

Non-Linear Analysis of Physiological Activities, And Physical Performance during a Self-Pace Time-Trial Cycling Exercise

Dineshen Chuckravanen¹, Andre Bester²

¹Department of Sport and Exercise Sciences, School of Life Sciences, Northumbria University, Newcastle Upon Tyne, NE1 8ST United Kingdom

²Bester Labs, 44 Beatrice Road, Newcastle Upon Tyne, United Kingdom

Abstract: *Recently, in exercise physiology, a new model to regulate the central neural effort and fatigue has been proposed. This model is called the Central Governor Model (CGM) which theorizes that physical activity is controlled by a regulator in the central nervous system, and that the human body works as a complex integrative system. However, CGM is a highly contentious theory which has far from complete acceptance within the exercise physiology community. Therefore, this paper addresses and analyses some important aspects of this model. To analyse the irregular and complex physiological control signals, nonlinear mathematical methods that are fractal analysis and recurrence analysis were employed in this research to find out respectively the complexity and the characteristics of physiological signals during a self-paced time-trial cycling exercise. Results showed that the characteristics and complexity of the cardiovascular control system were significantly different from that of the respiratory system. Moreover, different physical body anthropometrics demonstrated similar complexity and characteristics for each type of physiological control system. This research attempted to relate the complexity and characteristics of physiological activities with the performance of the cyclists.*

Keywords: control mechanisms, nonlinear analysis, pacing, physical performance, physiological system

1. Introduction

In exercise physiology, the study of complex rhythms arising from the peripheral systems (for example, the cardiovascular system and the respiratory system) and the central nervous system of the human body is important to optimize athletic performance while using a suitable type of pacing. Pacing plays an important part during athletic competition so that the metabolic resources are used effectively to complete the physical activity in the minimum time possible, as well as to maintain enough metabolic resources to complete that task (Ulmer, 1996). Moreover, according to a recently developed model named the Central Governor Model (CGM) (St Clair Gibson & Noakes, 2004), there is a central regulator that paces the peripheral systems during physical activity to reach the endpoint of that physical activity without physiological system failure. This central governor model of fatigue is a *complex integrative* control model which involves the continuous interaction, in a *deterministic way*, among all the physiological, and that of the central systems (Lambert et al, 2005). Therefore, since very few studies were conducted to examine these system control mechanisms and also their presence in physiological control systems (Tucker, Bester et al, 2006), this research study aims to investigate the complexity as well as the characteristics of these control mechanisms that regulate homeostasis, and control physical activity (St Clair Gibson et al, 2005) so that physical performance can be optimised. Couple with that, by describing the physiological systems quantitatively, their physiological behaviour and their characteristics can be predicted which could be used as biological markers to improve physical performance. Moreover, recent development in mathematical tools, specifically in biology and medicine, using nonlinear mathematical methods that are recurrence quantitative analysis as well as fractal analysis can

help in understanding the complex nature of nonlinear control mechanisms that regulate the physiological systems (Marwan et al., 2007; Marwan, 2008). Therefore, fractal analysis was employed here to elucidate the complexity of the physiological systems, and recurrence quantitative analysis was utilised to find out specific characteristics of the physiological control systems in terms of the predictability of the physiological control system states, the resilience of a particular physiological control system state to change and the percentage of occurrence of similar physiological control states. Then, these quantitative variables will be related to the performance of the cyclists in completing the physical exercise task in the minimum time possible. Next subsections present the two non-linear methods used in this research to determine the complexity and the characteristics of the physiological systems.

1.1 Complexity of physiological systems using fractal analysis

Fractal dimension (FD) is a means to measure the complexity of a physiological signal whereby the more complex a biological signal is, the higher the FD value. For instance, the fractal dimension of a single point is 0, a simple curve (line) is 1 and a plane is 2. In order to investigate the complexity of biological signals, fractal analysis using Higuchi's theorem (Higuchi, 1988) was used to determine the fractal dimension (See section 2.2.1 for further explanation). By finding the complexity of the physiological signal, one will be able to correlate it or observe how the complexity of the physiological signal affects the performance of the cyclists in terms of the finishing times of the cyclists for performing the same cycling distance.

1.2 Characteristics of physiological systems using recurrence analysis

Biochemical processes may have a distinct recurrent behavior that is periodicity (Eckmann et al., 1987). The recurrence of states (states are again close after some divergence time), is an important property of deterministic as well as dynamical systems and is typical for physiological systems. A recurrence plot (RP) is a graphical plot that shows for a particular moment in time, the times that a phase space trajectory visits about the same area in that phase space (Findlay 1911; Zbilut et al, 1995). This means it is a graph of $\vec{z}^i(t) \approx \vec{z}^j(t)$ where variable i represent the horizontal axis and the variable j represents the vertical axis, and the vector \vec{z} is a phase space trajectory. To investigate the characteristics of the complex system control mechanism in this research, recurrence analysis was used to locate rhythms and patterns in the data (Trulla et al, 1996; Zbilut et al, 1995). Then, from this recurrence plot, interested recurrence quantitative measures were determined using CRP toolbox (Marwan et al, 2007). These RQA measures were recurrence rate (RR), the determinism (DET), and the trapping time (TT) and these quantitative measures were used to find the characteristic features of a particular physiological system. These measures are further described in the section 2.2.2. The quantitative characteristics of the physiological signals were related to the performance of the cyclists, in successfully completing the same cycling distance in the minimum time possible.

2. Methods

Ten healthy and club-level male cyclists took part in this research study which was approved by the School Ethics Committee of School of Life Sciences, University of Northumbria at Newcastle, United Kingdom. The mean (\pm SD) age, height and the Body Mass Index (BMI) of these cyclists were 32.8 (\pm 7.3) years, 1.77 (\pm 0.06) m and 24.2 (\pm 1.8) kgm^{-2} respectively.

2.1 Study Protocol and Data Collection

The subjects were required to complete a 20-km cycling bout using self pace with instructions to complete that physical exercise task in minimum time possible. Physiological data that are heart rate (BPM) were recorded using a data acquisition system (Powerlab, ADI Instruments, Australia), volume of oxygen consumption ($\dot{V}O_2/\text{L min}^{-1}$) was measured using an online gas analyser (Cortex Metalyser, Cortex Biophysik, Germany). Self pace cycling power outputs were recorded at a frequency rate of 11Hz using Velotron 3D software which is an interface for the cycle ergometer (VelotronPRO, RacerMate Inc, USA) that was used for all cyclists' time trials. The gathered data were then analysed using Matlab software platform version R2009b to compute the fractal analysis and recurrence analysis, and then the SPSS version 20 was used for statistical inferences and correlation analysis.

2.2 Nonlinear Analysis

First of all, to understand the regulation of physiological control systems, it is necessary to differentiate between deterministic and stochastic signal as the common characteristics of biological activities (Kac and Logan, 1976; Nelson, 1985; Priplata et al., 2006). A signal is said to be deterministic if its future values can be produced according to a set of known parameters and rules (Najim et al., 2004). For example, a deterministic cosine signal $y_d(t) = \cos(2\pi ft)$ can be predicted accurately based on the condition that its frequency f is known (subscript d stands for deterministic and t is time). Two cases are considered to elaborate and distinguish between a deterministic outcome and a stochastic outcome. For example, if an output signal $y_r(k)$ is generated by repeatedly tossing an unbiased coin, there is no way to predict the k^{th} outcome of the output accurately, even if all the output values (head or tail) are known (subscript r in stochastic outcome $y_r(k)$ stands for random). These represent two distinct cases: $y_d(t)$ is purely deterministic while $y_r(k)$ is random or stochastic (Najim et al., 2004). The following sections describe the mathematical techniques used in this research, and they are known for their current applications in biology and medicine.

2.2.1 Fractal Analysis

To investigate the complexity of the pacing and physiological signals, fractal analysis using Higuchi's theorem was applied to the power outputs of the cyclists' self-paced power outputs as well as the physiological data that were heart rate and volume of oxygen consumption for this 20-km cycling time-trial. The fractal dimension (FD) was calculated using Higuchi's algorithm (Higuchi, 1988). The Higuchi's fractal dimension, D_f , was calculated directly from the real-time raw physiological signals, and it is always between 1 and 2 since a simple curve has a dimension 1, and a plane has dimension equal 2. For instance, as shown in Figure 1, the Koch Snowflake has a fractal dimension 1.26 ($\log_{10} 4 / \log_{10} 3$) where each new segment is scaled by one-third into four new pieces laid end to end with two middle pieces leaning toward each other between the other two pieces.

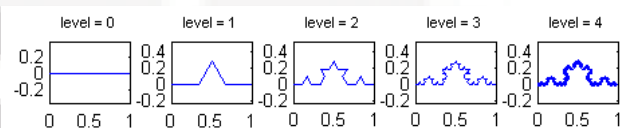


Figure 1: Koch Snowflake is an example of fractal curve and has fractal dimension 1.26

Therefore, from a given physiological data time series $X(1), X(2), \dots, X(N)$, the algorithm constructs k new self-similar (fractal) time series $X(k, m)$ as: $X(k, m) = \{X(m), X(m+k), X(m+2k), \dots, X(m + \text{int}[(N-m)/k] \cdot k)\}$ for $m = 1, 2, \dots, k$ where $\text{int}[\cdot]$ is an integer function. The length $L(m, k)$ is computed for each of the k time series or curves $X(k, m)$, and then averaged for all m forming the mean value of the curve length $L(k)$, for each k . Then the fractal dimension (FD) is determined as the slope of least squares linear best fit from the plot of $\log(L(k))$ versus $\log(1/k)$. This fractal dimension is a means to measure the complexity of a physiological signal whereby the more complex a physiological signal is,

the higher the FD value. Then, we should see whether this has any relationship with physical performance of the cyclists in completing this time-trial physical activity. The null hypothesis (H_0) was based on that the fractal dimensions of the self-paced cycling power outputs and the physiological data were similar for all cyclists, while the alternate hypothesis (H_a) would signify that the fractal dimensions of the self-paced power outputs and the physiological data were not similar.

2.2.2 Recurrence Quantitative Analysis measures

These RQA measures are obtained from the recurrence plot. Firstly, the recurrence rate (RR) is the amount of recurrence points in a recurrence plot, and it is the probability that a state will occur again in time. In equation 1, $R(i, j)$ represents all the recurrence points on the recurrence plot with notation i representing states in the x-axis and notation j representing states in the y-axis, and the variable N represents the total number of recurred points that appear in the recurrence plot.

$$RR = \frac{1}{N^2} \sum_{i,j=1}^N R(i, j) \quad \dots \text{Equ. 1}$$

The determinism (DET) of a system is the ratio of the recurrence points forming diagonal lines, and these lines represent periods of same time evolution of states of that system. The DET measure is the percentage of points that form diagonal lines in the recurrence plot of minimal length l_{min} . $P(l)$ represents the frequency distribution of the diagonal lines of lengths l , and this measure is known as determinism which is related to the predictability of the dynamical system. For example, white noise has a recurrence plot with practically only dots and very few diagonal lines (Webber Jr. and Zbilut, 1994), and the deterministic process has a recurrence plot with some single dots but many lengthy diagonal lines. Determinism is represented by *DET* as shown in the equation below (Equ. 2):

$$DET = \frac{\sum_{l=l_{min}}^N l \cdot P(l)}{\sum_{i,j=1}^N R(i, j)} \quad \dots \text{Equ. 2}$$

Furthermore, the trapping time (*TT* (s)) of a dynamical system (Equ. 3) is a measure of how long this system remains in a specific state or is locked in one state. *TT* is a measure of the average length of the vertical lines of the dynamical system (Zbilut et al., 1995). $P(v)$ is the average length of the vertical lines, v_{min} is the minimum length of the vertical lines and v is the length of the vertical lines.

$$TT = \frac{\sum_{v=v_{min}}^N v \cdot P(v)}{\sum_{i,j=1}^N R(i, j)} \quad \dots \text{Equ. 3}$$

The mathematical measures, described before, are commonly used in assessing the complexity of the biological signals (Webber and Zbilut, 1996), the occurrence of physiological events both in time and frequency domain as well as the predictability and stability of the physiological systems. The null hypothesis (H_0) was based on that the recurrence quantitative measures of the self-paced power outputs as well

as the physiological data were not significant for all cyclists, and the alternate hypothesis (H_a) would signify that the recurrence quantitative measures of the self-paced power outputs as well as the physiological data were statistically significant for all cyclists.

2.3 Statistical analysis

The collected data as well as the computed variables were tested for parametricity using Kolmogorov-Smirnov (K-S) test, and then confirmed using z scores of Z-kurtosis (Z_{kurt}) and Z-skewness (Z_{skew}). Afterwards, One Way Analysis of Variance (ANOVA) with repeated measures was used to compare the means of these parameters for all cyclists. When significant *F* ratios were found ($p < 0.01$), the means were compared using a Tukey's post-hoc test. Moreover, Spearman's correlation coefficient (*r*) was used for correlation analysis to test any relationships among the computed variables that are the fractal measures, recurrence quantitative measures and the finishing times of the cyclists.

3. Results

The Kolmogorov-Smirnov tests showed that all data were normally distributed and the Z scores were in fact within the ± 2 acceptable region for normality. Results from fractal analysis and recurrence analysis as well as respective correlation analysis are described in subsequent sections. Results are presented as mean (\pm standard deviation).

3.1 Fractal Dimension

As shown in Figure 2, the mean fractal dimension for the power outputs, volume of oxygen consumption ($\dot{V}O_2$) and heart rate (HR) for all cyclists were determined to be 1.33 ± 0.04 , 1.15 ± 0.03 and 1.40 ± 0.08 respectively. For each physiological variable, it was found that there was no significant difference ($p > 0.05$) for all cyclists, which means that the complexity of heart rate was similar for all cyclists and the complexity of volume of oxygen consumption was similar for all cyclists. However, the fractal dimension for volume of oxygen consumption was significantly different from the fractal dimension of heart rate for all cyclists ($p < 0.01$). This means that the complexity of the cardiovascular control system was different from that of the respiratory control system.

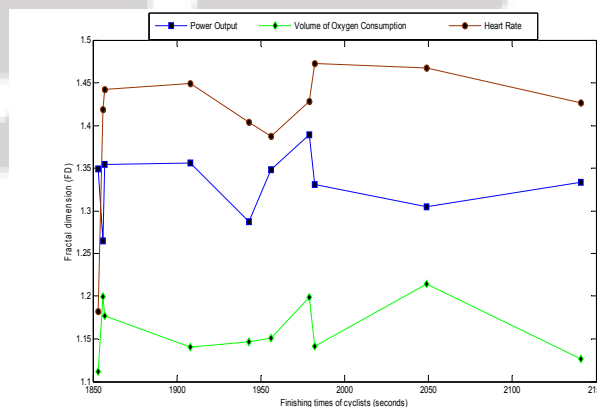


Figure 2: Fractal Dimension for all cyclists with different finishing times of cyclists and different rank orders for all

physiological variables. The ranking order of the cyclists was based on the finishing times of the cyclists for completing this cycling time trial physical activity. The one who finished this physical activity in least time possible is rank 1st and so forth.

Moreover, correlation analysis showed that there was no significant correlation between the fractal dimension of power outputs and the finishing times of cyclists as well as that of the fractal dimension of volume of oxygen consumption and the finishing times of the cyclists (statistical probability $p = 0.777$, non-significant as $p > 0.05$). In addition to that, there was also no significant correlation between the fractal dimension of heart rate and finishing times (correlation $r = +0.479$ and $p = 0.162$, non-significant as $p > 0.05$) even though there is the presence of low and positive correlation which would mean that as the complexity of the heart rate data increases, the finishing performance times of the cyclists would also increase.

3.2 Recurrence quantitative measures of physiological data

The recurrence plot depicts the underlying pattern for self paced power output of a cyclist who ranked 2nd to show the complex pattern which is produced from the 1-dimensional self paced power output signal. The left hand side figure (Fig. 4) represents the one dimensional view of the self paced power output signal, and the right hand side figure represents the corresponding recurrence plot of the self pace power output data.

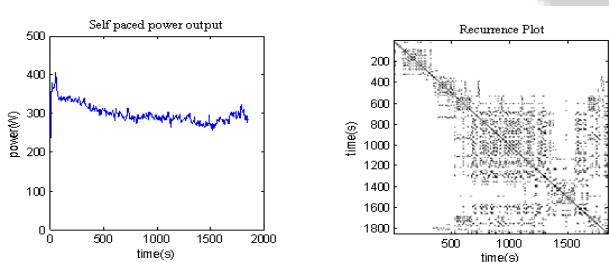


Figure 3: The self paced power output signal of a cyclist ranked 2nd (left hand side) and its corresponding recurrence plot (right hand side) with threshold ϵ (0.5) and embedding dimension m (1).

In Figure 3, the parameter threshold ϵ was chosen so that it does not exceed 10% of the mean phase space diameter (Mindlin and Gilmore, 1992) of the data distribution and also to obtain the recurrence structure contained in the signal. The other parameter which is the embedding dimension m was chosen so that the true behavior of the physiological signal is not underestimated because the main difference which occurred while increasing the dimension of representing a time series signal onto a recurrence plot is that the pattern becomes less complex.

The recurrence quantitative analysis (RQA) measures for self paced strategy for volume of oxygen consumption ($\dot{V}O_2/L.min-1$) were computed, and the mean recurrence rate (RR), determinism (DET) and Trapping Time (TT/s) were 0.09 ± 0.01 , 0.29 ± 0.04 and (2.54 ± 0.10) seconds respectively. The recurrence analysis measures for heart rate

activities of the cyclists were as follows: RR was 0.11 ± 0.05 , DET was 0.89 ± 0.18 , TT was (7.0 ± 3.9) seconds. It was found that there were significant differences ($p < 0.01$) between the RQA measures of heart rate activities and that of volume of oxygen consumption for all the cyclists. However, here was no significant difference within each physiological control variable for all cyclists. Also, the mean recurrence rate, determinism and trapping times for the self paced power outputs were 0.074 ± 0.01 , 0.69 ± 0.23 and (3.56 ± 1.03) seconds respectively.

Table 1: Summary of the correlation coefficient analysis of the recurrence quantitative measures. Symbols $\dot{V}O_2$ represents volume of oxygen consumption (litres/min), PO means power output, HR represents heart rate, FT means finishing times of cyclists, RR represents recurrence rate, DET represents determinism and TT means trapping time.

Correlation () between RQA measures and Finishing Times (FT)	Correlation coefficient (r)	Statistical probability (p)	Statistical significance (is $p < 0.05$?)
$VO_2_RR // FT$	-0.467	0.174	N.S (Not significant)
$VO_2_DET // FT$	-0.564	0.048	S
$VO_2_TT // FT$	-0.067	0.855	N.S
$PO_RR // FT$	-0.236	0.511	N.S
$PO_DET // FT$	-0.467	0.174	N.S
$PO_TT // FT$	-0.452	0.195	N.S
$HR_RR // FT$	-0.127	0.726	N.S
$HR_DET // FT$	+0.539	0.032	S
$HR_TT // FT$	0.442	0.200	N.S

Table 1 shows the correlation coefficient values between the RQA measures and the finishing times. It was found that there was a significant correlation between VO_2_DET and FT ($r = -0.564$; $p = 0.048$) as well as HR_DET and FT ($r = +0.539$ and $p = 0.032$). From these significant results, it was observed that there are the presence of either a low positive or a low negative correlation with the determinism value of heart rate and volume of oxygen consumption respectively. This insinuates that as the determinism (or predictability) of the heart rate data increases, there is an increase in the performance finishing times of the cyclists. However, as the determinism (or the predictability) of the volume of oxygen consumption data increases, there is a decrease in the performance finishing times of the cyclists.

4 Discussions

To determine the complexity of the pacing strategy for each cyclist, fractal dimension was used. It was found that the complexity of the self paced power output was similar for all cyclists and complexity of the physiological variables (HR and $\dot{V}O_2$) were similar for all cyclists. Similar results were found by Tucker, Bester et al. (2006) where in their study in South Africa, they demonstrated that the fractal dimension of the power outputs was similar for all subjects over the self-paced 20-km time-trial and they ranged between 1.5 and 1.9 ($p > 0.05$, not significant). In addition, in our study, we found significant difference between the fractal dimension of HR and $\dot{V}O_2$ which suggest that each physiological control system within any physical body system has its own complexity. Moreover, the percentage error in estimating the

fractal dimensions was 0.03, and it is good since fractal dimension cannot be derived exactly (Dubuc et al., 1989). Despite there was no significant correlation of the complexity of the physiological control variables and the performance finishing times, there is the presence of a low positive relationship between heart rate and the finishing times of the cyclists. This shows that the cardiovascular physiological control system may represent a factor in determining performance. Thus, based on the fractal analysis method, the human body subjected to physical activity comprises of physiological control systems functioning at different signal complexities to reach an overall optimal physical performance.

The recurrence plot of the self paced power output shows a rather complex behaviour. Therefore, recurrence quantitative analysis was then applied to these physiological data to determine the characteristics of the system control mechanisms underlying these physiological data. The significant difference in the recurrence rate, determinism and trapping times of the physiological systems that are cardiovascular system and the respiratory system implies that each physiological system has its own characteristic behaviour. This means that the system control mechanisms controlling these physiological systems are distinct in nature. The characteristics and complexity of these physiological systems are similar for all cyclists despite the cyclists' physical differences which imply that in different physical systems, the control mechanisms are similar. There was also mixed relationships (positive and negative) between the physiological variables' determinism (HR and $\dot{V}O_2$) and the finishing performance times of the cyclists but there were low mixed relationships (positive and negative) between the determinism of the physiological control signals and physical performance which favours one of the features predicted by the Central Governor Model.

5 Conclusion

Overall, this research showed that each physiological control system within a physical body system has its own characteristics based on the RQA measures and fractal dimensions which mean that different system control mechanisms or different number of system control mechanisms are controlling a particular physiological control system. The similarity of the fractal dimensions and the recurrence quantitative measures for all cyclists for each control system variable (cardiovascular system and respiratory system) implies that these system control mechanisms are similar in nature for all physical body systems. Moreover, there is the presence of fatigue especially when we consider that there is a low correlation between the complexity of heart rate data and finishing time's performance. Also, determinism of HR and $\dot{V}O_2$ physiological control signals play important roles in predicting the finishing times performance of the cyclists. For instance, an increase in determinism in $\dot{V}O_2$ decreases finishing times performance improving physical performance and less fatigued while an increase in determinism in HR increases finishing times performance degrading physical performance and more fatigued. Future studies could include different levels of pacing (Chuckravanen, 2012) associated with different levels of power output (70% of their mean

power output, mean power output of their self pace, 140% of their self pace power output) and their effects on the complexity of the physiological control signals and related to physical performance and fatigue levels. The research findings favour two predictions of the Central Governor Model especially the human body functions integratively and the complexity of these functions affect physical performance as well as the determinism characteristics of the physiological control systems influence physical performance. Future studies could replicate this work by involving elite-level cyclists to find out any similarities in the complexity of the self-pace power output as well as the physiological variables (HR and $\dot{V}O_2$) and also they may also include other physiological variable such as EMG at calf or quad muscles. It will be also useful to include ratings perceived exertion (RPE) to monitor the fatigue level of the cyclists at fixed distance of 1km or 2km for a 20-km cycling time trial and its relationship to the complexity of the physiological signals.

Acknowledgements

I would like to thank Professor M. Angelova for the use of Intelligent Modelling Lab, School of Computing, Engineering and Information Sciences and Dr. S. Rajbhandari for mathematical concepts. I would also seize the opportunity to thank also Professor A. St Clair Gibson, Professor K. Thompson and Dr L. Ansley for their suggestions in the design of this study protocol as well as colleagues Dr Kevin Thomas and Dr Mark Stone in School of Life Sciences at Northumbria University at Newcastle for their help in data collection.

References

- [1] D. Chuckravanen, "Multiple System Modelling and Analysis of Physiological and Brain Activity and Performance at Rest and During Exercise," Doctoral thesis, Northumbria University, Newcastle Upon Tyne, United Kingdom, 2012.
- [2] B. Dubuc, J.F. Quiniou, C. Roques-Carmes, C. Tricot, S.W. Zucker, "Evaluating the fractal dimension of profiles," *Phys. Rev. A*, 39, pp. 1500–1512, 1989.
- [3] J.P. Eckmann, S. O. Kamphorst, D. Ruelle, "Recurrence Plots of Dynamical Systems," *Europhysics Letters* 5 (9), pp. 973–977, 1987.
- [4] A. Findlay, *The Phase Rule and its Applications*, 3rd ed. Longmans, Green and Co., p8, 1911.
- [5] T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," *Physica D*, 31, pp. 277–83, 1988.
- [6] M. Kac, J. Logan, "In Fluctuation Phenomena," E.W. Montroll, J.L. Lebowitz, (Eds.) North-Holland, Amsterdam, 1976.
- [7] G.M. Mindlin, R. Gilmore, "Topological analysis and synthesis of chaotic time series," *Physica D*, 58(1-4), pp. 229–242, 1992.
- [8] E.V. Lambert, A. St Clair Gibson, T.D. Noakes, "Complex systems model of fatigue: integrative homeostatic control of peripheral physiological systems during exercise in humans," *British Journal of Sports Medicine*, 39, pp. 52–62, 2005.

- [9] N. Marwan, M.C. Romano, M. Thiel, J. Kurths, J. "Recurrence Plots for the Analysis of Complex Systems," *Physics Reports*, 438(5-6), pp. 237–329, 2007.
- [10] N. Marwan, "A historical review of recurrence plot," *The European Physical Journal - Special Topics*, 164 (1), pp. 3–12, 2008.
- [11] K., Najim, E. Ikonen, A. Daoud, *Stochastic processes: Estimation, Optimization and Analysis*. Kogan Page Science, 2004.
- [12] E. Nelson, *Quantum Fluctuations*. Princeton University Press, Princeton, 1985.
- [13] A. Priplata et al, "Noise-Enhanced Balance Control in Patients with Diabetes and Patients with Stroke," *Ann Neurol*. 2006; 59, pp. 4–12, 2006.
- [14] A. St Clair Gibson, T.D. Noakes, "Evidence for complex system integration and dynamic neural regulation of skeletal muscle recruitment during exercise in humans," *B J Sports Med*, 38, 797–806, 2004.
- [15] A. St Clair Gibson, J.H. Goedecke, Y.X. Harley, L.J. Myers, M.I. Lambert, T.D. Noakes, E.V. Lambert, "Metabolic setpoint control mechanisms in different physiological systems at rest and during exercise," *J Theo Bio*, 235, 60–72, 2005.
- [16] L.L. Trulla, A. Giuliani, J.P. Zbilut, Jr. C.L. Webber., Recurrence quantification analysis of the logistic equation with transients. *Physics Letters, A* 223, pp. 255 – 260, 1996.
- [17] R. Tucker, A. Bester, V.E. Lambert, T.D. Noakes, C.L. Vaughan, A. St Clair Gibson, "A. Non-random fluctuations in power output during self-paced exercise," *British Journal of Sports Medicine*, 40, 912–917, 2006.
- [18] H-V. Ulmer, "Concept of an extracellular regulation of muscular metabolic rate during heavy exercise in humans by psychophysiological feedback". *Experimentia*, 52, 416–20, 1996.
- [19] Jr. C. L. Webber, J.P. Zbilut, "Dynamical assessment of physiological systems and states using recurrence plot strategies," *J. Appl. Physiol.*, 76, 965–973, 1994.
- [20] Jr. C. L. Webber, J.P. Zbilut, "Assessing deterministic structures in physiological systems using recurrence plot strategies," In M.C.K. Khoo (Ed.), *Bioengineering Approaches to Pulmonary Physiology and Medicine*, New York: Plenum Press, 137–148, 1996.
- [21] J.P. Zbilut, M. Zak, Jr. C.L. Webber, "Nondeterministic chaos in physiological systems," *Chaos, Solutions, and Fractals*, 5, 1509–1516, 1995.

Author Profiles



Dr. Dineshen Chuckravanen received the BEng and M.Sc degrees in Electronic and Communications Engineering from University of Mauritius and University of Plymouth, United Kingdom respectively. He also received his Ph.D in Multiple System Modelling and Analysis of Physiological and Brain Activity at Rest and During Exercise at the University of Northumbria, Newcastle in 2012. He continues to investigate the physiological control mechanisms to elucidate the underlying human behavior subjected to physical activities.



Mr. Andre Bester obtained his M-Eng. in electronics from the University of Stellenbosch, South Africa in 1984. He joined the Council for Industrial and Scientific Research in the same year where he spent the next ten years doing research and development in sensor systems, managing projects and advising the divisional director on technology strategy. He then started his own business which did development of data acquisition instrumentation and software for the agricultural, defense and marine industries.