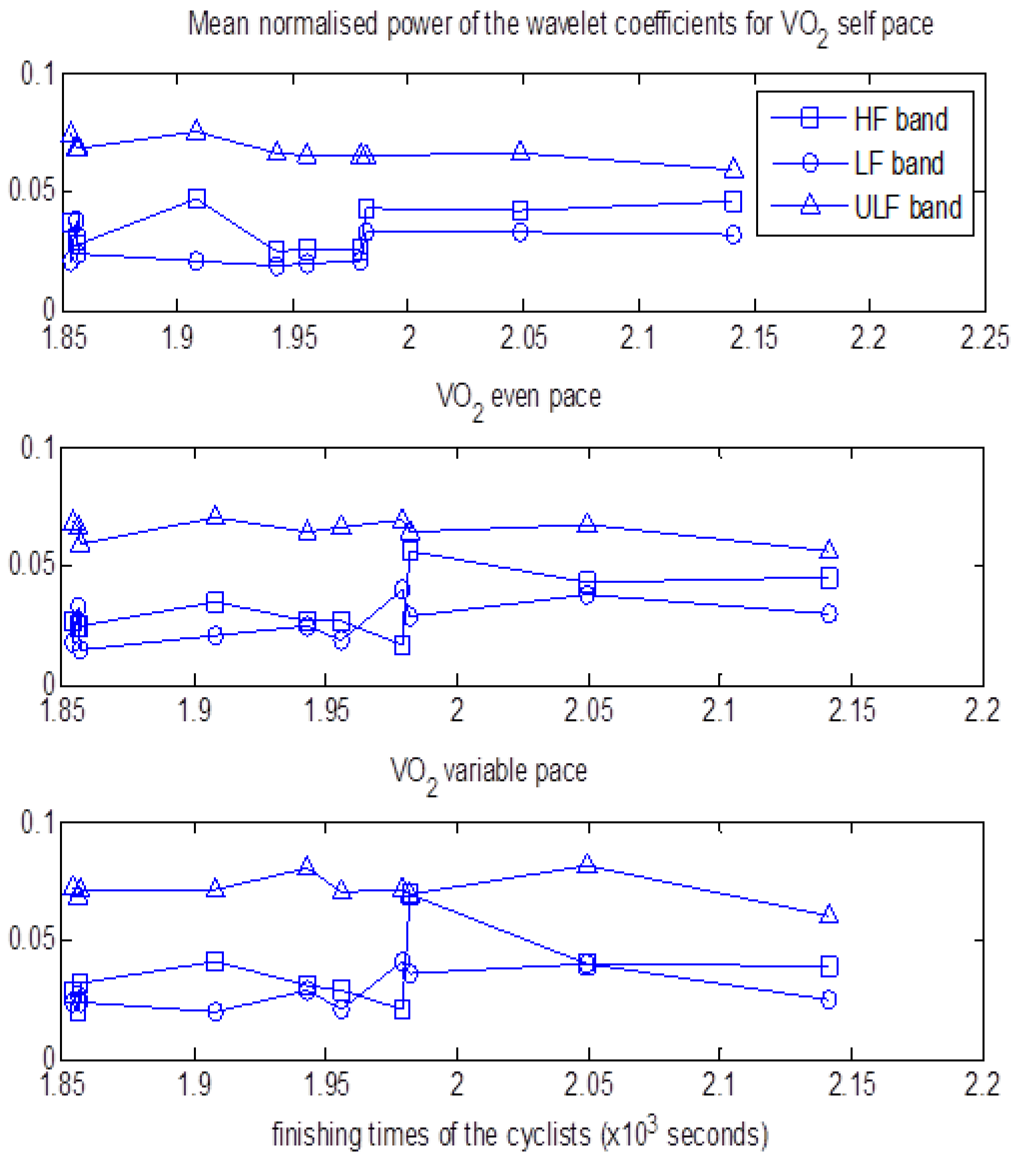

Figure A.1: The *x*-axis represents the finishing times of the cyclists and the *y*-axis represents the normalized wavelet power so that the changes in the three different frequency bands can be compared.

A.2 The frequency band power for heart rate (HR)

The mean normalized wavelet power for each frequency band for heart rate physiological activity for all cyclists for each pacing time trial is depicted in Figure A.2. Moreover, the changes in HF band, LF band and ULF band for this particular physiological activity are compared as shown below. There was a significant difference between HF band and LF band ($p < 0.01$), and there was a small positive correlation between HF band with increasing performance times of the cyclists (correlation $r = 0.3$ and statistical $p = 0.03$).

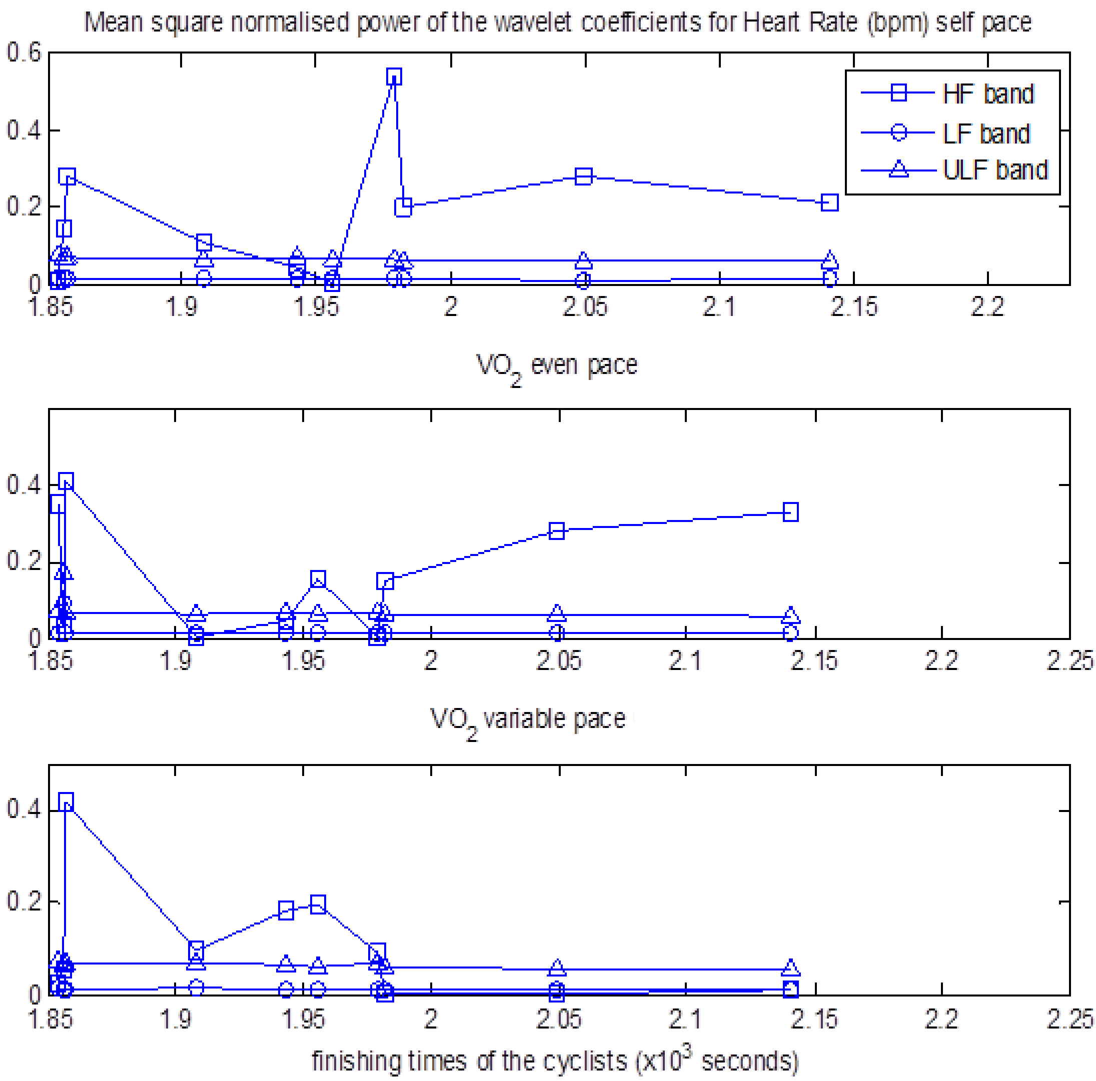

Figure A.2: The *x*-axis represents the finishing times of the cyclists, and the *y*-axis represents the normalized wavelet power of the heart rate activities so that the changes in the three different frequency bands can be compared.